COMPARISION OF DWT & WPT TO DETECT BEARING FAULTS IN 3 PHASE INDUCTION MOTOR USING CURRENT SIGANTURE ANALYSIS

K.K.C.Deekshit*, A.N.Chaitanya Kumar, B.Supraja, M.Sumanth, K.Prudvi Raju, Dr.M.Venu Gopala Rao

Department of Electrical & Electronics Engineering, K L University, Guntur, Andhra Pradesh.

Email*: kkcd10@kluniversity.in

Abstract: *Detection of bearing faults has become a central problem in industry over the past decade. A solution to embark upon this problem is by using a sensor less monitoring. Sensor less monitoring of the induction motors can radically reduce the cost of maintenance by allowing the early detection of faults and this is more predominant than the past conventional methods used. Therefore, in this work bearing fault components are estimated by Motor Current Signature Analysis (MCSA). The convectional FFT analysis has a fervent pace in the area of analyzing the current signature, on the other hand wavelets unambiguously represents the faithful detection and analysis of bearing fault using current signature analysis. In this paper, comparison of Discrete Wavelet Transform (DWT) and Wavelet Packet Decomposition (WPT) is done to detect the nascent stage bearing faults. The experimental results have affirmed the effectiveness of the proposed technique.*

Keywords: *Bearing Fault, Current Signature, DWT, Wavelet Decomposition, WPT.*

1. Introduction:

3- Phase Induction motors are widely used in many industrial applications due to their stalwart structure, low cost, and less maintenance and consumes more than 60% of electrical energy produced [1], [2]. However, these machines require less maintenance, they often faces the mechanical faults due to usage of these machines in critical part of material characteristics and non security margins [2]. If there is insipient damage in motors, and they have been operating for a long time without any sign, entire system including these motors will become more dangerous and may cause serious damage. Therefore, continuous monitoring of these machines is crucial to prevent such fraught consequences [3].

According to published surveys [4], [5], The faults experienced by induction motors can be classified into bearing failures, Stator faults, Rotor faults and other faults. The contribution of these faults in induction motor is summarized in Table 1. Therefore, from above table it is clear that the bearing faults are more repetitive. Conventional monitoring techniques like, noise, vibration analysis, temperature analyses are costly and they are suitable to large motors [6]. Consequently sensor less monitoring like stator current spectral analysis is cost efficient, reliable and provides online monitoring [7]. The challenge, however, in current based monitoring of bearing faults is to extract the fault component from stator current signature. For different types of bearing faults, there will be different fault signatures [8].

Table 1. Percentage of failure by component

Failed Component	Percentage of failures (%)	
	IEEE-IAS	EPRI
Bearings Related	44	41
Windings Related	26	36
Rotor Related	8	9
Others	22	14

Many researchers [9]-[13] have discussed the MCSA using conventional FFT analysis. For a stationary current signal, the frequency resolution and spectral leakage are two main disadvantages of frequency domain analysis [14]. To minimize the spectral leakage, window based FFT (STFT) has been proposed in [15].Frequency domain analysis using STFT is limited by number of data points to get high resolution, which is not always possible [14].Furthermore, the frequency resolution can be improved by many techniques like ZFFT, MUSIC [16]-[18]. However, ZFFT based fault detection in [18] requires long computation time for a large band width signals. For variable loads the motor current behaves as non stationary in nature. As mentioned in [19], [20] the FFT is not suitable for non stationary signals.

Frequency domain analysis by using wavelet transform will overcome all these drawbacks and provides the time-frequency analysis [21]. Wavelet transform is the method of multi resolution technique where analysis of the signal is done by applying appropriate mother wavelet [24]. DWT is the most efficient tool for the time-frequency analysis. DWT provides a platform for the non-stationary signals which has a special property of Multi- resolution [21]-[23]. The basic concept of WPT is to provide discriminative information by decomposing the signal using different resolutions at their respective time-frequency planes [21], [25], [26]. In the DWT the signal is divided into approximated and detailed coefficients depending on the level of decomposition. Instead in WPT the further division takes place in each level of the approximated and the detailed signal.

In this paper the MCSA is carried out using Different signal processing Techniques. Novelty in this is the comparison between DWT and WPT is done in terms of Standard Deviation (SD) and Energy of the Signal to detect both cyclic and non cyclic faults and the best method is proposed.

In this paper the section II deals with the bearing faults and their effect on the stator current and section III deals with the spectral analysis which is useful in detecting the fault. Experimental setup is presented in section IV and the results are discussed in section V.

2. Effect of Bearing Faults:

A. Cyclic Faults:

The cyclic faults are broadly categorized in to outer race faults, inner race faults, cage faults and ball defect. An unrelenting pressure on the bearings cause fatigue collapse, usually at the inner or outer races of the bearings [27]. High bearing temperature is another reason for bearing failure. The bearing temperature rise can be caused by degradation of the grease or the bearing [27]. These faults will produce rough surface between ball and raceway, which generates detectable vibrations and increased noise levels. These vibrating frequencies will impose predictable fault frequencies in to stator current. The characteristic vibrating frequencies generated by these faults are calculated from the below equations [28].

Outer race Fault

The characteristic fault frequency generated by hole or crack on the outer race of the bearing is given by

$$f_o = \frac{N}{2} S \left(1 - \frac{BD}{PD} cos\alpha \right) \tag{1}$$

Inner race Fault

The characteristic fault frequency generated by hole or crack on the inner race of the bearing is given by

$$f_i = \frac{N}{2} S \left(1 + \frac{BD}{PD} cos\alpha \right) \tag{2}$$

Cage Fault

The vibrating fault frequency generated by cage fault is given by

$$f_c = \frac{1}{2} S \left(1 - \frac{BD}{PD} cos\alpha \right) \tag{3}$$

Ball defect

The vibrating fault frequency generated by cage fault is given by

$$f_B = \frac{PD}{2BD} S \left(1 - \frac{BD^2}{PD^2} cos^2\alpha \right) \tag{4}$$

Where f_o=Outer Race Fault Frequency, f_i=Inner Race Fault Frequency, f_c=Cage Fault frequency, f_b=Ball defect fault frequency, S=speed of rotor in RPS, BD= Ball Diameter, PD =Pitch Diameter, N=No. of balls, α= Contact angle.

The cyclic fault will generate detectable vibrations between the ball and race way, which produces disturbances in relative air gap. This non uniform air gap flux will change the flux linkages, which consequently affects the Stator frequency. The change in the stator frequency (F_{BE}) can be predicted by below equation [28].

$$F_{BE} = |f \pm k * F_V| \tag{5}$$

Where f is the supply frequency, k=1, 2, 3… and F_V is the characteristic vibration frequency calculated from the above equations (1)-(4).

B. Non Cyclic Faults:

Non cyclic faults are generalized roughness faults like deformation of seal and corrosion, which are due to deterioration and long usage of the bearing. The frequencies produced by this mode are difficult to predict as they will not produce characteristic fault frequencies [29].

3. Proposed Method:

A. Current Monitoring:

Advanced technology in computerized data processing and acquisition made the possibility for the incipient detection of the bearing fault using MCSA method. The conventional methods like vibration, temperature, chemical methods etc.., were also suitable for the fault detection. However, Stator current monitoring has its own importance as it can identify the fault without any costlier and heavy sensors [30].

In this work the current is sensed by a current transformer and is given to data acquisition system. The digital signal obtained from data acquisition system is processed by signal processing tools in Matlab. The over view of the work is shown in Fig.1.

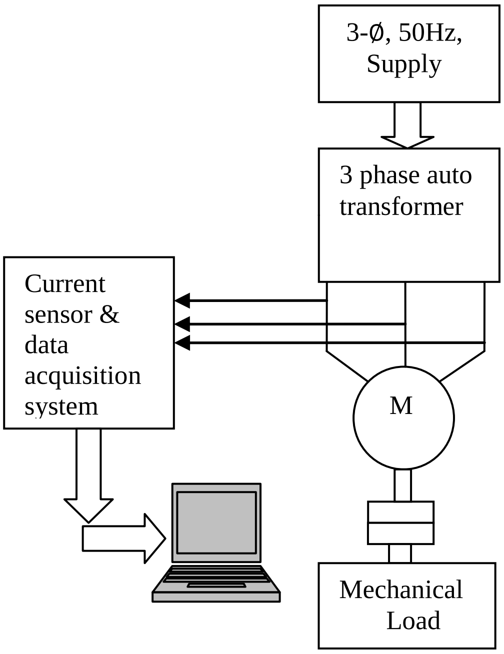

Fig.1. Block diagram

B. Spectral Analysis:

a. *FFT analysis:*

Fourier Transform has provided the good analysis for various real time problems. However, in some critical cases Fourier transform is not only the tool for representing the signal spectrum. For a given signal $x(n)$, the frequency content of averaged over the entire duration of the signal is given by Fourier Transform. Therefore, the information relating to time localization of the frequency content cannot be deduced from $X(w)$.

$$X(w) = \sum_{n=0}^{N-1} x(n)e^{-j\omega n} \qquad (6)$$

In this work FFT is done for the healthy current and faulty current of different bearing faults and they are compared. In some cases if the intensity of the fault is low then it is difficult to identify the impact of the fault.

b. *Wavelet Transform:*

Wavelet Transform provides better analysis as it has a unique advantage of providing a solution for non-stationary signals. The analysis using wavelet transform is easy as the wave is analyzed by making into small pieces. The reconstruction of the wavelet signal is done by the enabling the extraction of features that vary in time. This property makes wavelets an ideal tool for analyzing signals of a transient or non-stationary nature [32].

Discrete Wavelet Transform

DWT analysis is used to analyze time-frequency signal. In this work Daubechies wavelet is taken as mother wavelet function to analyze the current signature. The corresponding wavelet functions are given in below equations.

There exist many wavelet transforms. In this paper the DWT and WPT are considered.

$$\varphi_{j,k}(x) = 2^{-j/2}\varphi(2^{-j}x - k) \qquad (7)$$

Where j is the level of decomposition and k is scaling parameter.

DWT decomposes a signal into approximated and detailed coefficients which represent its low and high frequency components respectively as shown in the Fig.2.

The level of decomposition for the Daubechies wavelet is decided from the equation (8).

$$j = \text{int}\left(\frac{\log(f_s/f\ )}{\log(2)}\right) \qquad (8)$$

In order to satisfy the above equation the upper limit of its associated frequency band must be less than the fundamental frequency [34].

$$2^{-(j+1)}f_s < f \qquad (9)$$

Where f_s is the sampling frequency.

Usually, two additional decomposition levels (i.e. j +2) would be adequate for the analysis

$$j + 2 \quad = \text{int}\left(\frac{\log(1000/50\ )}{\log(2)}\right) + 2 \qquad (10)$$

$$= \quad int(7.46) + 2$$

$$= \quad 9^{th} level$$

In this paper DWT is done using db8, level 9 for the healthy and the fault signals. The comparison is done by calculating their fault indexing parameters.

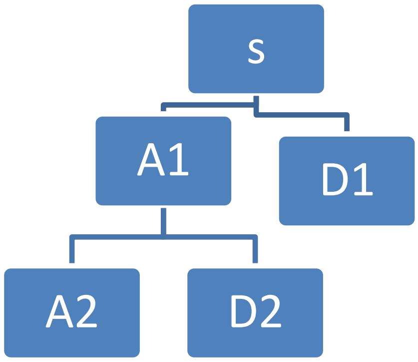

Fig.2. DWT decomposition

Wavelet Packet Transform

WPT will choose the size of the window depending on the lower and higher frequency levels. By this a finer frequency resolution of the signal is possible and easy to analyze the small part [35]. Wavelet packet transform performs a similar operating mechanism as wavelet transform, except that the detailed coefficients would also be decomposed to equal bandwidth data as shown in Fig.3. Wavelet packet transform will decompose the original signal, which is non stationary or stationary into independent frequency bands with multi resolution.

In the WPT the fault frequencies are settle in nodes 255, 256 i.e. (8, 0) & (8, 1) respectively for cage fault and for outer race fault 256, 261, and 266 i.e., (8, 1), (8, 6) and (8, 11).

The healthy and faulty current signals are analyzed for these nodes and the following fault indexing parameters are calculated.

Fault Indexing

The wavelet transform of healthy and faulty signals can be analyzed using different statistical parameters. These statistical parameters include RMS, Standard Deviation, Energy, power, mean, median, mode etc. In this paper the Standard Deviation and energy of the reconstructed signals are taken into account to analyze the fault.

Standard Deviation

$$\sigma = \sqrt{(\frac{1}{N}[(x_1-\mu)^2+(x_2-\mu)^2+\cdots+(xN-\mu)2,} \quad (11)$$

Where μ is the average of x_1, x_2, …x_N.

The relative standard deviation (healthy-fault) is used for the detection of fault.

Energy

Energy is another parameter used for the analyses purpose. The increase in the noise level and the occurrence of the fault results in the change of the energy level. The energy of the signal is given by the equation.

$$E_s = < x(t), x(t) > = \sum_{k=1}^{k=n} \left|D_{s,k}(n)\right|^2 \quad (12)$$

As the intensity of the faults increases, the change in relative parameters will also increases.

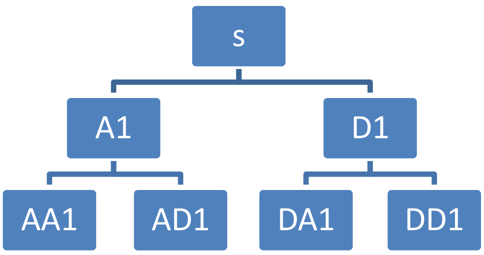

Fig.3. Wavelet packet decomposition

4. Experimental setup:

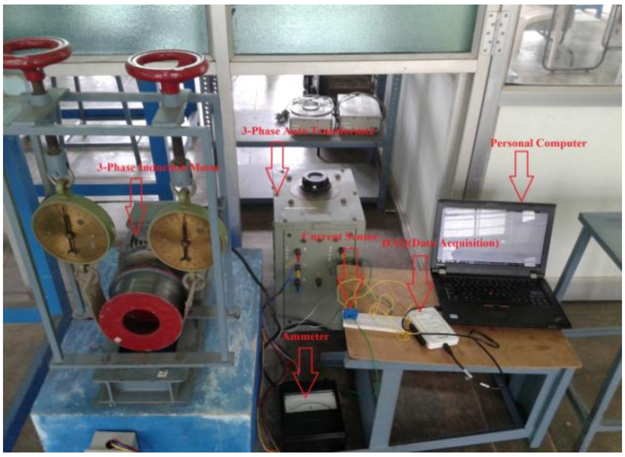

Fig.4. Experimental Setup

The experimental setup is shown in fig. 4. With this setup, a 2.2KW, 415V, three phase, 4-pole and with full load speed of 1435rpm induction motor is used. The motor is fed through 3 phase auto transformer. The current is sensed by using a Hall-Effect type current sensor LA 55P made by LEM and processed in to PC by the data-acquisition system NI MY DAQ. The current signal is processed by using MATLAB Programming. The sampling frequency is 10 KHz and number of samples N_s=10000. In this, SKF 6206ZZ single row deep grove bearing is used in both driving and non driving end of the motor. The test bearing 6206ZZ is mounted on driving end of the shaft. The specifications of this bearing are:

PD = 1.83inches, BD = 0.375inches, N= 9 and $\alpha = 0^0$

In this the outer race fault, cage fault and generalized roughness fault have been tested practically. Fig.5, 6 shows the cage fault and outer race fault of the bearing respectively. These two bearing are tested and the comparative analysis is done using the FFT, DWT, WPT.

Fig.5.Bearing with cage fault

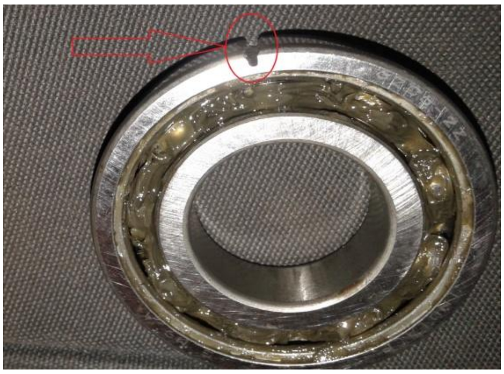

Fig.6. Bearing with outer race fault

Table.3. Fault frequencies under No-Load (1495rpm)

Fault type	K=1		K=2	
Cage fault	59.5666	40.434	69.132	30.868
Outer race	135.62	35.62	221.24	121.242
Inner race	179.62	79.62	309.24	209.24
Ball effect	105.964	5.964	161.928	61.928

Based on the equations (1) – (4) the bearing vibration frequencies are calculated for different types of single point faults. From the vibration frequencies the harmonics that induced in the stator current are calculated from equation (5). The fault frequencies for single point defect are shown in Table.3.

5. Experimental Results:

The frequency domain analysis is carried out for the current signal with and without faults. The spectral analysis is done by using FFT and Wavelet transform as mentioned in section III. The results with corresponding fault frequencies have been presented here.

FFT analysis

FFT analysis is done for healthy, cage fault, outer race fault and the generalized roughness faults as shown in Fig.7-10. Under healthy condition of the bearing, stator current spectrum gives fundamental component, supply harmonics and the noise due to sensor and EMI. Fig.8. shows current spectrum with severe cage fault. The fault frequencies in the table.3 are extracted from the current spectrum easily. Though the cage fault is severe, the magnitudes of the fault frequencies are less. This is due to the domination of fundamental component and noise. Especially at the early stage of the fault, these magnitudes are very less and are difficult to extract from the current spectrum. This is shown in the outer race fault spectrum in Fig.9.

As mention in section II, the generalized roughness fault should not impose characteristic fault frequencies in to stator current. Fig.10. shows the stator current spectrum with generalized roughness fault. These fault frequencies are difficult to extract from the current spectrum due to wide spread noise.

Hence for the early detection of these faults, stator current spectrum is analyzed by using wavelet transform as mentioned below.

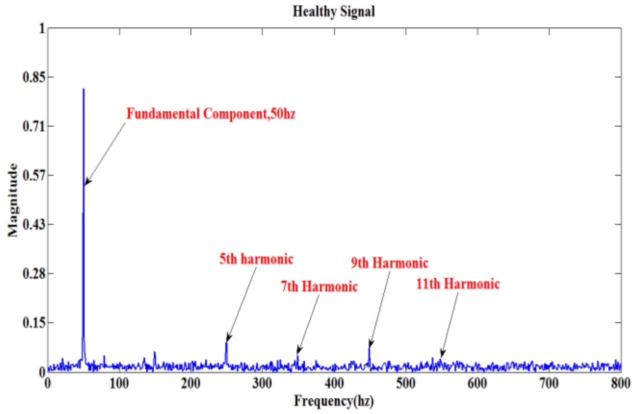

Fig: 7 FFT of a healthy Current Signal

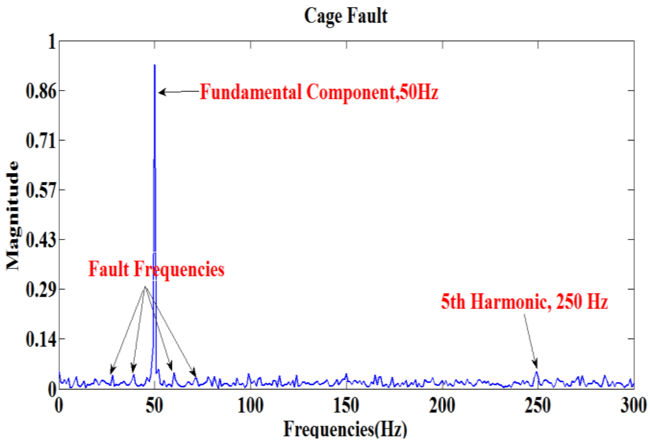

Fig.8.FFT of a Cage fault signal

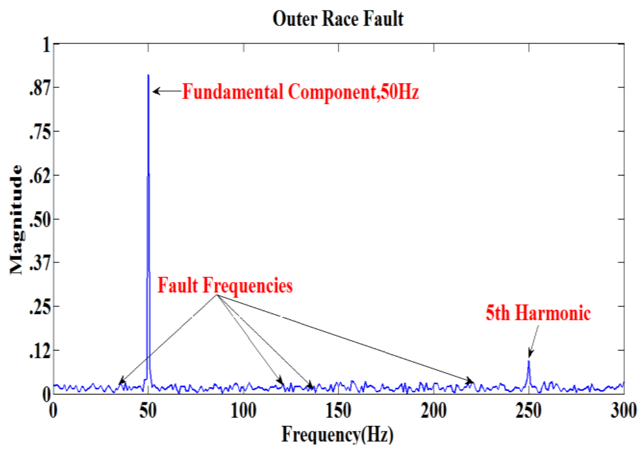

Fig.9 Outer race fault

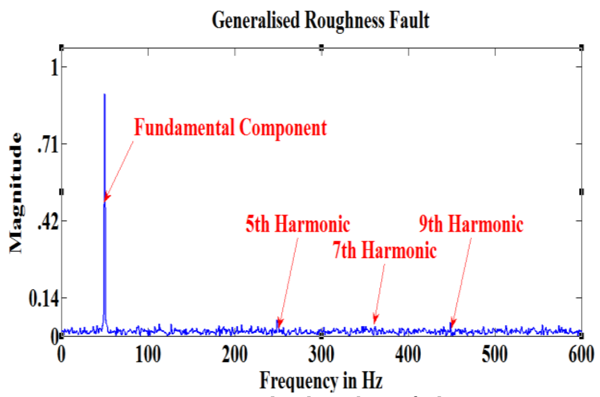

Fig.10 Generalized roughness fault

DWT analysis

As mentioned above DWT is done for the healthy and faulty current signals using db8, level 9. The reconstructed signals of healthy and cage fault using DWT are shown in Fig.11-12. The level of decomposition can be derived from equation (10). It is difficult to identify the fault component from the reconstructed coefficients directly. So these coefficients are analyzed using the statistical parameters as mentioned in equations (11), (12). The fault frequencies of outer race fault and cage fault from Table.3 are settled in 7^{th} and 9^{th} detailed coefficients of DWT. Hence the difference between healthy and faulty coefficients in terms of the standard deviation is shown in Fig.13.The relative energy is shown in Fig.14. For severe fault, the differences between healthy and faulty parameters are high and for early fault these will be less.

For generalized roughness faults, the fault frequencies may settle in all the coefficients as they are unpredictable. So the fault indexing parameters are calculated for all coefficients in 9^{th} level decomposition and are compared with healthy spectrum. The fault indexing parameters for generalized roughness fault is shown in Fig.15, 16.

WPT analysis

The WPT analysis is carried out for the current signal under both the conditions. In the WPT analysis the current signal is decomposed in to 8 levels and the range of node frequencies are given below. Node 255 ranges from (0 – 54Hz), node 256 ranges from (54-93Hz), node 261 ranges from (117-151Hz) and node 266 ranges from (215-249Hz). The node coefficients for healthy and cage fault are shown in Fig.17-18. The fault indexing parameters of healthy and faulty currents are calculated and are shown in Fig.19, 20.

For generalized roughness fault the fault indexing parameters are difficult to calculate due to 256 node coefficients are available in 8 level decomposition using WPT.

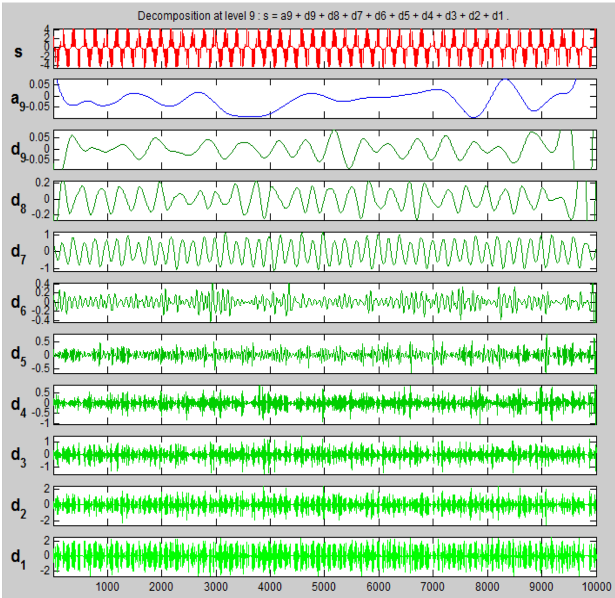

Fig.11. DWT Reconstructed coefficients for the healthy current

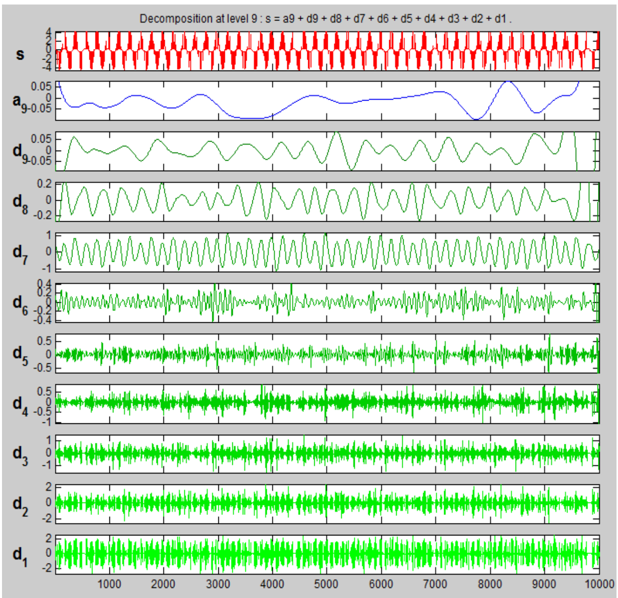

Fig.12. DWT Reconstructed coefficients for a cage fault

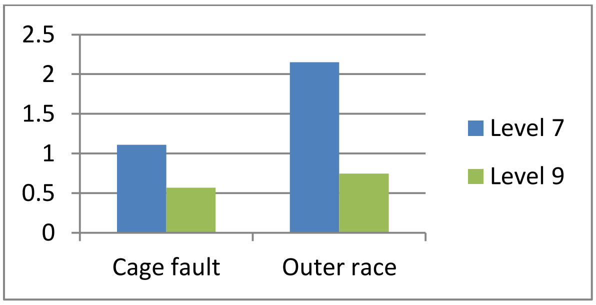

Fig.13Relative Standard Deviation for Cage and Outer race Fault using DWT

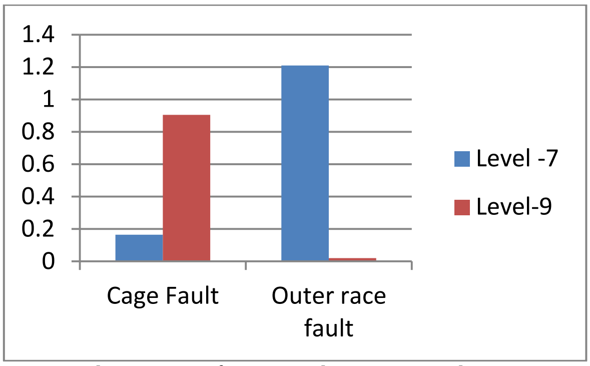

Fig.14.Relative Energy for Cage and Outer race Fault using DWT

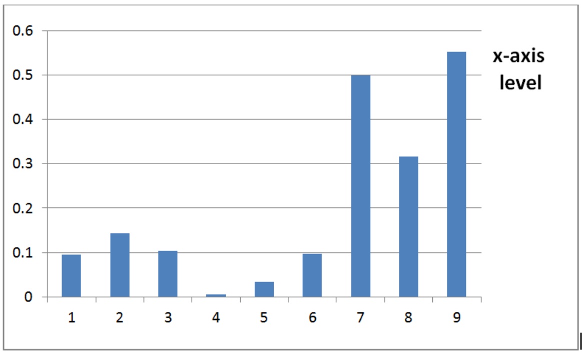

Fig.15.Relative Standard Deviation for Generalized Roughness Fault using DWT

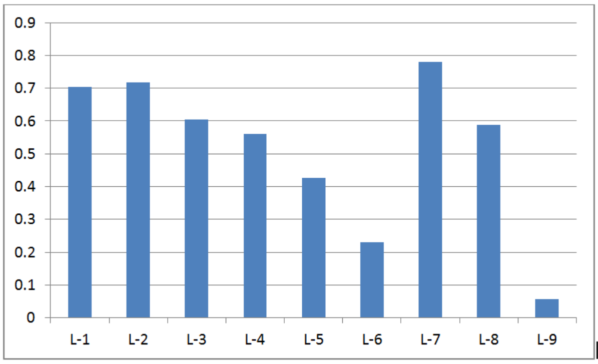

Fig.16.Relative Energy for Generalized Roughness Fault using DWT

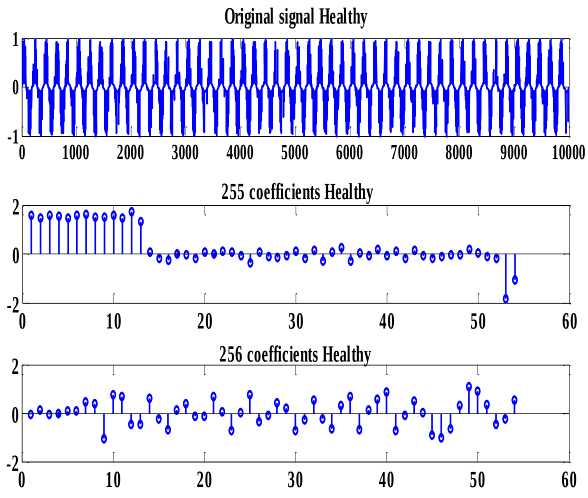

Fig.17 Healthy current coefficients using WPT analysis

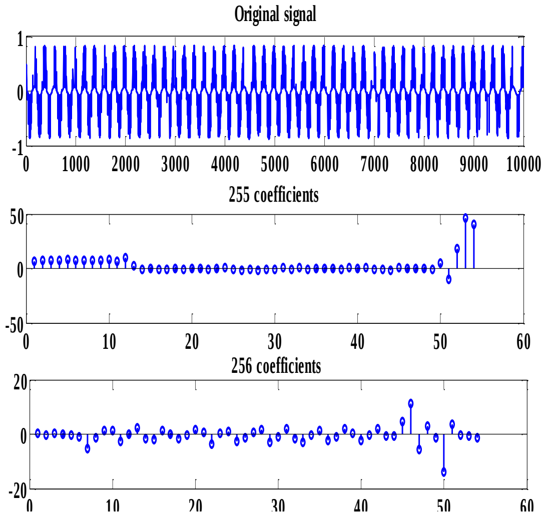

Fig.18. Cage fault coefficients using WPT

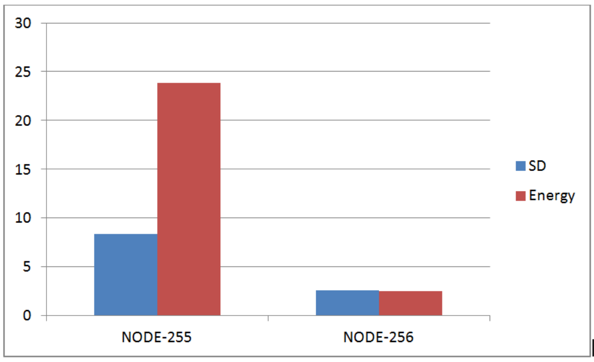

Fig.19.Fault indexing parameters for Cage Fault

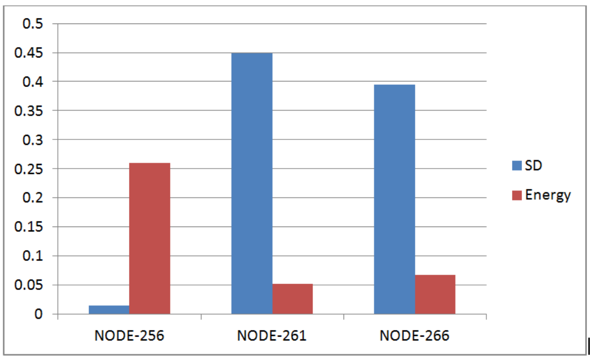

Fig.20.Fault indexing parameters for Outer Race Fault

Therefore, for severe fault frequencies WPT will give better performance compared to DWT and will give good indication for the fault. But for early stage faults, DWT will give good indication and better performance compared to WPT. As well as for the generalized roughness faults WPT is not suitable because of many calculations for fault indexing parameters.

5. Conclusion:

This paper contributes the detection of bearing faults in induction motor based on current signature analysis. The effect of bearing faults on the stator current was studied. Moreover, the single point defect and generalized roughness faults are created and tested with current signature analysis. This paper also presents comparative study of current signature analysis using DWT and WPT in detecting bearing faults. With comparing the results, it is observed that for early stage faults the DWT will give better performance compared to WPT. Especially for generalized roughness faults WPT is difficult to implement as they have many calculations. The fault frequencies with severe impact can be easily identified by WPT compared to DWT. Furthermore, this paper proposes two relative statistical parameter to indicate the fault severity. In future the current signature analysis can be done for more bearing faults and adaptive filtering can be implemented to reduce the effect of healthy components.

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