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Induction Motor Fault Diagnosis Using Variance Computation and Wavelet Transform

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Abstract :
The aim of this paper is to present a wavelet-based method for broken rotor bar fault detection in induction machines combined with variance computation. The frequency-domain methods which are commonly used need speed information or accurate slip estimation for frequency components localization in any spectrum. Nevertheless, the fault frequency bandwidth can be well defined for any induction machine due to numerous previous investigations. The proposed approach consists in the variance evaluation of this known bandwidth with time-domain analysis using the discrete wavelet transform (DWT). Furthermore, experimental results show this is truly an excellent approach for the detection of the broken rotor bars in squirrel-cage induction motors.

I. INTRODUCTION

The squirrel cage induction motors are one of the most used motors in the industry. They almost consume 60% of all generated electric power. Almost 70% of consumed electrical energy in manufacturing and 90% in process industries. Hence, fault detection of induction machines is one of the aspects where the industry most concentrates its efforts, especially after the entrance of low-cost induction motors in the market. Squirrel cage induction motors are usually recognized as robust machines in industry. However, due to the fact that low-cost machines are usually designed around the critical area of material characteristics, security margins disappear and the probability of fault increases [1]-[4]. It is unavoidable to research fault feature of the induction machines and improve the fault detection systems which can diagnose the typical faults of induction motors effectively.

It is estimated that about 40% of the induction motor failures are caused by bearing faults, 40% by stator faults, 10% by rotor faults, and 10% by other faults. It is necessary to understand that bearing failures are often result of increased vibration and shaft current, which are usually caused by rotor eccentricity, shaft misalignment or other rotor related faults. Besides, rotor faults can also lead to, reduced insulation life, decreased efficiency, excess heat and iron core damage. Therefore, early detection of induction machines rotor faults can help to avoid more severe motor faults [3]-[5].

In recent years, there is importance progress in the field of the fault analysis and maintenance of induction machines, with the extension of computer techniques, control techniques, and advance intelligence algorithms. Many methods of fault detection are proposed, such as the knowledge based method, the analytical model method and the signal processing method. The knowledge based method uses the interrelated information of objects diagnosed and the exact mathematics model of the system is not needed in knowledge based method. The precise mathematics model of object diagnosed is needed in the analytical model, including the state estimation, the parameter estimation, the equivalence space, etc. In the analytical model method the rigor diagnosis condition is required and this method has lots of limitation. The signal model is directly used in the signal processing method for the analysis of linear or non-linear systems, avoiding the difficulty of extracting mathematics models of objects. Signal processing method makes the spectral frequency analysis of the electric machines stator current [2], [6], [7].

The waveforms associated with electromagnetic transients are usually non-periodic signals which contain both high-frequency oscillations and localized impulses superimposed on the main frequency and its harmonics. Traditional discrete Fourier transform (DFT) is not suitable for this kind of waveforms because a periodic signal is assumed in DFT calculations and power system disturbances are subject to transient and non-periodic components. The entire frequency spectrum can be affected if a signal is altered in a localized time instant [1].

The multiple-signal-classification method with an algorithm to zoom on a specific frequency range is proposed to overcome this drawback and for extraction of the meaningful frequencies from the signal. However, this method has only been implemented on stationary signals. Wavelet analysis is a new branch of mathematics since the late of 1980s. Wavelet transform technique provides a powerful tool for the field of fault detection. Wavelet transformation is both time-frequency analysis, and time scale analysis, with the multiresolution characteristic. It can detect partial feature of the signal in both time and frequency domain [2]-[7]. Induction motor is modelled and rotor broken bars fault is detected experimentally using park transform by k.ahmadian and A.Jalilian [8]. In [9] variance of wavelet coefficients energy in different areas is used to detect broken rotor bars by H.Sadri and A.Jalilian.

The objective of this paper is to present a wavelet-based method for broken rotor bar fault detection in induction machines combined with variance computation. The remainder of this paper is organized as follows.

Section II describes the most common faults in induction motors (IM) and their diagnosis using classical MCSA. A brief review of wavelet transform and proposed detection method is presented in section III, in section IV experimental result obtained by FFT calculation and wavelet transform are presented and compared and finally the summary and conclusions drawn from this study are presented in Section V.

II. SPECTRUM ANALYSIS OF STATOR CURRENT

The rotating magnetic field induces rotor voltages and currents at slip frequency, and an effective three phase magnetic field is

produced by these induced currents at slip frequency with regard to the rotor.
Two different cases can be appeared.

1) Symmetrical cage winding → only forward-rotating field
2) Asymmetric rotor → a backward-rotating field with respect to the rotor will result at slip frequency.

A voltage will be induced in the stator three phases by this backward-rotating field at the corresponding frequency and a related current which alters the stator-current frequency spectra also appears. Different faults will result in different rotating fields in squirrel cage machines, such as broken rotor bars, air-gap eccentricity, stator-windings short circuits and bearing damage.
The current frequencies associated with the rotating fields are expressed by (1), (2), (3), and (4).

1) Air-gap-eccentricity associated frequencies.

$$f_{ecc} = f_s\left[1+m\left(\frac{1-s}{p}\right)\right] \quad (1)$$

where m = 1, 2, 3 . . . is a positive integer number, s is the per-unit slip, p is the number of pole pairs and f_s is the electrical supply frequency associated frequencies.

2) Broken rotor bars.

$$f_{bdb} = f_s\left[l\left(\frac{1-s}{p}\right)\pm s\right] \quad (2)$$

where $\frac{l}{p}$ = 1, 5, 7, 11, 13 . . . are characteristic values of the induction machine.

3) Bearing damage associated frequencies.

$$f_{bng} = \left|f_s \pm f_{i,o}\right|$$

$$f_{i,o} = \frac{n_b}{2} f_r\left[1\pm\frac{b_d}{p_d}\cos\beta\right] \quad (3)$$

where n_b is the number of bearing balls, $f_{i,o}$ are the characteristic vibration frequencies, b_d is the ball diameter, p_d is the bearing pitch diameter, f_r is the mechanical rotor speed in hertz and β is the contact angle of the balls on the races.

4) Shorted turns associated frequencies.

$$f_{sth} = f_s\left[1+mZ_2\left(\frac{1-S}{P}\right)\right] \quad \text{d.1) medium frequencies}$$

$$f_{stl} = f_s\left[\frac{m}{p}(1-s)\pm k\right] \quad \text{d.2) medium frequencies}$$

(4)

where z_2 is the number of rotor bars or rotor slots, and k = 0, 1, 3, 5 . . . [3].

III. WAVELET TRANSFORM AND PROPOSED METHOD

The wavelet transform [WT] is a powerful tool in the field of power systems signal processing [1]. It has the advantage of flexibility in describing nonstationary signals which is an important advantage for variable load applications and power quality problems. Similarly, wavelet transform is the breaking up of a signal into shifted and scaled versions of the source (or mother) wavelet. There are many different wavelets.
The wavelet transform is divided in to two main categories, continuous wavelet transform and discrete wavelet transform [4]. In wavelet transformation, the analyzing wavelet functions will adjust their time-widths to their frequencies in such a way that lower frequency wavelets will be very broad and higher frequency ones will be narrower. Therefore, transient components of the signal in the upper frequency witch is isolated in a shorter part of power frequency cycle can be detected. The ability of WT to concentrate on long time intervals for low frequency components and short time intervals for high-frequency components leads to better evaluation of the signals with localized transients [1].

A. Continuous Wavelet Transform

Wavelet transform has the ability of performing through a multi-resolution analysis (MRA), several overlapped projections of a signal. For a signal *f (t),* the generating function of the MRA can be expressed as

$$\varphi_k^j = 2^{-j/2}\varphi\left(2^{-j}t-k\right) \tag{5}$$

where, φ is the so-called mother wavelet; *k* is the time shift factor, and *j* indicates the decomposition level. The wavelet coefficients obtained by applying an orthogonal wavelet can be expressed as

$$d_k^j = \int_{-\infty}^{\infty} f(t)\psi_k^j(t)dt \tag{6}$$

where, ψ_k^j is the wavelet analyzing function. For instance, Shannon, Morlet, Debauche, Haar, etc, could be used. During the transformation process, the mother wavelet is shifted and scaled contiguously and the correlation of the examined signal and the mother wavelet produces the wavelet coefficients.

B. Discrete Wavelet Transform

In discrete wavelet transform, the mother wavelet is scaled in the power of 2. Therefore, it is a good choice for implementation in digital computers.

Assume *S* is a discrete-time signal to be decomposed using the discrete wavelet analysis into its approximate and detailed versions. In the first decomposition level, the coefficients are cA_1 and cD_1 *;* where, cD_1 is the detailed representation of *S*, and cA_1 is the approximate version of *S*. cA_1 and cD_1 are expressed as

$$cA_1 = \sum_k^n L(k-2n)S(k) \tag{7}$$

$$cD_1 = \sum_k^n H(k-2n)S(k) \tag{8}$$

where, *L* and *H* are the decomposition filters of *S(n)* in $cA_1$and cD_1, respectively. The base of the second decomposition level is cA_1 and the coefficients can be expressed as

$$cA_2 = \sum_k^n L(k-2n)cA_1(k) \tag{9}$$

$$cD_2 = \sum_k^n H(k-2n)cA_1(k) \tag{10}$$

Computation of the higher-level decompositions has a similar way. Hence, it can be seen that cA_1 is the approximate version of the original signal *S*. *L* behaves as a low-pass filter. If cD_1 contains only high frequency components of signal *S*, then *H* will behave as a high-pass filter. After the decomposition process, the original signal can be reconstructed again.

This recursive process can be expressed as

$$S' = A_n + D_n + D_{(n-1)} + \ldots\ldots D_2 + D_1 \tag{11}$$

and if the detail and approximation coefficients are not modified before the reconstruction process then *S'* will be equal to *S*. Fig. 1 shows frequency distribution up to 3 levels of decomposition [4].

In Fig. 2 the implementation procedure of a discrete wavelet transform is depicted. In this picture s is the original signa, 2↓ denotes a down sampling by a factor of 2, and LPF and HPF are the low-pass and high-pass frequency filters respectively.

The original signal is divided into tow halves of the frequency bandwidth at the first stage and sent to both LPF and HPF. The same procedure will be repeated and the output of the LPF will be further cut into half of the frequency bandwidth, and will form the input of the second level.

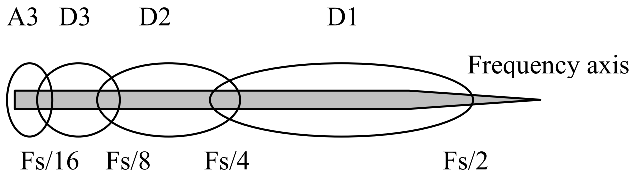

Fig.1 frequency distribution of a third level decomposition

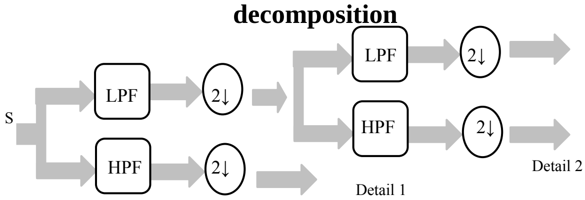

Fig. 2 implementation of discrete wavelet transforms

This procedure is repeated until the signal is decomposed to the desired level. From Nyquist's theorem, if the sampling rate of the original signal is f_s Hz, the highest frequency that the original signal could contain, would be $f_s/2$ Hz. This frequency can be obtained at the output of the high frequency filter (first detail). Thus, the band of frequencies between $f_s/2$ and $f_s/4$ would be captured in detail 1; similarly, the band of frequencies between $f_s/4$ and $f_s/8$ would be captured in detail 2, and so on [1].

The sampling frequency in experimental test is adjusted to be 1000 Hz and Table I shows the frequency levels of the wavelet function coefficients. Daubechies-8 and Daubechies-12 wavelet are used in this paper as mother wavelet. The efficiency of Daubechies wavelets based on the accurate reconstruction of power system transient signals and the suitability of this family for the analysis of power system transients is the basis for choosing Daubechies-8 and Daubechies-12 [1].

As it can be seen from (2), frequency of goal harmonics for detection of broken rotor bar faults are $f_s[(1-s)\pm s]$, $f_s[5(1-s)\pm s]$, etc.

TABLE I. frequency levels of wavelet coefficients

Wavelet analysis	Frequency components Hz
D1	500 - 250
D2	250 - 125
D3	125 - 62.5
D4	62.5 - 31.2
A4	31.2 - 0

Supply frequency of the test set is 50 Hz so the frequency band of 30 Hz to 60 Hz is a good choice for detection of broken rotor bar fault. In this paper, relative Variance value of the correspondent detail to the mentioned frequency band is used as a diagnosis parameter. Relative Variance value can be expressed as:

(detail coefficients variance) / (signal variance) (12)

Where variance of each parameter can be determined by

$$s = \frac{1}{n-1}\sum_{i=1}^{n}\left(x_i - \bar{x}\right)^2 \qquad (13)$$

IV. EXPERIMENTAL RESULTS

Experiments on a three-phase 1.5-hp 380-V 50-Hz induction motor are carried out for normal and faulty conditions (two, three, four and five broken rotor bars). The rated speed of the induction motor is 1445 r/min. The induction motor is run around full-load condition, and the terminal voltages are sinusoidal.

Fig. 3 shows the block diagram of the experimental setup used for the tests and Fig. 4 shows the photograph.

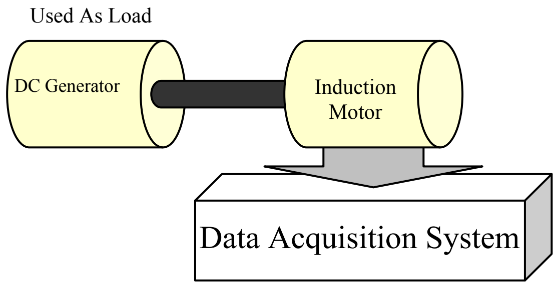

Fig 3. Block diagram of experimental setup

Fig. 4. Experimental Test setup: Motor-Generator System (Right) and data acquisition system (left) [8]

In Fig. 5 and Fig. 6 healthy and damaged motor spectra are shown. As it can be seen, frequency amplitudes of the selected frequency band (100 Hz to 260 Hz) are greater in the case of faulty motor but the frequency components are not clearly visible in the spectrum. Relative variance of the correspondent detail to the mentioned frequency band is a good choice for the detection of broken rotor bars in induction motor. Fig. 7 shows the variation of the proposed parameter for healthy and faulty motor.
The experimental results show the validity of the proposed approach to successfully classify healthy and faulty motors with high percentage of accuracy.

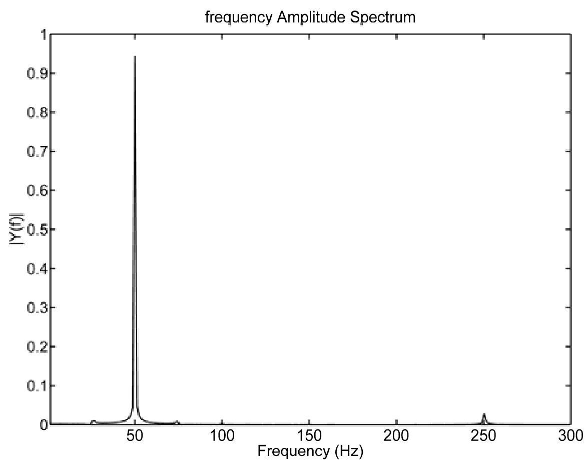

Fig 5. Frequency spectra of healthy motor

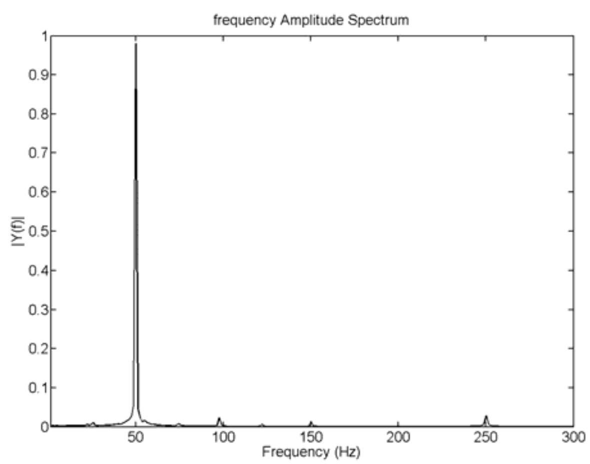

Fig 6. Frequency spectra of a motor with two broken rotor bars

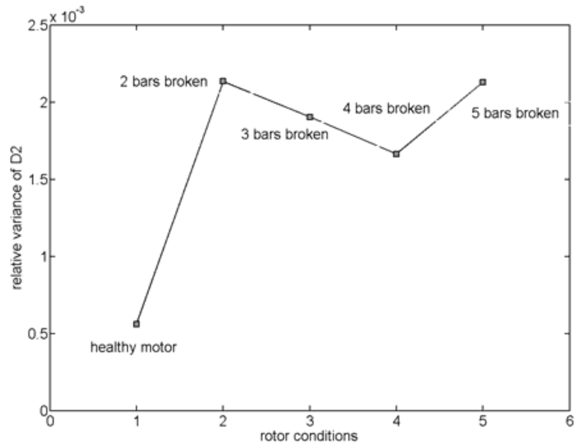

Fig 7. Variation of relative detail variance for different conditions of motor

V. CONCLUSION

In this paper, the development and testing of a signal processing-based fault detection methodology for the detection of induction-motor broken rotor fault based on variance computation and wavelet analysis of the stator current is presented.
For demonstrating its efficiency, the fault detection and diagnosis method is tested on a 1.5-hp induction motor. The experiments performed and the results obtained show that wavelet analysis in combination with variance computation is able to detect the faulty conditions with high accuracy. Furthermore, the method allows an easy implementation for further expert systems.

VI. REFFRENCES

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