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Classification of Faults in DTC Induction Machine using Wavelet Decomposition Method

P. Govindamoorthi* and **K. Valarmathi**

Department of Electronics and Communication Engineering, P.S.R. Engineering College, Sivakasi - 626 140, Tamil Nadu, India; govindaccet@gmail.com, krvalarmathi@yahoo.co.in

Abstract

Background: Fault detection is essential problem in machinery. The different type faults can occur in induction machine due to stator short circuits and rotor failures. Direct Torque Control (DTC) is a well known control design for induction motor drive in high power applications. **Methods:** Generally, the classification of faults is done by Principal Component Analysis (PCA) and Support Vector Machine (SVM) techniques. In this paper Discrete Wavelet Decomposition (DWD) technique is used to categorize the stator and rotor faults of DTC induction machine. Using the DTC Simulink model a variety of faults are generated and tested. **Finding:** By using wavelet decomposition, the information on the health and fault of a system can be extracted from signal over wide a range of frequencies. The extracted features are used to classify the healthy machine from faulty machine. **Application:** This method can be applicable in windmill, lathe and drilling machines to increase the efficiency.

Keywords: Classification, DTC Induction Machine, Fault, Motor Current and Torque Analysis, Wavelet Decomposition

1. Introduction

Induction motor fault can be classified into mechanical and electrical faults[1]. Current spectrum analysis and Receiver Operating Characteristic (ROC) are used as fault parameter an induction motor. De-noising and feature extraction is done by wavelet transform and Principal Component Analysis (PCA) approach[2]. Different operating conditions are taken such as health, broken bars and stator shorted turns circuit. Motor Current Signature Analysis (MCSA) is used as analysis of these different conditions with Power Spectral Density (PSD) in the wavelet transform. It consumes the diminutive amount of power[3]. Support Vector Machine (SVM) is worn for a verdict of electrical faults an induction motor[4]. Stator current analysis is done by Park's Vector Stator current amplitude and fuzzy logic are used for diagnostic purpose of stator phase short circuit and open circuit fault[5].

MEMS accelerometer and Fast Fourier Transform (FFT) based vibration analysis is worn for the detection of three phase power supply and ground fault[6]. Bearing damage, mechanical inequality and faulty control of Variable Frequency Drives (VFD) is detected by vibration measurement. The place of pulsation analysis in the realm of expert systems for motor health monitoring[7]. Bearing failure and rotor bars broken at different load condition. Fault Detection and Diagnosis (FDD) is completed by pattern recognition, parks vector approach and artificial ant clustering technique. The contrast between supervised and unsupervised categorization techniques[8].

End ring and eccentricity faults are perceived by current spectrum analysis. Higher Order Statistics (HOS) and Park's Vector Approach (PVA) were extensively used for feature extraction purposes[9]. Inter turn faults are notified by current signal scrutiny with wavelet decomposition method[10]. Stator current spectral analysis is performed by Fast Fourier Transform (FFT)[11]. These methods present as the main limiting factors low accuracy, estimative nominal motor data and the need of typical efficiency-versus-load curves[12]. The experimental bearing fault recognition of a three-phase induction motor is performed by investigate the squared cover spectrum of the stator current[14].

2. Process Description

In this paper, the change of motor resistance are fault creation parameter. Motor signals of rotor current and

*Author for correspondence

torque were taken. These signals are used to detect the faults of induction motor. This paper four operating condition of the machine was handled such as healthy machine, stator fault, rotor fault and both fault conditions. These faults diagnosed by machine parameter of rotor current and torque. Signals are decomposed by Discrete Wavelet Decomposition (DWD) method. The architecture of the proposed approach of induction machine condition monitoring and fault diagnosis system illustrated in Figure 1. The details of each section of the system are given hereinafter.

2.1 DTC Induction Motor

Direct Torque Control (DTC) as presumed from the name of directly controlled torque and flux. Indirectly controlled stator current and voltage. Vector control is an alternative method for dynamic control of machinery. DTC has some advantages compared to other conventional vector controlled drives[1]. Its main motivation to choose of DTC machine for this experiment. This control technique provides notable self-motivated performance for parametric disparity produced by a lot of faults in the machines. The induction motor model takes into the following assumptions: Negligible saturation and skin effect, Uniform air-gap, Rotor bars are insulated from the rotor and Relative permeability of machine armatures is assumed infinite.

The induction developed between the air-gap can be written as.

$$B_s(\theta) = \frac{2\mu_0 N_s i_a}{\pi e p^2} cos\theta \tag{1}$$

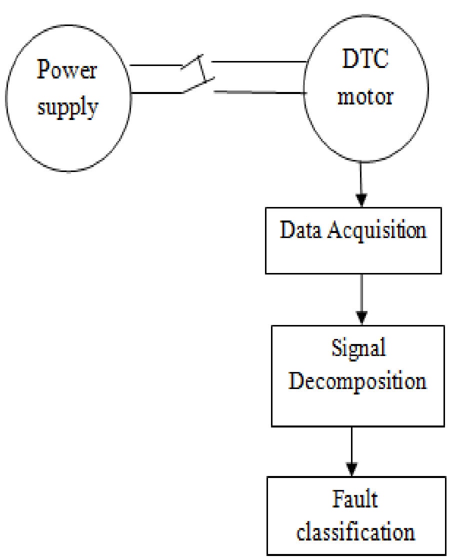

Figure 1. Schematic diagram of the DTC induction motor.

The flux is written as:

$$\varphi_{sp} = \frac{4\mu_0 N_s^2}{\pi e p^2} i_a \tag{2}$$

N_s is number of turns per stator phase, L is length of rotor, p is pole number and e is air gap mean diameter.

Stator principle inductance is:

$$L_{sp} = \frac{\varphi_{sp}}{i_a} = \frac{4\mu_0 N_s^2 RL}{\pi e p^2} \tag{3}$$

Rotor principle inductance is:

$$L_{rp} = \frac{N_r - 1}{N_r^2} \mu_0 \frac{2\pi}{e} RL \tag{4}$$

Obtain induction machine model for the following canonical form:

$$[L]\frac{d[I]}{dt} = [V] - [R][I] \tag{5}$$

N_r is number of rotor bars, M_{sr} is mutual inductance, R_b is rotor bar resistance, R_e is resistance of end ring segment and R_r is rotor resistance.

Where:

$$[L] = \begin{bmatrix} L_{sc} & 0 & -\frac{N_r}{2} M_{sr} & 0 & 0 \\ 0 & L_{sc} & 0 & -\frac{N_r}{2} M_{sr} & 0 \\ -\frac{3}{2} M_{sr} & 0 & L_{rc} & 0 & 0 \\ 0 & -\frac{3}{2} M_{sr} & 0 & L_{rc} & 0 \\ 0 & 0 & 0 & 0 & L_e \end{bmatrix}$$

$$L_{rc} = L_{rp} - M_{rr} \frac{2.L_e}{N_r} + 2.L_e\left(1 - \cos\cos(a)\right)$$

$$[R] = \begin{bmatrix} R_s & -L_{sc}\omega_r & 0 & \frac{N_r}{2} M_{sr}\omega_r & 0 \\ L_{sc}\omega_r & R_s & -\frac{N_r}{2} M_{sr}\omega_r & 0 & 0 \\ 0 & 0 & R_r & 0 & 0 \\ 0 & 0 & 0 & R_r & 0 \\ 0 & 0 & 0 & 0 & R_e \end{bmatrix}$$

$$R_r = 2.\frac{R_e}{N_r} + 2.R_b\left(1 - \cos\cos(a)\right)$$

2.2 Discrete Wavelet Transform (DWT)

Wavelet renovates breaking awake of a signal into shifted and scaled description of the mother wavelet. The discrete wavelet transforms to find accurate width and location of zero current intervals. This transformation, among the obtainable signal processing approaches, has fascinated great kindness in some studies of power system, because of its suitability for analysis of certain types of unusual waveforms[15]. Wavelet scrutiny can expose features of data that other signal analysis conditioning techniques not succeed to spot, breakdown points, self resemblance and discontinuities in superior derivatives. Wavelet transform of the discrete version consists of sampling the shifting and scaled parameters. This leads to high frequency resolution at low frequencies and high time resolution at higher frequencies.

A signal x[n] could be decomposed as

$$x[n] = \sum_{k} a_{j0,k}\phi_{jo,k}[n] + \sum_{j=j0}^{J-1}\sum_{k} d_{j,k}\varphi_{j,k}[n] \qquad (6)$$

Where ϕ[n] is scaling function and is the source wavelet. $\varphi_{j0}, k(n) = 2^{j_0/2}\phi\left(2^{j_0}n - k\right)$ is the scaling function at a scale of $s = 2^{j_0}$ altered by $k, \varphi_j, k[n] = 2^j\varphi(2^j n - k)$ is the source wavelet. The approximation coefficients at a scale of $s = 2^{j0} d_{j,k}$ are the detail coefficients at scale of $s = 2^{j_0}$ and, $N = 2^J$ where N is the number of x[n] samples. An aggregation of wavelets at larger than one scale is called as scaling function. A sum of detail and approximation to one of the signal is constructing a discrete signal at a scale of $s = 2^{j_0}$.

The wavelet decomposition first step was to choose the mother wavelet or source wavelet. In this work discrete approximation of meyer wavelet (dmey) transform is chosen and calculate the decomposition level of wavelet. The decomposition level is defined as below.

$$n_f = integer\left[\frac{\log\log\left(f_s/f\right)}{\log\log(2)}\right] \qquad (7)$$

n_f is number of levels, f_s is defined as number of samples and f is frequency. f_s = 15000 and f = 60 Hz.

$$n_f = integer(7.965)$$

The above calculation number of decomposition level is obtained in equation (6). Each decomposition level has some original information. The original signal is compared to final approximation signal is same but data dimension will be reduced. Decomposition tree is shown in Figure 2.

After the signal decomposition each level of decomposed signal frequency band is calculated. Frequency band is defined as.

$$f(d_k) \in \left[2^{-(k+1)}\cdot f_s, 2^{-k}\cdot f_s\right] Hz \qquad (8)$$

$$f(a_k) = \left[0, 2^{-k}\cdot f_s\right] Hz \qquad (9)$$

d_k is detail coefficient, a_k is defined as approximation coefficient and k is the level of decomposition. Table 1 clearly shows the frequency band of each level.

3. Fault Classification

Fault classification is also called as fault diagnosis. This method can classify two types of induction motor malfunction such as stator and rotor. Rotor current signals and torque is used in conjunction with machine learning techniques based on wavelet models. The detailed design of the proposed approach of induction machine condition monitoring and fault diagnosis system illustrated

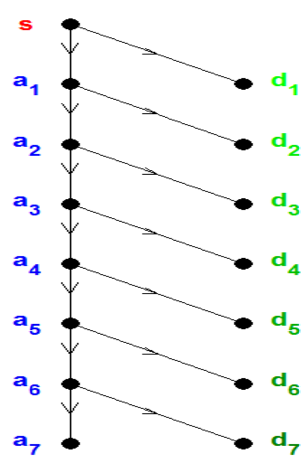

Figure 2. Wavelet decomposition tree.

Table 1. Frequency bands of decomposition level

Level	Approximation	Level	Details
A1	0–3750	D1	3750–7500
A2	0–1875	D2	1875–3500
A3	0–937.5	D3	937.5–1875
A4	0–468.75	D4	468.75–937.5
A5	0–234.375	D5	234.375–468.75
A6	0–117.1815	D6	117.1815–234.37
A7	0–58.59	D7	58.59–117.1875

in Figure 3. Signal measurement and signal decomposition is important to fault diagnosis. There are numerous fault verdict methods which have been developed, such as habitual threshold detection, trend supervising. After the signal decomposition some of the parameters are calculated to diagnosis the motor malfunction.

3.1 Parameter Calculation

3.1.1 Energy

The multilevel decomposition of the rotor current and torque was performed using discrete approximation of meyer wavelet; the suitable level of decomposition is calculated according to equation (6). When defect of the stator, rotor and both of the induction motor appear, the defect information in the rotor current and torque is included in each frequency band determined by the decomposition in the wavelet. By calculating the energy associated to each level, one can build a very effective diagnosis tool. The energy value for each frequency band is defined by

$$E_j = \sum_{k=1}^{k=n} \left| D_{j,k}(n) \right|^2 \quad \textit{Joules.} \tag{10}$$

3.1.2 Entropy

Entropy is a common concept in many fields, mainly in signal processing. In the following expressions *s* is the signal and (s_k) are the coefficients of *s* in an orthonormal basis. Entropy is intensity of signal. The entropy based criterion is used to find the desired levels of resolution. Entropy is defined by

$$E = \sum_k E(s_k) \qquad \textit{Joules / Kelvin.} \tag{11}$$

$$E(s_k) = -s_k^2 \log\left(s_k^2\right) \tag{12}$$

E is total entropy of signal and k is level of decomposition.

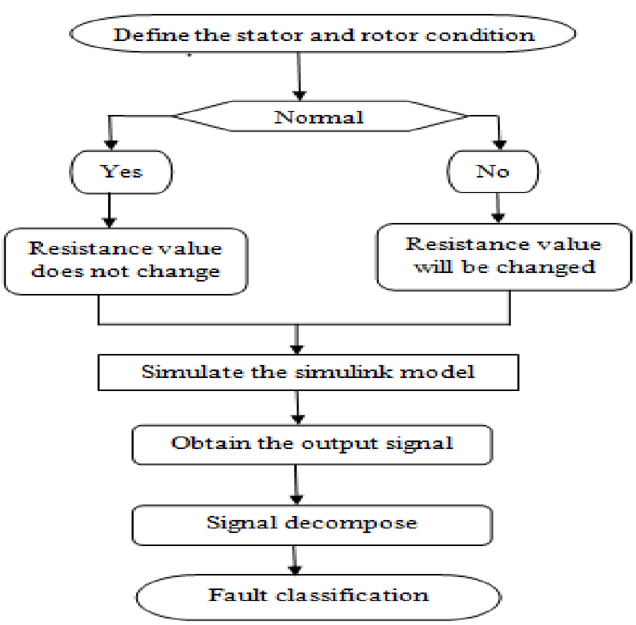

Figure 3. Detailed design of the proposed system.

4. Results and Discussion

The simulation of the DTC induction motor drive was carried out using the Mat lab/Simulink simulation package. DTC control attitude makes use of torque and flux fabricating capabilities of each machine when fueled by a voltage basis inverter that does not require current control device loops, still attaining related performances to that obtained by a vector control drive.

4.1 Signal Decomposition

The signal will be break upped by several details and one final approximation coefficients using wavelet analysis. The dissimilar components cover the whole frequency band with different bandwidths.

- **Case 1: Healthy motor**

The motor is supplied with a sinusoidal voltage of 60 Hz as the foremost frequency. A test under irregular load torque was carried out and the resulting rotor current amplitude that becomes visible in Figure 4. A quick way to achieve the forward DWT coefficients by means of filter bank structure. The approximation coefficients at lower level are passed through a high pass (h [n]) and a low pass filter (g [n]) and this is tracked by a down sampling to calculate both the detail and the approximation coefficients at a higher level. The two filters are related to each other and they are known as quadrature mirror filters. Figure 5 shows the wavelet decomposition for a healthy machine. For all levels of decomposition has information about the signal varies. The wavelet decomposition appears virtually only as a ground line.

- **Case 2: Stator Faults**

In case of a change of stator resistance produce short circuit turns in a stator phase. The change of machine torque and rotor current signal. These signals are shown in Figure 6. And Figure 7 shows the wavelet decomposition for a

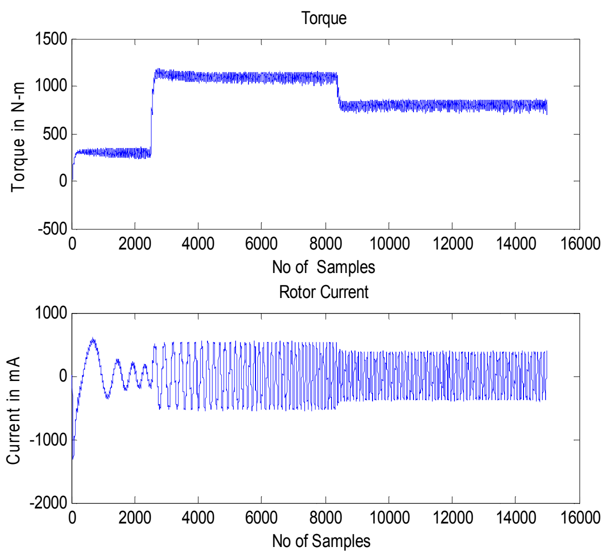

Figure 4. Torque and rotor current of healthy motor.

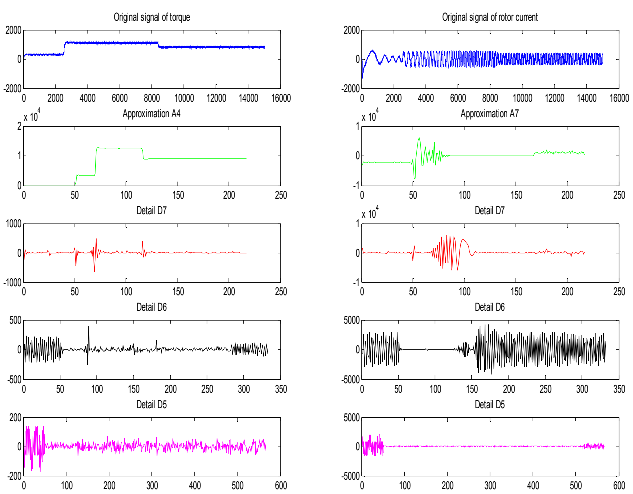

Figure 5. Wavelet decomposition for healthy machine torque and rotor current.

stator fault machine. This figure clearly explains the call for the use of wavelets for diagnostic aims with resistance variations.

- **Case 3: Rotor Fault**

In case of change in rotor resistance produces short turn in rotor phase. In normal condition machine torque is 1200 N-m and rotor current is 500 mA. The change of resistance value increases the rotor current and decreases the torque. It clearly shows that in Figure 8. The Figure 9 shows the wavelet decomposition for a rotor fault machine. This figure clearly explains the call for the use of wavelets for diagnostic aims with resistance variations.

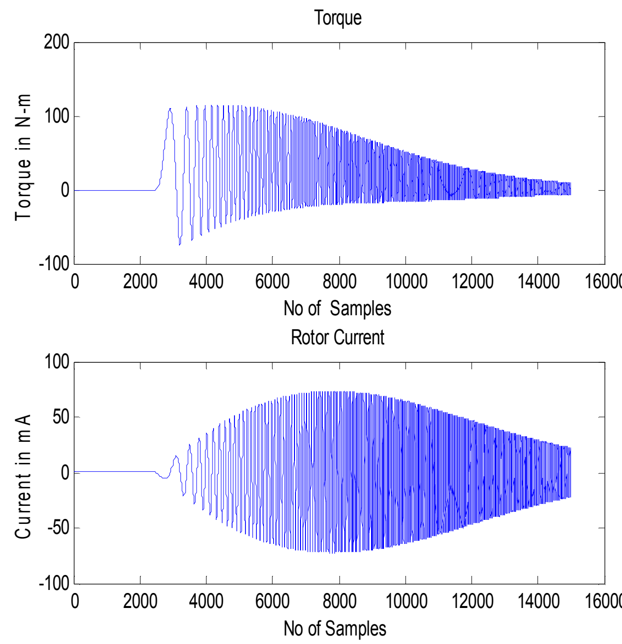

Figure 6. Torque and rotor current for stator fault.

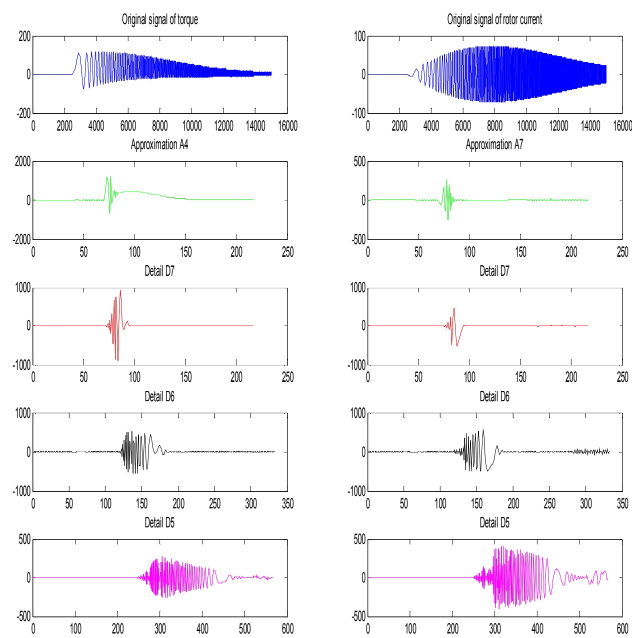

Figure 7. Wavelet decomposition for stator fault machine torque and rotor current.

- **Case 4: Both Fault**

In this case the change of resistance value in stator and rotor core. It produces short turn winding in stator and rotor phase. This short turn windings decrease the torque and rotor current of induction motor. It clearly shows

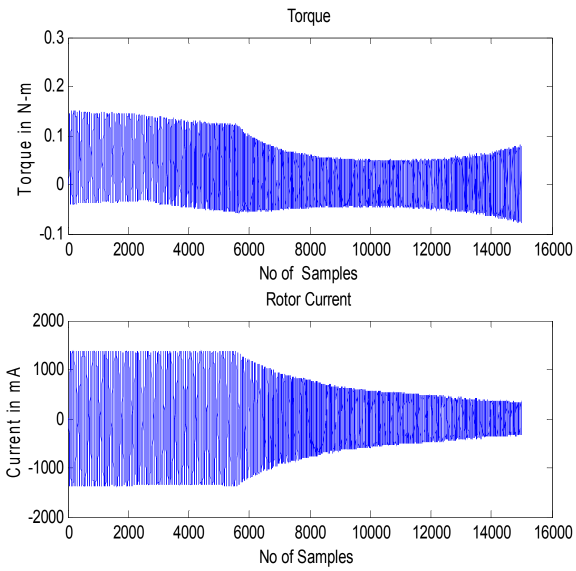

Figure 8. Torque and rotor current for rotor fault.

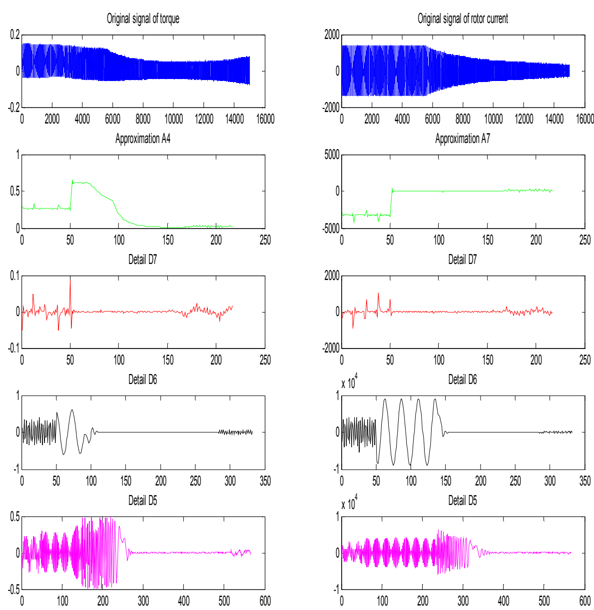

Figure 9. Wavelet decomposition for rotor fault machine torque and rotor current.

Figure 10 and Figure 11 shows the decompose signal of torque and rotor current.

4.2 Analysis

The energy for every detail has been calculated by adding the squared coefficients of the details and the final approximation. Tables 2 and 3 shows the energy increment of the decompositions chosen for analyzing the

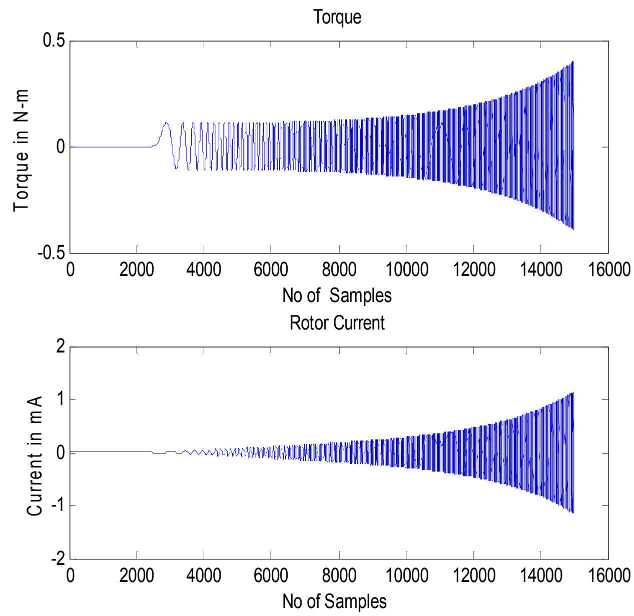

Figure 10. Torque and rotor current for both fault.

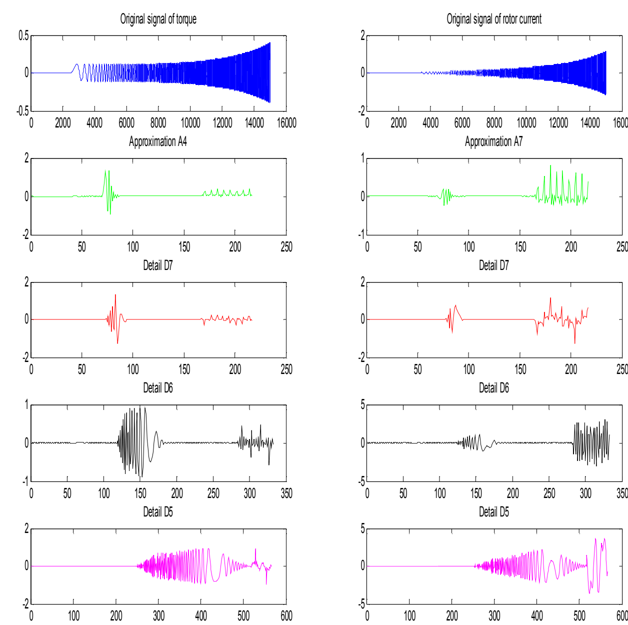

Figure 11. Decomposition for both fault machine torque and rotor current.

motors. Although most wavelet-decomposition coefficients shown in the table can be used to detect faults in the induction motor, the energies in details one to seven are the most suited for the detection of faults an induction motor. Energy calculation in each coefficient done by using equation (9). These different fault energies are plot in Figures 12 and 13. These figures clearly differentiate the

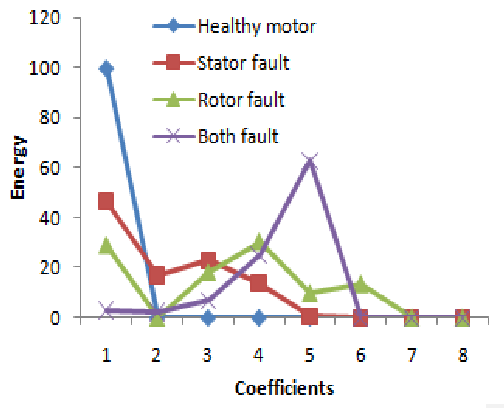

Figure 12. Energy calculation from torque for each fault.

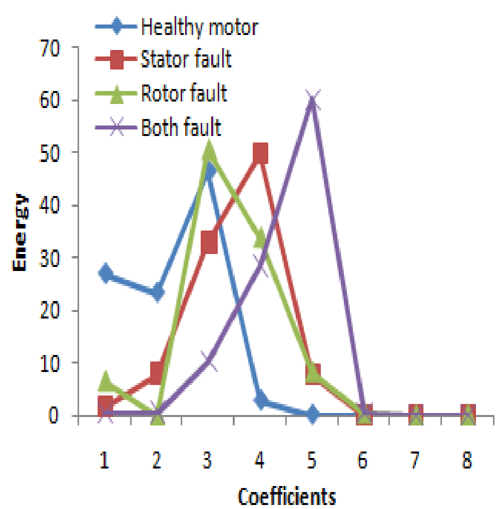

Figure 13. Energy calculation from rotor current for each fault

Table 2. Energy (in J) of decomposition level (Torque)

Levels	Healthy motor	Stator fault	Rotor fault	Both fault
A7	99.908	46.1752	28.7102	3.08508
D7	0.009	16.7295	0.04289	2.37491
D6	0.0117	22.8202	18.0078	6.68346
D5	0.0041	13.5653	29.9871	25.0807
D4	0.0035	0.70899	9.77678	62.7715
D3	0.0071	0.00058	13.3883	0.00424
D2	0.01706	1.08e-5	0.048335	8.66e-5
D1	0.03875	1.56e-7	0.038365	1.09e-6

energy variation from healthy machine to faulty machines. Detail coefficients of 4 to 7 have peak variations for different condition of machines. These coefficients are used to classify machine conditions. The entropy for every detail has been calculated. Tables 4 and 5 shows the entropy increment of the decompositions chosen for analyzing

Table 3. Energy (in j) of decomposition level (Rotor Current)

Levels	Healthy motor	Stator fault	Rotor fault	Both fault
A7	26.9932	1.54106	6.53509	0.20916
D7	23.3952	7.89341	0.05358	0.50772
D6	46.4582	32.9468	50.7215	10.3044
D5	2.8426	49.8678	33.9682	28.4939
D4	0.12410	7.73894	8.32802	60.2208
D3	0.01702	0.01149	0.35810	0.25681
D2	0.02774	0.00032	0.00842	0.00690
D1	0.14170	8.67e-6	0.02702	0.00018

Table 4. Entropy (jk^{-1}) of decomposition level (Torque)

Level	Healthy	Stator fault	Rotor fault	Both fault
D1	−2.4e7	0.1826	0.13623	2.39e-5
D2	−975802	6.7079	0.11721	0.00147
D3	−403132	52.5249	16.2644	0.04458
D4	−212278	−631809	10.0747	−7.7801
D5	−285168	−1.8e9	20.7884	27.4867
D6	−990108	−3.6e7	8.38646	7.58972
D7	−604000	−3.2e7	0.08564	1.21906

Table 5. Entropy (jk^{-1}) of decomposition level (Rotor current)

Levels	Healthy motor	Stator fault	Rotor fault	Both fault
D1	−1.1e7	1.386057	−67791	0.010249
D2	−18555	−57.3484	−20569	0.278333
D3	−12961	−4838.3	−1.8e8	3.394901
D4	−1.5e7	−633184	−5.1e9	−1150.54
D5	−4.5e8	−5e7	−2.3e10	−376.547
D6	−8.4e9	−2.7e7	−3.9e10	−141.361
D7	−5.4e9	−395428	−3.2e7	5.389386

the motors. Although most wavelet decomposition coefficients shown in the table can be used to detect faults in the induction motor, the entropies in details one to seven are the most suited for the detection of faults an induction motor.

5. Conclusion

Signal decomposition via wavelet transform provides a good approach of multi resolution analysis. The decomposed signals are self-sufficient due to the orthogonality of the wavelet function. There is no redundant information in the decomposed frequency bands. Based on the information from set of frequency bands, mechanical condition monitoring and fault diagnosis can be efficiently performed. This paper has shown a discovery of stator and rotor faults an induction motor having rotor current and torque as input. The recognition is based on the discrete wavelet decomposition method and both an energy and entropy value coefficients of the DWT are calculated in order to differentiate between healthy and faulty values. This study is based on simulation. It will be set up hardware design as a next study.

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