Diagnosis of Induction Motor Faults due to Broken Rotor bar and Rotor Mass Unbalance through Discrete Wavelet Transform of Starting Current at No-Load

The present paper proposes a method of diagnosis of faults of an induction motor due to broken-bar and mass-unbalance rotor through analysis of its no-load starting current. Starting current is analyzed by discrete wavelet transform (DWT). The discrete wavelet coefficients are processed to determine the spectral energy for different spectral frequency bands containing the harmonics due to fault and statistical parameters of detail coefficients are calculated for different levels of wavelet for faulty and healthy motors. The parameters are used successfully for detection of fault in a motor. Advantage of this method is that it requires less computational time and less processing power. Also motor starting current being higher than the steady state current, this method does not require running the motor at load to obtain higher magnitude of current for better analysis. This method has been validated in a laboratory prototype.

Keywords: Broken rotor-bar, Discrete Wavelet Transform, Induction motor, Motor Current Signature Analysis (MCSA), Rotor mass-unbalance.

1. Nomenclature

- \( x(t) \) the current signal
- \( \psi(t) \) the mother wavelet
- \( a \) and \( b \) real denotes the wavelet scale and position
- \( f_s \) sampling frequency
- \( 2^n \) number of data points in the signal.
- \( m \) decomposition level
- \( f \) higher frequency limit of the frequency band/supply frequency.
- \( N \) total number of samples in the signal
- \( x(n) \) time domain discrete signal

\[
\sum_{n=1}^{N} |x(n)|^2 \quad \text{total wave energy of the signal } x(n)
\]

\[
\sum_{n=1}^{N} |a_j(n)|^2 \quad \text{total energy concentrated in the level “j” of the approximated version of the signal.}
\]

\[
\sum_{j=1}^{m} \sum_{n=1}^{N} |d_j(n)|^2 \quad \text{total energy concentrated in the detail version of the signal, from level 1 to } m.
\]

- \( s \) slip
- \( k \) an integer equal to1,2,3,4,………..
- \( P \) the number of pole pairs
- \( N_r \) the number of rotor slot (bars)

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2. Introduction

Induction motors being robust, low cost, very efficient and reliable in operation are widely used as electrical drives in industrial processes. They are used in such a bulk volumes and quantities that about 60% of the total electrical energy produced are consumed by these induction motors. Hence the main aspect of the users is to make the induction motors failure proof to reduce the down time of the industries. And to do so early detection of motor faults is highly desirable which requires condition based monitoring (CBM) of the induction motor. This CBM provides useful information continuously to the operator, maintainer and designer regarding health of the system. By early detection of faults any catastrophic damage or any potentially dangerous situation can be avoided.

There are various types of faults in the induction motor both internal and external. Internal faults like unbalanced rotor occur mainly due to manufacturing defect, if not, even may occur after an extended period of operation, for non-symmetrical addition or subtraction of mass around the center of rotation of rotor or due to internal misalignment or shaft bending due to which the centre of gravity of the rotor does not coincide with the center of rotation. Mass unbalance rotor fault may be of different type: (i) couple unbalance, as shown in Fig.1, where shaft rotational axis and weight distribution axis of rotor intersect at the centre of the rotor, (ii) static unbalance, as shown in Fig.2, where shaft rotational axis and weight distribution axis of rotor are parallel but offset, (iii) dynamic unbalance, where shaft rotational axis and weight distribution axis of rotor don’t coincide, as shown in Fig.3, is the combination of coupling unbalance and static unbalance.

![Fig. 1: Couple unbalanced rotor](image-url)
Even though motor failure can be detected mainly by means of mechanical vibration analysis [1],[2], various detection methods, including detection by acoustic diagnostic technique [3], by measurement of air gap fluxes [4], have been proposed by many researchers in their different works. But all these detection methods require transducers, to be fitted in or around the machine, which interrupt the operation [5]. For this reason, due to its easy availability, stator current has become a practical parameter for detecting rotor faults of squirrel cage induction motor.

There has been ample research works on the fault detection technique using MCSA [6]-[16]. Out of these maximum works are performed on the current signature while the motor is running in the steady-state condition under full load or near to full load [6]-[9] using Fast Fourier Transform (FFT). But in FFT analysis averaging of spectrum during sampling time may introduce some errors. For these difficulties new technique was developed based on the analysis of transient signals such as starting current [10], shut down voltage [17] and startup vibration transient [18]. Nowadays, due to advancement of signal processing technique, analysis of starting current transient through wavelet transform is widely used in detection of motor faults. Advantages of this technique are: (i) during direct-on-line (DOL) starting, the rotor current is 7-10 times the steady-state current and this avoids the requirement to run the motor at full-load for obtaining high magnitude of current for better analysis, (ii) magnitude of starting current is less sensitive to load [10] hence for analysis purpose motor current signature can be captured even when the motor is under no-load or light-load, (iii) it can be applied when a new motor is being tested prior to delivery or the motor has been removed from the service for maintenance. Disadvantage of this starting transient current analysis is that during starting period, due to accelerating condition of the
motor both the amplitude and frequency of the current varies. For this reason, analysis of transient current signal in frequency domain or time domain alone is not sufficient to extract the features. To overcome this problem, wavelet transform technique is used. It provides a local representation of non-stationary signals in both time and frequency, and uses wavelet-coefficients (detail and approximate) to distinguish between healthy and faulty motors. The wavelet technique uses variable sized window and higher frequency resolution for which it overcomes the limitation of short time Fourier Transform.

A number of research works [10]-[13] have been done based on wavelet transform to detect motor fault by analyzing motor current signature of which some uses starting current to detect motor fault based on wavelet technique. For a non-stationary signal, it is better to calculate the energy over an envelope for different frequency bands rather than one specific harmonic. To calculate the energy, Parseval’s theorem is used. Combination of wavelet transforms and energy calculation of the envelope will provide good results.

It is also observed that some researcher look into the prospect of using higher order harmonics for rotor asymmetry fault detection, order greater than P which are induced in the stator current as given in (5). This is especially useful, when load fluctuation or any external cause making torque or speed oscillation, induce similar harmonics to those side harmonics which makes diagnosis confusing. The wavelet transform takes into account these higher order harmonics by considering the lower wavelet level frequency bands.

In the present paper, the starting current is taken as the signal for motor fault analysis. It has been recorded by a data acquisition system, for three different motors, first one being a healthy motor, second one with rotor mass unbalance and the third one with broken rotor-bar – all of same rating. These current envelopes and the corresponding data have been analyzed using DWT. The wavelet “db10”, from Daubechies family, is used as mother wavelet. To get more prominent difference between healthy and faulty motors wavelet coefficients are further processed to calculate wave energy. Results exhibit remarkable difference between a healthy and a faulty motor.

3. Theoretical Background

3.1 Wavelet transform: Wavelet transform is a time-frequency analysis technique. The unique property of the wavelet transform that keeps intact the time and frequency information is very important during transient analysis. It decomposes a signal in both time and frequency in terms of a wavelet, called mother wavelet. The wavelet transform is governed by the equation (1)

\[ C(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} x(t) \psi\left(\frac{t-b}{a}\right) dt \]  

where, \(x(t)\) is the signal, \(a\) and \(b\) being real denotes the wavelet scale and position, \(\psi(t)\) is the wavelet. A high scale wavelet corresponds to a low frequency stretched wavelet and low scale wavelet corresponds to a high frequency compressed wavelet. To analyze the induction motor starting current two types of wavelet transform, the discrete wavelet transform (DWT) and the continuous wavelet transform (CWT) can be used.

The DWT uses a specific subset of scale \(a\) and positional values \(b\) but CWT operates over every possible scale and position. DWT is less computationally complex taking less
computational time, compared to the CWT [19]. Generally DWT is used for data compression if signal is already sampled and CWT for signal analysis.

The DWT is computed by passing the signal successively through low pass and high pass filters. A signal can be approximated by DWT with different scales. Each step of the decomposition of the signal corresponds to a certain resolution. The Fig.4 shows typical two-level wave decomposition. Here HPF and LPF are high pass filter and low pass filter respectively. At each level of scaling and for various positions, the correlation between the signal and the wavelet are called wavelet coefficients. The high pass filter coefficients are termed as detail coefficients (CD) and the low pass filter coefficients are termed as approximate coefficients (CA).

![Wave decomposition up to 2nd level](image)

Each of the wavelet scales corresponds to a frequency band given in (2) [20]

\[ f = \frac{2^{m-n} f_s}{2^n} \]  

(2)

where, \( f \) is higher frequency limit of the frequency band represented by decomposition level \( m \), \( f_s \) is sampling frequency and \( 2^n \) is the number of data points in the signal.

The high frequency band extends from half the Nyquist frequency to Nyquist frequency, while low frequency band extends from DC to half the Nyquist frequency where Nyquist frequency is given as \( f_s/2 \).

The first decomposition level is known as analysis level 1 and the corresponding coefficients are approximate CA1 and detailed CD1. Further decomposition of CA1 gives CA2 and CD2 at level 2 and the process continues. After decomposition of the signal, one can reconstruct and examine the constituent components of the original signal at each detail level. The spectral frequency bands of the detailed coefficient at different decomposition level is shown in Table 1.
3.2 Energy calculation: The transient starting current being non-stationary its energy is calculated by Parseval’s theorem. In mathematics this theorem refers to the result that the sum of the square of a function is equal to the sum of the square of its transform. Now using wavelet coefficient the Parseval’s theorem can be stated as “the energy that a time domain function contains is equal to the sum of all energy concentrated in the different decomposition levels of the corresponding wavelet transformed signal”. This can be mathematically expressed in (3) [13]

\[
\sum_{n=1}^{N} |x(n)|^2 = \sum_{n=1}^{N} |a_j(n)|^2 + \sum_{j=1}^{m} \sum_{n=1}^{N} |d_j(n)|^2
\]  

(3)

where \(x(n)\) is time domain discrete signal, \(N\) is total number of samples in the signal, \(\sum_{n=1}^{N} |x(n)|^2\) is total wave energy of the signal \(x(n)\), \(\sum_{n=1}^{N} |a_j(n)|^2\) is total energy concentrated in the level “\(j\)” of the approximated version of the signal, \(\sum_{j=1}^{m} \sum_{n=1}^{N} |d_j(n)|^2\) is total energy concentrated in the detail version of the signal, from level 1 to \(m\) and \(m\) is the maximum level of wavelet decomposition.

3.3 Induction motor models: Induction motor models under normal and abnormal conditions have been developed by many researchers. Models for broken rotor bar [21],[22],[23]and dynamic eccentricity due to mass unbalance [24],[25]are developed using the concepts of magnetically coupled circuit theory between stator coils and rotor loops formed by rotor bars with end rings, and winding function approach for calculation of inductances under the following assumptions.

- negligible saturation of magnetic field
- identical stator windings with symmetric axes
- identical rotor windings/bars with symmetric axes and bars are insulated from each other
- negligible losses of eddy current, friction and windings
3.3.1 Model for Broken Rotor Bar Motor: In the models [21],[22],[23] for broken bar motor, due to changes in the rotor circuit resistances along with the changes in the self inductances of the rotor circuit and mutual inductances between the stator and rotor loops, the air gap flux distribution changes. The space distribution of mutual inductances between the stator and rotor loops is non-sinusoidal resulting space harmonics. The non-sinusoidal backward magnetic field [11], [15], [16], [26] from the rotor interact with the stator forward field produces side band harmonics given by equations (4) along with space harmonics known as rotor slot harmonics [27] due to non sinusoidal distribution of mutual inductances given by equation (5)

\[ f_{bb} = f (1 \pm 2ks) \]  

\[ f_{bb} = (\lambda \frac{N_r}{P}(1-s) \pm 1 \pm 2ks)f \]  

where \(P\) is the number of pole pairs and \(s\) is the slip, \(f\) is supply frequency, \(N_r\) is the number of rotor slot (bars) and \(\lambda\) is a positive integer.

3.3.2 Model for Mass Unbalance Rotor Motor: This accounts on the rotor eccentricity caused by unbalanced force. The rotor having mass unbalance develops the centrifugal force which increases with speed, resulting increase in the dynamic eccentricity. This unbalance force tries to pull it further away from stator bore centre, resulting variation of the air gap which generates excessive vibration on the rotor and rotor bearing.

As the air gap continuously changes, causing changes in the dynamic eccentricity, the air gap length is given by (6) [28]

\[ g(\theta ) = g_0(1 - \rho \cos \theta ) \]  

where \(\rho\) is the degree of eccentricity \(\rho < (0,1)\), \(g_0\) is the radial air gap length in case of uniform air gap, to avoid rotor rub \(\rho < 1\), \(\theta\) is the rotor position.

Although for healthy condition of the motor mutual inductances between the stator and rotor loops, are symmetrical, during rotor mass unbalance condition the distribution of mutual inductances between the stator and rotor loops become non-sinusoidal which induces harmonics in the stator current same as given by (5)

On the basis of the above background experimental studies have been carried out on a laboratory prototype to discriminate between healthy and faulty motors having broken rotor bar and rotor mass unbalance. This has been achieved by analyzing the motor starting current through discrete wavelet transform.

4. Experimentation

4.1 Block Diagram: The block diagram is shown in Fig. 5a. 3ph, 110V, 50Hz, supply is provided to the three induction motors of same rating one healthy, one with mass unbalanced rotor and the other one with three number broken rotor-bars, last two being intentionally made, faulty motors. The motors are run by direct-on-line supply.
4.2 Experimental Setup: Experiment was carried out on test-rig built by Spectra Quest, USA, having a high-speed data acquisition system (OROS OR35, 8 channels, 100 mbps). Ratings of the induction motors are 3ph, 1/3HP, 190V, 50Hz, and 2980rpm. For capturing current signature, Hall Probe (LEM PR30 ACV 600V CATIII 30Ampac/3Vac) is used. The experimental set up is shown in Fig. 5b. Transient current envelope has been captured with a sample frequency of 5120 Hz.

Fig.5a: Block diagram of the experiment

Fig.5b: Experimental Setup
5. Results and Discussion

For lower order Daubechies wavelets, the scaling function and wavelet function are discontinuous for which no considerable difference between the healthy and faulty conditions are obtained. To avoid ambiguous diagnosis, Daubechies wavelet of the order of at least 8, which have higher smoothness, should be used [29]. In this paper, “db10”, from Daubechies family, is used for analysis purpose. Experiment has been carried out with the motors having same ratings as given in the experimental Setup above, following the connection as shown in the Fig 5a.

On the captured data, DWT is performed up to decomposition level 8, using mother wavelet “db10” of Daubechies family. After decomposition of the signal into detail and approximation coefficients, signal was reconstructed using MATLAB to examine the constituent components of the original signal at each detail level. Figs. 6, 7 and 8 show the wavelet decomposition details of the reconstructed signals, up to level eight along with final approximation level for the healthy and two faulty motors respectively.

Fig.6: Wavelet decomposition details of the reconstructed signals for healthy motor
Fig. 7: Wavelet decomposition details of the reconstructed signals for motor with mass unbalance rotor

Fig. 8: Wavelet decomposition details of the reconstructed signals for broken rotor-bar motor
Wave energy has been calculated using (5) up to wavelet level 8. Values of the energies at different levels calculated from the right hand side of (5) are shown in Table 2 and the corresponding graph is shown in Fig. 9. Wave energy calculated from the left hand side of (5) is given in Table 3. Fig.10 shows the percentage error in calculation of wave energy at different levels of DWT. From this experiment, it is observed that in the 4th, 5th and 6th decomposition levels, shown in Table 4, motor having mass-unbalance-rotor has large reconstructed detail coefficients than the healthy motor whereas broken-bar-rotor motor has less reconstructed detail coefficients. In energy level analysis, motor having mass-unbalance rotor consumes more energy whereas broken rotor bar motor consumes less energy than the healthy motor. These variations of statistical parameters of wavelet coefficients and values of energy at different wavelet levels are used as detection of motor fault. Frequency band corresponding to wavelet level 6 indicates the presence of side band harmonics close to supply frequency whereas frequency bands corresponding to level 4, and level 5 contain higher order harmonics including space harmonics.

![Graph showing total energy of transient starting current envelope of different motors using Parseval’s theorem](image)
Table 2: Energies (joules) at different levels using Parseval’s theorem

| Wavelet level | Approximate energy at level j = $\sum_{n=1}^{N} |\psi_j(n)|^2$ | Detail energy at level j = $\sum_{n=1}^{N} |\phi_j(n)|^2$ | Total energy = $\sum_{n=1}^{N} |\phi_j(n)|^2 + \sum_{j=1}^{m} \sum_{n=1}^{N} |\phi_j(n)|^2$ |
|---------------|------------------------------------------------|------------------------------------------------|--------------------------------------------------|
| Motor Condition | Healthy | MUBM | BRB | Healthy | MUBM | BRB | Healthy | MUBM | BRB | Healthy | MUBM | BRB |
| 1              | 32.6935  | 34.0489 | 29.491 | 8.4e-06 | 1.1e-05 | 1.9e-05 | 32.6925  | 34.0489 | 29.491 |
| 2              | 32.6930  | 34.0481 | 29.490 | 5.1e-04 | 4.3e-04 | 3.6e-04 | 32.6935  | 34.0489 | 29.491 |
| 3              | 32.6844  | 34.0386 | 29.483 | 0.0087  | 0.0099  | 0.0075  | 32.6935  | 34.0489 | 29.491 |
| 4              | 32.6511  | 33.9943 | 29.454 | 0.0336  | 0.0441  | 0.0288  | 32.6938  | 34.0487 | 29.491 |
| 5              | 32.5056  | 33.7641 | 29.318 | 0.1444  | 0.2018  | 0.1286  | 32.6927  | 34.0210 | 29.483 |
| 6              | 24.160   | 1.4969  | 1.986  | 29.890  | 32.1508 | 27.042  | 32.4931  | 33.9039 | 29.192 |
| 7              | 0.0532   | 0.0949  | 0.071  | 2.3703  | 1.4102  | 1.9306  | 32.5028  | 33.9121 | 29.208 |
| 8              | 0.0381   | 0.0354  | 0.042  | 0.0182  | 0.045   | 0.0785  | 32.5210  | 33.9571 | 29.287 |

Legend: MUBM = Mass unbalance rotor motor, BRB = broken rotor-bar motor

Table 3: Wave Energy of the Starting Current Envelope

<table>
<thead>
<tr>
<th>Motor Condition</th>
<th>Healthy</th>
<th>Mass unbalance Rotor motor</th>
<th>Broken-bar rotor motor</th>
</tr>
</thead>
<tbody>
<tr>
<td>Energy (Joules)</td>
<td>32.6935</td>
<td>34.0489</td>
<td>29.4907</td>
</tr>
</tbody>
</table>
Table 4: Statistical Data of Discrete Wavelet Transform

<table>
<thead>
<tr>
<th>Wavelet level</th>
<th>Motor Condition</th>
<th>Max</th>
<th>STD</th>
<th>RMS</th>
</tr>
</thead>
<tbody>
<tr>
<td>4</td>
<td>Healthy</td>
<td>1.001</td>
<td>0.1832</td>
<td>0.1832</td>
</tr>
<tr>
<td></td>
<td>Mass unbalance</td>
<td>1.019</td>
<td>0.21</td>
<td>0.2099</td>
</tr>
<tr>
<td></td>
<td>Broken rotor-bar</td>
<td>0.7713</td>
<td>0.1697</td>
<td>0.1696</td>
</tr>
<tr>
<td>5</td>
<td>Healthy</td>
<td>1.686</td>
<td>0.38</td>
<td>0.3799</td>
</tr>
<tr>
<td></td>
<td>Mass unbalance</td>
<td>1.90</td>
<td>0.4493</td>
<td>0.4493</td>
</tr>
<tr>
<td></td>
<td>Broken rotor-bar</td>
<td>1.328</td>
<td>0.3586</td>
<td>0.3586</td>
</tr>
<tr>
<td>6</td>
<td>Healthy</td>
<td>11.38</td>
<td>5.468</td>
<td>5.4672</td>
</tr>
<tr>
<td></td>
<td>Mass unbalance</td>
<td>11.94</td>
<td>5.671</td>
<td>5.6702</td>
</tr>
<tr>
<td></td>
<td>Broken rotor-bar</td>
<td>11.43</td>
<td>5.201</td>
<td>5.2002</td>
</tr>
</tbody>
</table>

Fig.10: Percentage error curve: I for Motor with mass unbalance rotor; II for Healthy motor; III for Motor with broken rotor bar

6. Conclusion

Main contribution of this paper is that the presented method provides a technique to detect the fault in a motor extracting the statistical parameters of DWT coefficients of reconstructed signal at different level corresponding to different spectral bands and estimating the spectral energy without focusing on a particular frequency or harmonic as in the case of absolute FFT of MCSA approach. It is shown here that using DWT, the inherent non-stationary nature of the starting current of a motor can be accurately considered for its fault detection. This method is the right choice for industry because of lesser complexity, computational time and lesser cost. The method may be extended to other faults due to asymmetry of rotor and bearing fault.
References:


