Research Article
A Real Time Data Acquisition and Vibration Analysis through Wavelet Transform for Fault Detection of Industrial Drives

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Abstract: Prevention is better than cure is not only applicable to medical domain but also equally applicable to engineering field. By analyzing the symptoms and taking appropriate corrective measures before the actual failure takes place would avoid costly cateroscopic damages. In line with this approach a fault analysis through vibration study with wavelet transforms has been attempted in this study. The previous researchers adopted a wavelet analysis for stator fault, such as stator current signature analysis. But the present study had adopted frequency pattern using the decomposition of wavelet pocket for induction machine fault analysis. Subsequently the machine would be determined by analyzing the data obtained through HAAR wavelet. Induction motor, one with good condition and another with two broken ball bearing were taken up for fault analysis using above techniques. The proposed investigation of vibration analysis is done through frequency pattern using the decomposition of wavelet packet. The wavelet approximate and detailed coefficients for the vibration signal have been extracted over a wide range and the analysis could be percolated on the frequency domain. In this study, healthy and unhealthy motor are used to experimentally observe the vibration signals are transformed into power spectral density through Matlab tools and the steady state rotor frequency was introduce with a new frequency pattern for fault diagnosis.

Keywords: Broken ball bearing, decomposition level, frequency, fault diagnosis, HAAR wavelet, Induction Machines (IM), power spectrum, vibration, Wavelet Transform (WT)

INTRODUCTION

The induction machines are widely used for their simplicity, robustness and low cost. Induction Motors are a critical component of many industrial and manufacturing processes and are frequently integrated in commercially available equipment. Because of this, many researchers have been made since long ago to detect fault that occur in electrical machines. The risk of motor failure is manifestly reduced if normal service conditions are known in advance. In other words, one may avoid very costly expensive downtime from plant by proper time scheduling of motor replacement or repair if impending failure can be warned in advance. In recent years, fault diagnosis has become a challenging topic for many researchers. The major faults of electrical machines are identified based on one or more of the following symptoms and accordingly classified (Nandi and Toliyat, 2005):

- Unbalanced air-gap voltages and line currents
- Increase in torque pulsations
- Increase in losses and reduction in efficiency
- Excessive heating

Fault identification methods which are taken into account for analysis of induction motor are Electromagnetic field monitoring, Temperature measurements, Infrared recognition, Radio Frequency (RF) emissions monitoring, Noise and vibration monitoring, Motor Current Signature Analysis (MCSA), Model and AI based techniques. These methods have their own limitations in approaching a problem and are selected based on the nature of fault and application of electrical machines (Nandi and Toliyat, 2005; Bouzida *et al.*, 2011).

Wavelet Transforms method is used to analyze the faults in bearing of an induction motor based on noise and vibration monitoring method. Wavelet is the powerful mathematical tool to analyze local structure of vibration spectrum to identify singularities and edges. The main attraction for wavelets in this application is their ability to analyze singularities and irregular structures and the tradeoffs they provide in terms of handling metrics such as frequency resolution of the spectra, variance of estimated power spectra and complexity. Vibration problems can occur at anytime of fault or mal-functioning of motor. When they occur, it is normally critical, so that immediate attention needs to be given to solve the problem. If not solved quickly,

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one could either expect long term damage to the motor or immediate failure, which would result in immediate loss of production. The loss of production is often the most critical concern. To solve the problem of fault based on vibration monitoring, one must differentiate cause and effect. In this study, the vibration and vibration spectrum response of an induction motor (driven by a variable operating frequency) is taken into account to diagnose the effect of bearing fault.

MATERIALS AND METHODS

Induction motor fault: The major faults of electrical machines can broadly be classified as follows:

- Broken rotor bar or cracked rotor end-rings
- Static and dynamic air-gap irregularities
- Bent shaft (akin to dynamic eccentricity)
- Bearing and gearbox failure

The percentage of various faults that occur in induction motors is shown in Fig. 1 and is identified that bearing fault is normally occurring. Therefore, the bearing fault of induction motor is considered in this study (Gaeid and Mohamed, 2010). The generalised block diagram for diagnosis of faults in induction machines with intelligent techniques is shown in the Fig. 2. It divulges the combination with advanced Digital Signal Processing (DSP), Fuzzy logic, computerized data acquisition and processing. The illustration is a new way of analysing the fault diagnosis through spectral analysis of acquired signal (Benbouzid, 2000; Yang, 2007).

This scheme has the merits like low cost and easy operation. Monitoring Electric Machines with conditional setting may significantly reduce the risk of unexpected failures and it consents the existing detection which does not have that much potential to calamitous faults and maintenance (Vas, 1993). In conditional maintenance, one does not do the scheduling on maintenance or machine replacement. It is based on previous record failures/Statistical estimation of machine failure. On the other hand,

information provided by condition monitoring system assesses the machine's condition (Chow and Hai, 2004). Thus the success of condition is based on maintenance and moreover it is having an accurate conditional assessment and fault diagnosis. The illustration also shows a block of on-line conditional monitoring system/subsystem for proposed mechanism (Medoued *et al.*, 2010). Sensors can be employed to measure up the signals that detect the faults zone. The block of advanced signal processing techniques can as well be applied to extract particular fault sensitive zones.

Discrete wave transform: The method of wavelet analysis includes a discussion of different wavelet functions and gives details for the analysis of the wavelet power spectrum (Salloum and Ping, 2011). A wavelet is a function ψ belonging to $L^2(R)$ with a zero average. It is normalized and centred in the neighbourhood of $t = 0$. A family of time - frequency atoms is obtained by scaling ψ by a and translating it b. $L^2(R)$ represents the space vector of square integral functions on the real line R with:

$$\|\psi\| = 1$$
$$\int_{-\infty}^{+\infty} \psi(t)dt = 0 \tag{1}$$

$$\psi_{b,a}(t) = |a|^{\frac{-1}{2}} \psi\left(\frac{t-b}{a}\right) \tag{2}$$
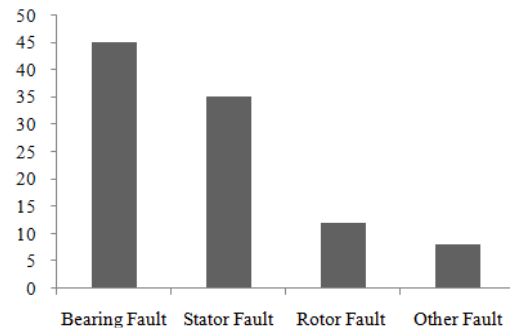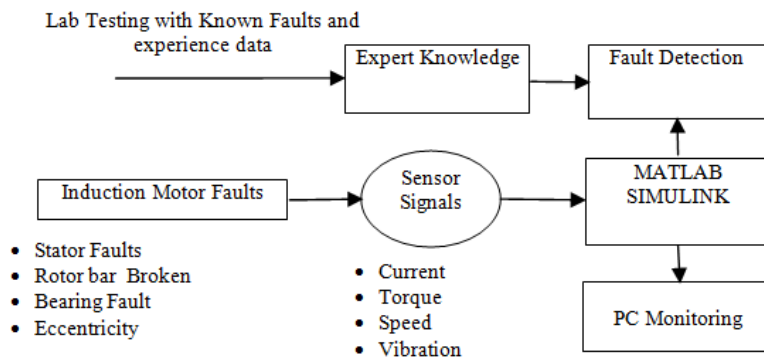

Fig. 1: Percentage of faults in induction machines

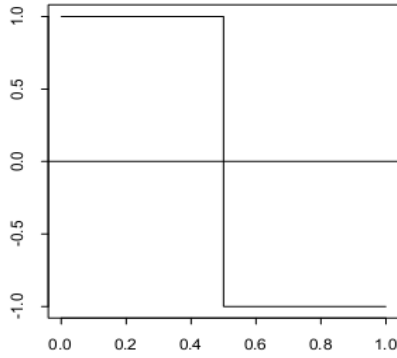Fig. 2: Block diagram of proposed system

Fig. 3: Haar wavelet

These atoms also remain normalized. The wavelet transform (WT) of belonging to $L^2(R)$ at the scale and the position b:

$$W_f(b,a) = \{f, \psi(b,a)\} = \int_{-\infty}^{\infty} f(t)|a|^{\frac{-1}{2}} \psi\left(\frac{t-b}{a}\right) dt \qquad (3)$$

The real wavelet transform consists of the energy conserving nature, when it is satisfies a weak admissibility conditions. The Discrete version of Wavelet Transform (DWT) contains the sampling neither the signal nor the transform but sampling the scaling and shifted parameter (Ponci *et al.*, 2007; Stanković and Falkowski, 2003). These significances in high frequency resolution at low frequencies and high time resolution at high frequencies correspondingly through eliminating the redundant information.

Haar wavelet: The WT classified into many categories and there are more than 10 models of WT. The Haar Wavelet transforms are popular for fault detection and diagnosis of induction motors. Haar wavelet is the simplest type of discrete wavelet transforms and it is related to a mathematical operation called the Haar transform. The Haar transform serves as a prototype for all other wavelet transforms. Like all wavelet transforms, the Haar transform decomposes a discrete signal into two sub signals of half its length. One sub signal is a running average or trend, the other sub signal is a running difference or fluctuation. It is known that any continuous function can be approximated uniformly by Haar functions. Dilations and translations of the function:

$$\psi_{jk}(x) = const \cdot \psi(2^j x - k) \qquad (4)$$

The discrete Haar transform consists of functions on a matrix row-wise finding the sums and differences of consecutive elements (Salloum and Ping, 2011). While each Haar function contains just one wavelet during some subinterval of time and remains zero

elsewhere, the Haar set forms a local basis. It is noticed that all the Haar wavelets are orthogonal to each other and define an orthogonal basis in $L^2(R)$ (the space of all square integral functions). This means that any element in $L^2(R)$ may be represented as a linear combination (possibly infinite) of these basis functions. The or thogonality Ψ_{jk} is easy to check:

$$\int \psi_{jk} \psi_{j^1 k^1} = 0 \qquad (5)$$

Whenever $j = j^1$ and $k = k^1$ is not satisfied simultaneously. If $j \neq j^1$ (say $j^1 < j$), then nonzero values of the wavelet $\Psi_{j^1 k^1}$ are contained in the set where the wavelet $\Psi_{j^1 k^1}$ is constant. That makes integral equal to zero. If $j \neq j^1$, but, then at least one factor in the product $\Psi_{j^1 k^1} \cdot \Psi_{jk}$ is zero. Thus the functions are Ψ_{jk} orthogonal. It is a step function taking values 1 and -1, on $\left(0, \frac{1}{2}\right)$ and $\left(\frac{1}{2}, 0\right)$ respectively (Stanković and Falkowski, 2003). The graphical representation of the Haar wavelet is shown in Fig. 3. In generating each of averages for the next level and each set of coefficients, the Haar transform performs an average and difference on a pair of values. Then the algorithm swings over by two values and calculates another average and difference on the next pair. The high frequency coefficient spectrum should reflect all high frequency changes. The Haar window is only two elements wide. If a big change takes place from an even value to an odd value, the change will not be reflected in the high frequency coefficients. Haar 2-tap wavelet has been chosen for this implementation (Salloum and Ping, 2011). It is conceptually simple, fast and memory efficient, since it can be calculated in place without a temporary Array. Also it is exactly reversible without the edge effects that are a problem with other Wavelet transforms.

WAVELET PACKET AND COEFFICIENT

The wavelet-packet method is a generalization of wavelet decomposition that offers a richer range of possibilities for signal analysis. In wavelet analysis, a signal is splitted into an approximation and a detail. Then, the approximation is itself splitted into a second-level approximation and detail and the process is repeated (Salloum and Ping, 2011) until the targeted results are obtained. For n-level decomposition, there are n+1 possible ways to decompose or encode the original signal. Wavelets and wavelet packets decompose the original signal, which is of no stationary or stationary in nature into independent frequency bands with multi-resolution. The wavelet transform is also known as multi scale decomposition process.
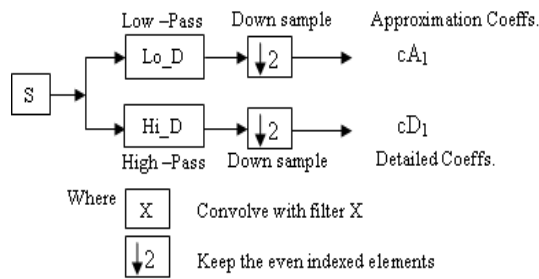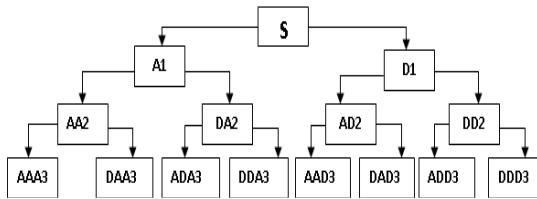
Fig. 4: Coefficients with filters

Fig. 5: Signal 'S' in the wavelet packet

Fig. 6: Experimental set up

Table 1: Parameters of induction motor

Sl. No.	Descriptions	Specification
01	Power rating	0.5 Hp
02	Voltage rating	230 Volts
03	Current rating	400 mA
04	Speed	1500 rpm

They form bases which retain many of the orthogonality, smoothness and localization properties of their parent wavelets. The algorithm starts from a Signal (S) as shown in Fig. 4 and two sets of coefficients are computed that is approximation coefficients cA_1 and detail coefficients cD_1. The vectors are obtained by convolving S with the low-pass filter Lo_D for approximation and with the high-pass filter Hi_D for detail, followed by dyadic decimation (Faiz *et al*., 2009). The length of each filter is equal to 2N. If n = length(s), the signals F and G are of length n + 2N - 1 and then the coefficients cA_1 and cD_1 are of length and floor for an illustration the wavelet packets decompose the signal into one low-pass filter and (2*l* − 1) band pass filters and provide diagnosis information in two frequency bands. A_j is the low-frequency approximation and D_j is the high-frequency detail signal. After decomposing the signal, we obtain approximation signals $A_1, A_2 ..... A_j$ and $D_1, D_2 ....,. D_j$ detail signals (Bouzida *et al*., 2011) as shown in Fig. 5.

EXPERIMENTAL RESULTS AND DISCUSSION

The proposed mechanism detects the broken bars proficiently to analyse the healthy/faulty systems. In case, if the system is healthy then the instantaneous power contains one modulation signal around the carrier frequency at 50 Hz. Indeed, the modulation signal is created by a natural rotor asymmetry. If there is an occurrence of broken bearing ball then the asymmetric rotation increase and their corresponding sidebands frequency appears to be around $2Kf_s$. The broken bearing ball detection mechanism of analysis, a global modulation of index is considered. If the fault appears in the healthy system, then there will be an increase in the global index and consequently the fault
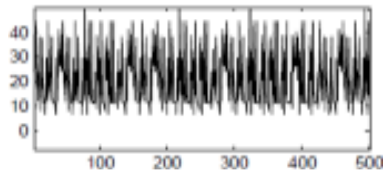
diagnosis could be done at on-time. To evaluate the global index, the frequency and sideband amplitude modulation must be found and it helps to estimate the index magnitude. To reduce the spectrum variation, the magnitude of the component should be improved (Faiz and Ebrahimi, 2008). Thus we apply a non-parametric estimator of power spectrum. In fact, while the record length N increases, then the resolution frequency will be better, though the augmentation does not vary.

The experimental set up is shown in Fig. 6 under healthy and unhealthy conditions. The test bed composes of single-phase with healthy and unhealthy conditions, Process Control Board comprising PIC Micro-Chip 16F874A/877A, Vibration Sensing Unit, Speed Sensing Unit, Torque Evaluator and Zero Crossing Detector. The specification of induction motor under test is given in Table 1. The motor is tested with bearing balls under normal and broken condition without affecting the electrical and magnetic features (Aroui *et al*., 2007).
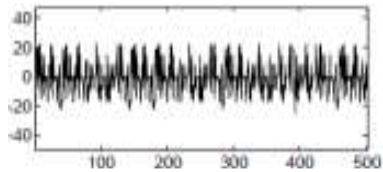
The sampling frequency is set to 5 Hz and the data length is 2^{10} values. The motor was running for 30 minutes and 25000 set of data generated. The experimentally generated sample data are given in the Table 2. The performance of induction motor under broken ball bearings is analysed using wavelet transform and compared with healthy motor and the results are verified. In steady state operation, damaged bearings produced harmonic components of frequency pattern $f_s \pm 2f_r, f_s \pm 4f_r, f_s \pm 6f_r, ... f_s \pm 2kf_r$ in the vibration. Here, f_r is the rotor frequency and is given as sfs, where fs is the supply or fundamental frequency and s is slip. Since s is varying with respect to rotor speed and it is load dependent (Faiz and Ebrahimi, 2008; Stack *et al*., 2003). The broken or damaged bearings
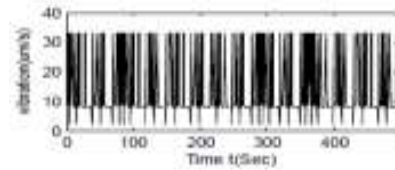
Table 2: Generated data

Healthy motor				Unhealthy motor			
Voltage in volts	Current in mA	Frequency in Hz	Vibration in (µm/s)	Voltage in volts	Current in mA	Frequency in Hz	Vibration in (µm/s)
230	425	50.00	32.39	229	680	49.19	44.18
230	425	50.00	32.52	229	682	49.20	3.680
230	425	50.00	33.00	229	682	49.18	8.230
230	426	50.00	30.68	229	682	49.19	31.17
230	425	50.00	30.40	229	682	49.19	12.38
230	424	50.00	33.00	229	682	49.20	8.080
230	425	50.00	32.89	229	682	49.20	8.070
230	425	50.00	34.49	229	682	49.20	8.150
230	425	50.00	33.00	229	680	49.20	30.41
230	426	50.00	30.55	229	680	49.21	1.320
230	425	50.01	29.63	229	687	49.20	7.980
230	427	50.00	28.54	229	681	49.20	34.72
230	427	50.00	30.52	229	683	49.20	1.280
230	424	50.00	32.30	229	682	49.20	8.700
230	425	50.00	34.51	229	680	49.20	35.37
230	425	50.00	33.00	229	682	49.20	9.930
230	425	50.00	34.12	229	682	49.20	8.520
230	425	49.98	34.59	229	680	49.20	3.700
230	425	50.00	32.05	229	680	49.20	30.42
230	426	50.00	30.88	229	681	49.19	30.49
230	426	50.00	33.09	229	681	49.19	2.270
230	427	50.00	32.41	230	681	49.17	33.30
230	427	50.00	34.09	229	679	49.18	32.55
230	425	50.00	33.00	229	681	49.17	28.74
230	427	50.00	30.05	229	680	49.18	3.660
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.

(a) Healthy motor

(b) Unhealthy motor with two broken ball bearings

Fig. 7: Plot of vibration measured experimentally

(a) Approximate coefficients

(b) Detailed coefficients

Fig. 8: Coefficient of healthy motor

is analysed by identifying the harmonic components around the fundamental component of vibration. The vibration of healthy and unhealthy motor is measured experimentally and plotted as shown in Fig. 7 and it is observed that the magnitude of vibration plot of healthy motor is almost constant and has fewer ripples, where as the plot of broken ball bearings has more ripples.

As seen in the Table 3, the amplitude of component increase from -15 dB in healthy motor to -13 dB in the two bearing ball broken motor and the corresponding

Table 3: Frequency pattern with harmonics

NBB	$f_s + 2kf_r$ Amplitude	Harmonics	$f_s - 2kf_r$ Amplitude	Harmonics
0	54	-15	46	-20
	58	-20	44	-24
	62	-20	38	-22
2	54	-13	46	-14
	58	-17	44	-19
	62	-18	38	-20

values for $f_s - 2f_r$ are -20 and -14 dB respectively. By increasing the number of broken ball bearings, the

(a) Approximate coefficients

(b) Detailed coefficients

Fig. 9: Coefficient of unhealthy motor with two broken ball bearings

(a) Healthy motor

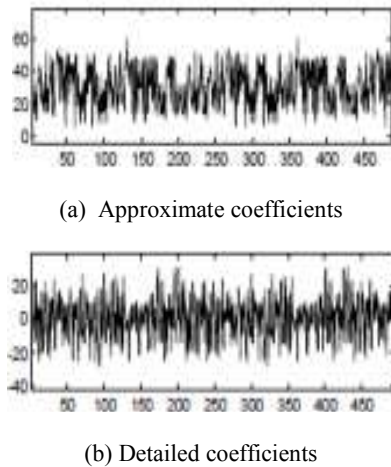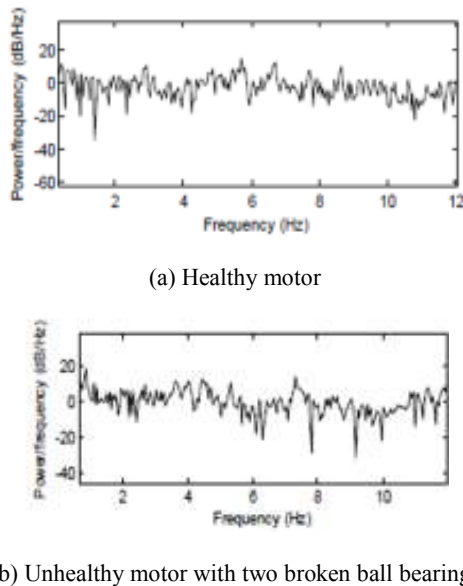(b) Unhealthy motor with two broken ball bearings

Fig.10: Vibration spectrum of frequency scale 12 Hz

amplitude of harmonics are also increased. Therefore amplitude of harmonics components may be used in fault diagnosis of an electrical machine. Figure 8 to 10 shows the vibration Spectrum for the healthy and unhealthy induction motor obtained experimentally through wavelet transform and it indicates the presence of the frequency components $fs \pm 2kf_r$ which confirm the experimental result.

CONCLUSION

The diagnosis of faults in induction motor under healthy and unhealthy with two broken ball bearings is done using signal decomposition based wavelet transform. The decomposed signals are independent due to the or thogonality of the wavelet function and there is no redundant information in the decomposed frequency bands. The amplitude of $f_s + 2f_r$ component in the vibration spectrum is increase from -15 dB in healthy motor to -13 dB in the two bearing ball broken motor and the corresponding value for $f_s - 2f_r$, are -20 and -14 dB respectively. By increasing the number of broken ball bearings, the amplitude of harmonics $f_s \pm 2kf_r$ are also increased. The experimentally observed vibration and current signals are transformed into power spectral density with the help of approximate and detailed coefficients. The steady state rotor frequency was used to introduce a new frequency pattern for fault diagnosis. The vibration and current spectrum of the motor under healthy and unhealthy are analysed, it was shown that the broken ball bearings lead to increase in magnitudes of harmonic component in vibration and current and there by decrease in motor performance.

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