DETECTION OF BROKEN ROTOR FAULTS OF THREE-PHASE INDUCTION MOTOR USING MCSA BY DIFFERENT WAVELET TRANSFORM TECHNIQUES

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Abstract: *Induction motors being robust, efficient, low cost and reliable in operation and are widely used as electrical drives in industries. So, safe operation of induction machines is a major problem. Among the different mechanical faults experienced by induction motor, rotor faults contribute to 5%-10%. According to location of fault the rotor faults can be categorized into cracked bar, End ring, bar ring joint, melted bars, air gap eccentricity etc... The motor current signature analysis (MCSA) is commonly employed for detection of these faults due to less cost, reliable and non-intrusive in nature. Conventional FFT based analysis of MCSA has many drawbacks like poor resolution, noise problems etc. Therefore, in this paper, the MCSA using different wavelet transforms like Discrete Wavelet Transforms (DWT), Stationary Wavelet Transforms (SWT), and Wavelet Packet decomposition (WPD) have been proposed and compared. The proposed topologies have been tested by experimental setup interfacing with MATLAB programming.*

Key words: *MCSA, FFT, wavelet transform, discrete wavelet transform, stationary wavelet transform, wavelet packet decomposition.*

1. Introduction.

Induction motors are popularly used in all types of industrial applications owing to their advantages like simple construction, high reliability and the availability of power converters using efficient control strategies, low cost and have an ability to work under any discordant working conditions. Despite of their high usage, Induction motors have a pretty well chance of undergoing the disturbances like unwanted stresses, aging while rendering their services in industries [1]. These disturbances are due to faults experienced by the induction motors. The faults experienced by the machine can be categorized into: Bearing faults, Stator faults, Rotor faults, Bent Shaft and due to external devices [2-3]. According to several survey reports on induction motor above 200hp, bearing faults contribute to 41%, stator faults 37%, Rotor faults 10% and other faults 12% [4, 5, 6]. Based on the survey reports of EPRI and IEEE in [2], [7], cage fault contribute to 5%, shaft 2%, core 1% and other 2% of 10% rotor faults experienced by motor. Therefore the major problems in the rotor faults are related to cage and are broadly classified into broken rotor bars and end ring faults. These faults are due to thermal, electrical, mechanical or environmental stresses and/or due to manufacturing defects [8]. Moreover, the broken rotor fault occurs by thermal stress, hot spots or fatigue stresses during transient operations such as startup, especially in huge motors [6, 9]. A Rotor broken bar can significantly changes torque and turn out to be dangerous to the safety and consistent operation in huge motors. The end ring rotor fault is related to air gap eccentricity. This fault is related to a range of mechanical problems in induction motor such as load unbalance or shaft misalignment [2, 10]. To avoid sudden shut down of the machine, preventive measures should be taken in order to protect motors from these rotor faults. To do so early detection of motor faults is highly desirable which requires online condition monitoring of the induction motor. It provides useful information continuously to the operator, maintainer and designer regarding healthiness of the system. By early detection of the faults any potential dangerous situated can be avoided. The study of behavior of an induction motor under unwanted stress or abnormal conditions has always been a challenge [11].

There are many condition monitoring techniques like Vibration monitoring, thermal monitoring, acoustic emission monitoring are available to protect the induction motor [12]. Even though thermal and vibration monitoring have been utilized for decades most of the recent researches has been directed towards Electrical monitoring of the motor with emphasis the stator current of the motor [12]. All such techniques require specialized tools or expensive sensors. Hence current monitoring techniques, which are not in need of special expensive tools, are most used in industrial applications.

The paper is organized as; Section II reviews the motor current signature Analysis (MCSA) for Induction motor. Section III reviews various wavelet techniques used for fault diagnosis. Section IV presents the hardware setup. Section V is presented with the analysis and results. Paper is concluded in Section VI.

2. Motor Current Signature Analysis (MCSA).

Motor Current Signature Analysis (MCSA) is the most popularly used for detecting induction motor faults. In the MCSA, current frequency spectrum is analyzed and obtained focusing to find out specified frequency components which indicates an incipient fault or a possible degradation in the machine condition. As stated, these frequencies are related to well-known machine faults. Therefore, after the stator current has been processed, it is possible in inferring the machine condition. The other important feature of this method is that the current can be sampled while the machine is under operating condition. Therefore, the detection and diagnosis of the fault can be made online without disconnecting the machine from the mains.

MCSA is one of the best popularly used methods because of the reasons as follows: it is non-invasive, economical due to no additional sensors required, reliable and easy to access [13]. It is clear that MCSA uses the stator current to identify fault characteristic frequency components. It can easily detect faults like: broken rotor bars, air gap eccentricity, bearings, short circuit turns, etc. [10, 14]. The frequency spectrum of stator current can be obtained by Spectral Analysis. Spectral analysis is the given name to describe methods that transform time signals into the frequency domain. Although the broken rotor bars of a squirrel-cage induction machine initially do not cause the failure of the motor, they can have serious secondary effects. The breakings or cracks of a rotor bar can easily extended to the nearby or closer bars [10]. This type of fault slowly progresses in time and can easily be detected by using MCSA monitoring technique. The fault frequencies developed by broken rotor bar faults is given by [1, 15, 16, 17].

$$n_1 = \frac{120 f_1}{p} \tag{1}$$

Where f_1 is the supply frequency and p is the number of poles.

$$Slip(s) = \frac{n_1 - n}{n_1} \tag{2}$$

$$n = n_1(1-s) \tag{3}$$

Where n is the speed of the induction motor, s is the slip of the induction motor. The backward rotating magnetic field speed produced by the rotor due to broken bars and with respect to the rotor is

$$n_b = n - n_1 \tag{4}$$

$$n_b = n_1(1-s) - sn_1 \tag{5}$$

After simplifying Eq (5)

$$n_b = n_1(1-2s) \tag{6}$$

From Eq (1) & (6)

$$f_b = f_1(1-2s) \tag{7}$$

$$f_b = (1 \pm 2ks) f_1 \tag{8}$$

Where k= 1, 2, 3 …

From the Eq (8), it is observed that, the fault frequencies are very nearer to the fundamental especially at less value of k. Therefore, it is necessary to use a high resolution spectral analysis to separate the fault frequencies from the fundamental component. Conventional FFT have few drawbacks like poor resolution, spectral leakage, unable to provide time –frequency relation etc. In order to overcome the resolution problems in FFT, zoom FFT (ZFFT) [18],[19] and MUSIC algorithms [20] have been proposed but have implementation problems due to high acquisition time and computational complexity. On the other hand, the spectral leakage in FFT is removed using window functions. To avoid spectral leakage and get time frequency resolution short time Fourier transform (STFT)[21] and Wigner-Ville distribution (WVD)[22], [23] are used. But these methods are difficult due to fixed window size in STFT and cross terms in WVD. In contrast to these, the variable size window based spectral analysis using Wavelet Transform (WT) has proposed [24]-[26]. Therefore, in this paper, wavelet transform based spectral analysis of stator current is proposed to detect broken rotor faults. The complete description of wavelet analysis is presented in the following section.

3. Wavelet Analysis.

In order to overcome this serious problem of detection of fault at no load condition, the existence of the wavelet transforms came into picture. Wavelet transforms are used for the easy detection of the faults in the induction motor. As mentioned in the earlier subsections, the wavelet transforms have an advantage of variable window size. Three different wavelet transforms decomposition techniques are used. They are Discrete Wavelet Transforms (DWT), Stationary Wavelet Transforms (SWT), and Wavelet Packet Decomposition (WPD).

In the DWT decomposition, the stator current is decomposed into sufficient levels using following expressions. [27]

$$A_j(m) = \sum_n L(n-2m)b(n) \tag{9}$$

$$D_j(m) = \sum_n H(n-2m)b(n) \tag{10}$$

From the decomposition procedure of DWT, the decomposed signal is down sampled by 2 units in each stage. Therefore, after each decomposition level the length of the signal may become half. This decomposition will continue up to the required level. The decomposition level j can be obtained using following equation

$$j = \text{int}\left[\frac{\ln\left(\dfrac{F_s}{8s_r f}\right)}{\ln 2} - 1\right] \tag{11}$$

Where s_r is slip and f is the fundamental component. After computing the j^{th} level coefficients, fault estimation criteria can be done.

In this paper, daubechies of order 8 (db8) is chosen as mother wavelet. In this DWT method, the coefficients are classified into two types approximation coefficient and detailed coefficient. The low frequency components are known as approximated coefficients and high frequency components are called as detailed coefficients. In the first level decomposition, the DWT has one approximated coefficients (ca1) and one detailed coefficients (cd1), where as in the next level of decomposition the approximated coefficient is again decomposed into approximated coefficients (ca2) and detailed coefficients (cd2) in the second level. In the similar way, at j^{th} level decomposition one approximated coefficients (caj) and j number of detailed coefficients (cd1-cdj) will be available for analysis. But the DWT decomposition is time variant decomposition and has redundancy of coefficients due to down sampling.

The Stationary Wavelet Transform (SWT) is a time invariant transform and is similar to Discrete Wavelet Transform (DWT) but the process of down-sampling is suppressed. SWT is also known as decimated wavelet transform, Invariant Wavelet transform as the name itself reveals that it provides linear and time invariant transformations [28]. SWT is known for its good resolution and identification of fault. Similar to DWT, SWT also having caj and cd1-cdj coefficients at j^{th} level decomposition but the length of each coefficient is same.

Wavelet Packet Decomposition (WPD) is another decomposition tool, which gives higher resolution compared to DWT and SWT. The decomposition process is similar to DWT including down sampling, but both approximated and detailed coefficients are decomposed. They form bases which retain many of them orthogonally, smoothness, and localization properties of their mother wavelets. The algorithm of discrete wavelet packet transform is executed by two-channel filter banks having a half-band low pass filter and half band high pass filter pair. The study of a signal is processed by decomposing the signal in to a low pass and high pass filter continuously. In DWT, each level is calculated by passing the previous approximation coefficients through a high and low pass filters based on their ranking, the signal which is to be programmed is successively split into high and low frequency modules. The number of progressions are usually limited by the desired level of frequency resolution and obtained computational power. The frequency order of the wavelet packet coefficients are quite in binary.

In this present work, j is taken as 8 and in each decomposition the stator current is decomposed into 8 levels. Therefore, in DWT & SWT cd1-cd8 and ca8 will be available, where as in WPD 2^8 number of coefficients are available in 8^{th} level decomposition and is difficult to analyze. Therefore the first 9 coefficients (c1-c9) are taken for analysis purpose.

Table 1
Rotor Fault Frequencies

	Speed	**Slip**	**Frequencies (Hz)**	
K=1			49.069	50.933
K=2	1486	0.009	48.134	51.866
K=3			47.201	52.799

4. Experimental Setup.

A 3-phase induction motor of 1 HP, 1.4A, 1500 rpm, 415V, 50Hz is taken to test the proposed methodology practically. The experimental setup is shown in the Fig.1. The rotors with healthy and faulty conditions are shown in Fig.2 & 3 respectively.

A healthy and faulty stator current is obtained by running the motor under no-load conditions. The stator current is extracted by DAQ connected through a current sensor to a laptop. The above figure shows the healthy and faulty current signature of the stator. The faulty stator current can be achieved by creating a hole or getting rotor bar broken. This method will create huge vibrations in the machine when it is subjected to the operation.

5. Results & Discussion

The frequencies domain analysis is carried out for the current signal with and without faults. The spectral analysis is done by using Wavelet transforms as mentioned. The below results are obtained by conducting different wavelet transforms on the above obtained healthy signal and as well as the faulty signal by using MATLAB code with respect to the Wavelet techniques. The different wavelet transforms involves DWT, SWT and WPD transforms. The results corresponding wavelet analysis are presented here:

Fig. 1. Experimental setup for rotor fault detection

It is clear that from the reconstructive coefficients from the above figures (Fig (5) to Fig (10)) are unable to detect the existence of the fault. Here requires some other parameters for identification of the fault. Among many statistical parameters Standard deviation has been chosen. The standard deviation ratios are taken at decomposition levels in each wavelet transform technique for both healthy and faulty stator current signals is done. Finally standard deviation ratios of faulty by healthy in each level of decomposition are taken and compared among all the three wavelet transforms like Discrete Wavelet Transform technique, Stationary Wavelet Transform technique and Wavelet packet Decomposition Transform technique. The tables which are below reflects the comparison among these three techniques are given below in order to analyze which transforms gives the best outcome in order to detect the severity of the fault.

Fig. 2. Rotor under healthy signal

Fig. 3. Rotor under faulty signal

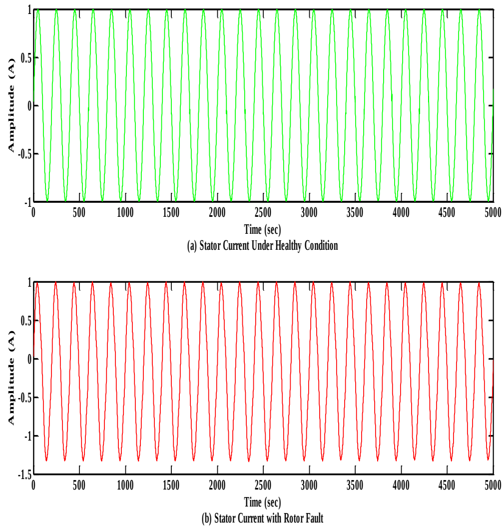

Fig. 4. Subplot of healthy and faulty stator current obtained due to the healthy rotor and one rotor broken bar respectively

The above table (1) shows the fault variations clearly from fifth to eighth level of decompositions. It reflects that the fault frequencies which are calculated in the above table will fall in this levels so the variation is detectable at these levels.

The above table (2) shows that fifth to eighth levels of the decomposition and the severity of the fault can be shown when the variation of the fault is quite above the value 1. It reflects that the fault frequencies which are calculated in the above table will fall in this levels so the variation is detectable at these levels.

The above table (2) shows variation in one to two levels of the decomposition and the severity of the fault can be shown when the variation of the fault is quite above the value 1.

When the full length current signal x which is of 10,000 length it is decomposed with the help of mother wavelet daubechies into 8 levels because the calculated fault frequencies will be surly fallen there. For the DWT analysis the fault frequencies are fallen at one fault frequency 49.067 at 8th level 1st node and the other frequency 50.933 at 8th level 2nd node respectively. It reflects that the fault frequencies which are calculated in the above table will fall in this levels so the variation is detectable at these levels. .This analysis is clear enough in showing at one two levels of decomposition. Therefore, for severe fault frequencies WPD will give better performance compared to DWT and will give good indication for the fault.

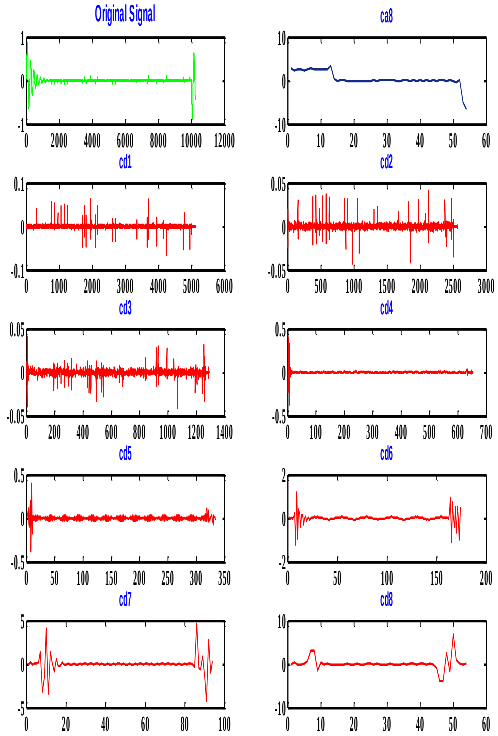

Fig. 5. DWT analysis is carried out for current signal under healthy conditions

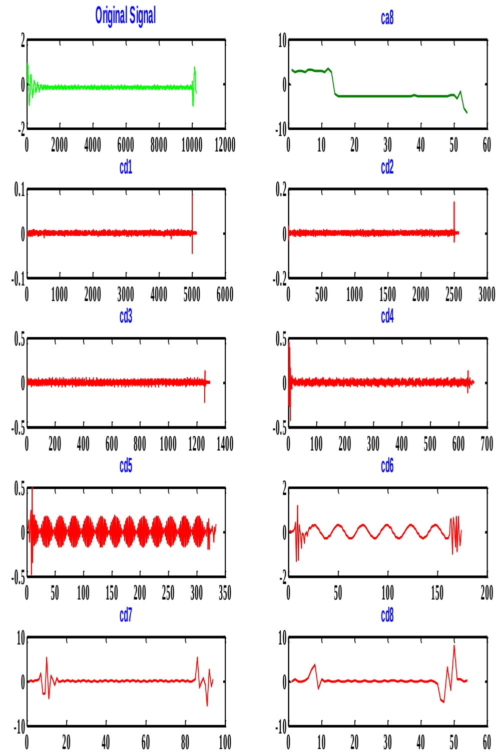

Fig. 6. DWT analysis is carried out for current signal under fault conditions

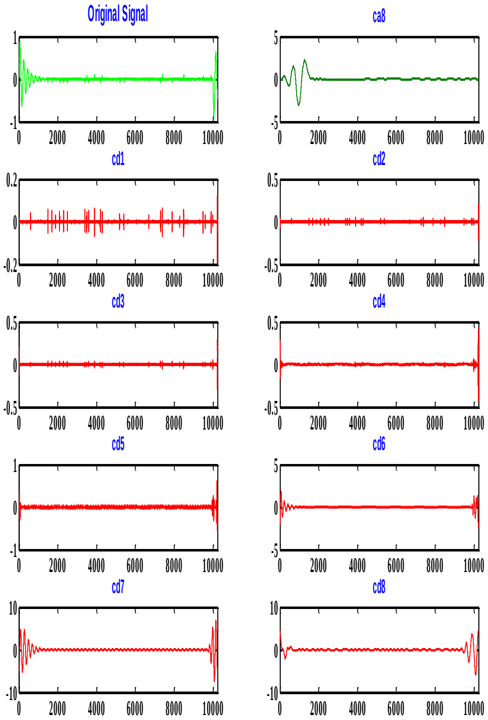

Fig. 7. SWT analysis is carried out for current signal under healthy conditions

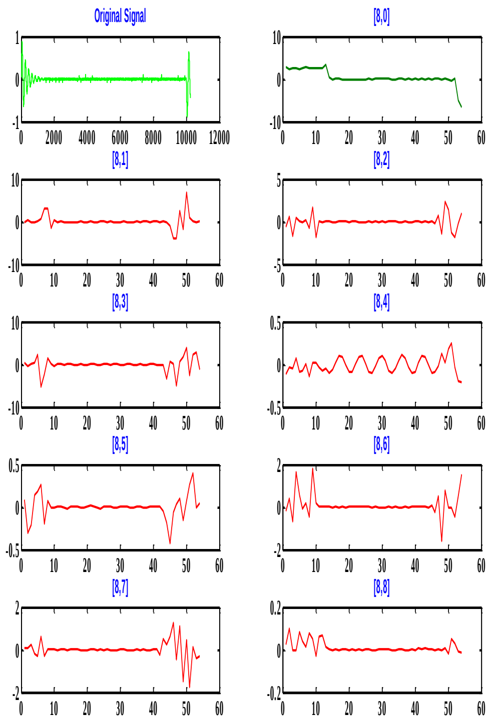

Fig. 9. WPD analysis is carried out for current signal under healthy conditions

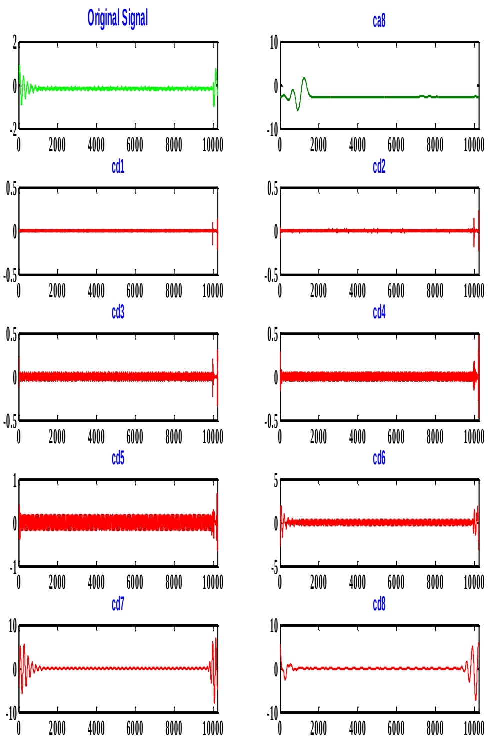

Fig. 8. SWT analysis is carried out for current signal under fault conditions

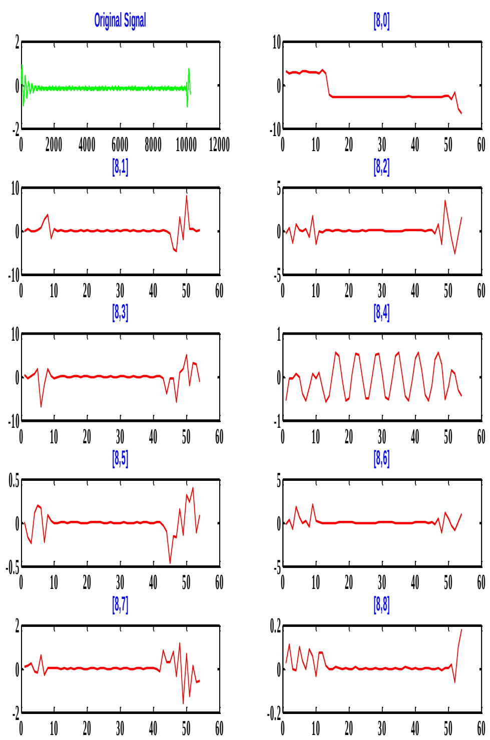

Fig. 10. WPD analysis is carried out for current signal under faulty conditions

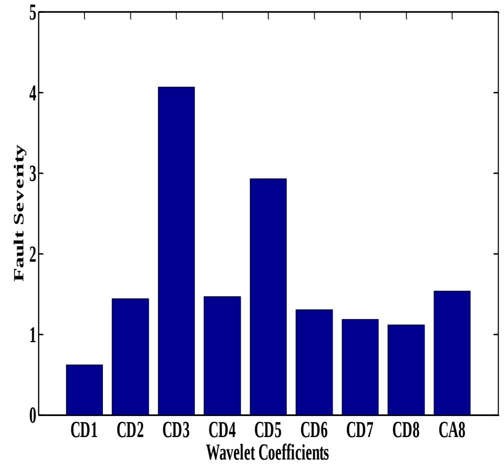

Fig.11. Standard deviations of faulty by healthy for DWT analysis

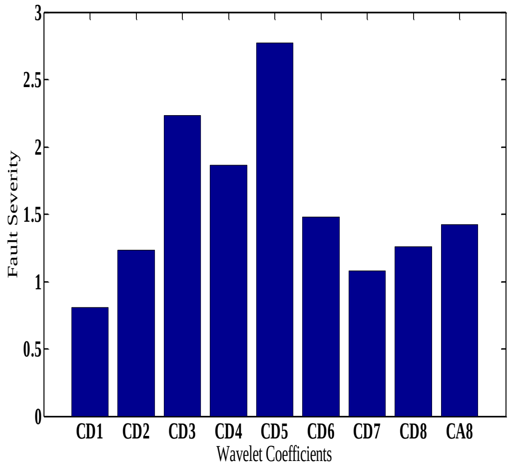

Fig.12. Standard deviations of faulty by healthy for SWT analysis

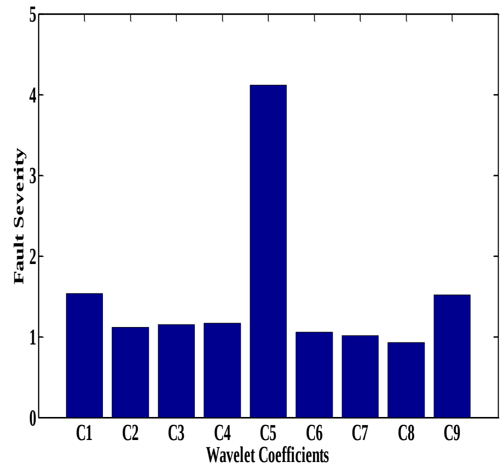

Fig.13. Standard deviations of faulty by healthy for WPD analysis

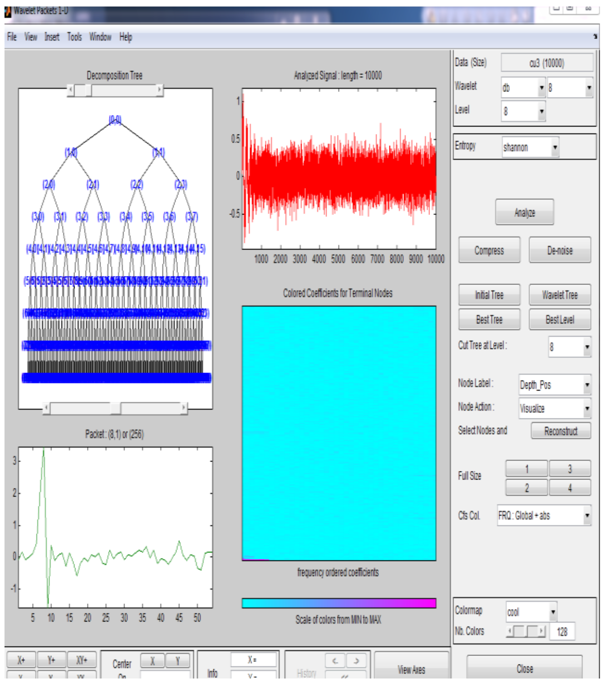

Fig.14. Signal decomposition into 8 levels using WPD

5. Conclusion

This paper contributes the detection of the broken rotor bar faults in induction motor based on current signature analysis. The effect of rotor broken bar is analyzed. Moreover, the broken rotor bar is created and tested with current signature analysis using DWT, SWT and WPD in detecting broken rotor bar faults. With comparing the result it is observed that for early stage faults the WPD will give good fault indication when compared to DWT. The fault frequencies with severe impact can be easily identified by WPD compared to DWT. Furthermore, this paper proposed one relative statistical parameter i.e. Standard deviations in order to indicate the fault severity. The MSCA technique is best method for identifying the faults severity is proven. Among the MCSA, wavelet transforms played a key role in identifying the fault in this application. Moreover among all the proposed three Wavelet transform techniques like Discrete Wavelet transforms, Stationary Wavelet transforms and Wavelet packet decomposition transforms, Wavelet packet decomposition transforms clearly shown the severity of the fault in this application of the paper. So, this paper also states that the proposed three techniques are good enough for the detection and diagnosis of the fault, but the intensity of the transform techniques for detecting and diagnosing are varied according to the applications.

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