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A WAVELET BASED DIAGNOSIS AND CLASSIFICATION OF RACEWAY DEFECTS IN BEARINGS OF AN INDUCTION MOTOR

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Abstract- This paper addresses the method for the diagnosis and classification of bearing defects in an induction motor. The normal current of the running motor and voltage of the respective phase is used as the medium for the analysis. The method uses discrete wavelet transform as a tool for the classification of the faults. The proposed method is independent of the loading conditions of the motor and therefore analysis can also be done on the no load condition of motor. The proposed method can reliably distinguish between the inner race defect and the outer race defects of the bearings. The application of the same method is advantageous to detect an incipient fault of the bearing in its early stage.

Keywords: Induction Motor, Fault Diagnosis, Wavelet Analysis, Bearing Defects.

I. INTRODUCTION

Nowadays induction motor has got prime importance in industries as well as in the power system. The induction motor for the various electrical applications consumes ample amount of power generated in the world, as it has got a wide range of applications in the industries. Having such an application range, induction motor is always subjected to various electrical as well as mechanical faults. These faults can be classified as follows stator winding fault or inter turn short circuit fault

- Bearing faults
- Air gap eccentricity
- Broken rotor bars
- Misalignment of rotor

If preventive maintenance is not given due importance such faults can turn into failure of motors. Failure of an induction motor can result into loss of production or it may shutdown the processing units. One cannot afford a loss because of failure of motor. Therefore a reliable monitoring technique is required in order to reduce the loss and the maintenance cost of the motor. Since a decade or more substantial amount of work is going on in the field of condition monitoring. A study has been made to know the cause of failure of an induction motor, the survey report of EPRI suggests that the main cause of failure is the defective bearing that figures 42% of total causes of failure. Therefore to avoid the failure and reduce the downtime and maintenance cost the early stage detection of the fault is essential. Presently reasonably reliable techniques are available for detecting bearing degradation. The most popular amongst these methods are vibration signal analysis and the motor current signature analysis. The approaches generally involve monitoring and analysis of vibration signal. Artificial intelligence plays a dominant role in the field of condition monitoring and different techniques, such as neural network; fuzzy logic and genetic algorithms are being widely used for the feature extraction and classification purposes [1-3]. Another tool that seems very useful in fault detection is HMM. Its success in speech recognition causes it to be used in fault detection [4]. Though the vibration signal analysis plays an important role in detection of mechanical faults associated with motor the current signature analysis is over taking it. The method that uses current or voltage measurement offers several advantages over test procedures that require machine to be taken off- line or the methods that require special sensors to be mounted on the motor. Whereas the current signature analysis does not require such costly sensors, using current transformers and data acquisition system, signals can be captured.

The wavelet is now becoming more and more popular than other methods of fault diagnosis because it permits systematic decomposition of signal into its sub band levels. If the current signal consists of the non-stationary or transient conditions the conventional Fourier transform is not suitable and the time-frequency or time-scale method has to be adopted. The wavelet was introduced by Jean Morlet a French engineer in 1982. Newland was the one whose work made wavelet transforms popular in engineering field especially in vibration analysis. He has not only proposed the harmonic wavelet but also identified the peaks and packets of the transitory signals [5]. The method based on the wavelet packet for the diagnosis of failure of ball bearings was proposed by B. Liu and S.F. Ling [6]. Loparo used the wavelet transform as tool for feature extraction and fuzzy classifier for detection of fault in bearing [7]. In [8], J.C. Garcia-Prada, C. Castejon, and O.J. Lara have proposed a new condition monitoring technique for detection and classification of bearing faults. They used DWT for the feature extraction and extracted features are then used as input to the neural network for the classification of faults.

In this paper, a wavelet-based analysis is used for the discrimination of the raceway defects in the ball bearings. The proposed method is an experimental work carried out in the laboratory. The motor is tested with different sets and combination of bearings in different load conditions. The stator current and phase voltage of the motor is used, as the medium of analysis. It is worth to mention that the results of the method are independent of the loading condition of the motor and the analysis can be made on no load. The results shows that proposed method can reliably detect and discriminate the defects of ball bearings.

II. WAVELET TRANSFORM AND DENOISING

A. Wavelet Transform

Wavelet analysis is about analyzing the signal with short duration finite energy functions. They transform the considered signal into another useful form. This transformation is called Wavelet Transform (WT). Let us consider a signal $f(t)$, which can be expressed as

$$f(t) = \sum_l a_l \, \phi_l(t) \tag{1}$$

where, l is an integer index for the finite or infinite sum. Symbol a_l are the real valued expansion coefficients, while $\varphi_l(t)$ are the expansion set.

If the equation (1) is unique, the set is called a basis for the class of functions that can be so expressed. The bases are orthogonal if

$$\langle \varphi_l(t), \varphi_k(t) \rangle = \int \varphi_l(t) \varphi_k(t) dt = 0 \quad k \neq l \tag{2}$$

Then coefficients can be calculated by the inner product as

$$\langle f(t), \varphi_k(t) \rangle = \int f(t) \, \varphi_k(t) \, dt \tag{3}$$

If the basis set is not orthogonal, then a dual basis set $\varphi_k(t)$ exists such that using (3) with the dual basis gives the desired coefficients. For wavelet expansion, equation (1) becomes

$$f(t) = \sum_k \sum_j a_{j,k} \, \varphi_{j,k}(t) \tag{4}$$

In (4), j and k are both integer indices and $\varphi_{jk}(t)$ are the wavelet expansion function that usually form an orthogonal basis. The set of expansion coefficients a_{jk} are called Discrete Wavelet Transform (DWT).

There are varieties of wavelet expansion functions (or also called as a Mother Wavelet) available for useful analysis of signals. Choice of particular wavelet depends upon the type of applications. If the wavelet matches the shape of signal well at specific scale and location, then large transform value is obtained, vice versa happens if they do not correlate. This ability to modify the frequency resolution can make it possible to detect signal features which may be useful in characterizing the source of transient or state of post disturbance system. In particular, capability of wavelets to spotlight on short time intervals for high frequency components improves the analysis of signals with localized impulses and oscillations particularly in the presence of fundamental and low order harmonics of transient signals. Hence, Wavelet is a powerful time frequency method to analyze a signal within different frequency ranges by means of dilating and translating of a single function called Mother wavelet.

Formulation of DWT is related to filter bank theory in many of the good references. It divides the frequency band of input signal into high and low frequency components by using high pass $h(k)$ and low pass $g(k)$ filters. This operation may be repeated recursively, feeding the down sampled low pass filter output into another identical filter pair, decomposing the signal into approximation $c(k)$ and detail coefficients $d(k)$ for various resolution scales. In this way, DWT may be computed through a filter bank framework, in each scale, $h(k)$ and $g(k)$ filter the input signal of this scale, giving new approximation and detailed coefficients respectively. The filter bank framework is shown in Figure 1. The down pointing arrow denotes decimation by two and boxes denote convolution by $h(k)$ or $g(k)$.

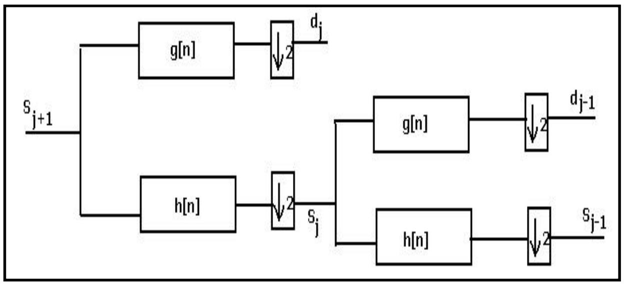


Figure 1. Two band multi-resolution analysis of signal

The coefficients of filter pair are associated with the selected mother wavelet. Daubechies wavelet family is mostly used for analysis of power system transients. In this paper, Daubechies (db-4) wavelet is used as the mother wavelet, due to its good time resolution that provides accurate detection of fast transients.

B. Wavelet Denoising

Assume a finite length signal with a additive noise of the form

$$y_i(t) = f_i(t) + \varepsilon \, n_i(t) \tag{5}$$

In equation (5), $f_i(t)$ is finite length signal that is corrupted with zero mean, white Gaussian noise $n_i(t)$ with noise level ε. The goal is to recover the signal $f_i(t)$ from the noisy data $y_i(t)$ without assuming any parametric structure for $f_i(t)$.

There are major three steps for carrying out denoising of signal, generally called as wavelet coefficients shrinkage technique:

Step 1: Calculate wavelet coefficients w applying a wavelet transform (WT) to a signal or data.

$$WT\{y_i(t)\} = WT\{f_i(t)\} + WT\{\varepsilon \, n_i(t)\} \tag{6}$$

Step 2: Modify the detail coefficients w by applying certain threshold value to obtain shrink version detailed coefficients $\tilde{w}$ of $f_i(t)$.

$$w \xrightarrow{\text{yields}} \tilde{w} \tag{7}$$

Step 3: Inverse transform the modified detailed coefficients to obtain denoised coefficients.

$$\hat{f}_i(t) = WT^{-1}\{\tilde{w}\} \tag{8}$$

There are variety of wavelets those can be used, which differ in their support, symmetry and number of vanishing moments. In addition to wavelet, one has to select the number of multi-resolution levels and options for handling values at the edges.

As mentioned in step 2, the detailed coefficients can be modified using the threshold selection. The thresholding method can be grouped in following two categories:

B.1. Global Threshold: Here, a single value for threshold λ to be applied globally to all empirical wavelet coefficients.

B.2. Level Dependent Threshold: In this, a different threshold value λ_j is chosen for each resolution level j. These thresholds require an estimate of the noise level ε. The robust estimate for the ε is proposed as

$$\hat{\varepsilon} = \frac{\text{median}\{|w_k|\}}{0.6745} \qquad k = 1, 2, ..., \frac{N}{2} \tag{9}$$

In equation (9), w_k is the detailed coefficients at the finest level and the detailed coefficients can be obtained as

$$\tilde{w} = \hat{\varepsilon}\, D^{\lambda}\left(\frac{w}{\hat{\varepsilon}}\right) \tag{10}$$

where, $D^{\lambda}(.)$ is called shrinkage function, which determines how threshold is applied to data sets. There are commonly four threshold functions used in practice. These are given below:

1. Hard Threshold

$$D_H^{\lambda}(w) = \begin{cases} w & \text{for} |w| > \lambda \\ 0 & \text{otherwise} \end{cases} \tag{11}$$

2. Soft Threshold

$$D_S^{\lambda}(w) = \text{sgn}(w)\max(0, |w| - \lambda) \tag{12}$$

3. Garrote Threshold

$$D_G^{\lambda}(w) = \begin{cases} w - \dfrac{\lambda^2}{W} & \text{for} |w| > \lambda \\ 0 & \text{otherwise} \end{cases} \tag{13}$$

4. Semi Soft Threshold

$$D_{SS}^{\lambda}(w) = \begin{cases} 0 & |W| < \lambda_1 \\ \text{sgn}(w).\dfrac{\lambda_2(|w| - \lambda_1)}{\lambda_2 - \lambda_1} & \lambda_1 < |w| \le \lambda_2 \\ w & |w| > \lambda_2 \end{cases} \tag{14}$$

Threshold λ can be obtained through various shrinkage rules like, min FDR, top, sure, translation invariant thresholding, Bays shrink etc. The universal rule for one-dimensional signal for calculation of threshold value λ independent of shrinkage function is given by (15).

$$\lambda = \hat{\varepsilon}\sqrt{2\log N} \tag{15}$$

In this paper, global universal threshold rule is used with soft threshold shrinkage function.

III. BEARING: AN OVERVIEW

The ball bearing generally comprises of balls, cage, inner race and an outer race. The large race that goes into a bore is called as the outer race, and the small race that the shaft rides in is called as the inner race. A cage is that part of bearing which holds all the balls together. General defects that cause-bearing failure are inner race defects, outer race defects, cage defects and rolling element or ball defects. There may be several reasons of bearing failure but very common are improper lubrication and a leakage current causing capacitance to form between the rings of bearing. Rolling-element bearings often work well in non-ideal conditions, but sometimes-minor problems cause bearings to fail quickly and mysteriously. For example, with a stationary (non-rotating) load, small vibrations can gradually press out the lubricant between the races and balls, without lubricant the bearing fails. The failure of bearings causes the eccentricity to be produced inside the motor. The eccentricity makes the air gap between stator and rotor uneven that changes the rate of change of flux linkage. This change in rate of flux linkage forces the current to change in such a way that motor takes larger current than normal condition. This excessive current results in over heating of winding that leads to the failure of motor. This makes the bearing fault the most severe and hence need to monitor the bearing condition.

IV. EXPERIMENTAL SET UP

Figure 2 shows the set up used for the experimental purpose. Mains fed 2 Hp, 3 phases, 50 Hz squirrel cage induction motor made by the leading Indian Electrical industry has been used for the analysis of bearing faults. The spring and belt arrangement is used for the mechanical loading of the motor. The motor comprises of two bearings numbered as 6204 and 6205. The bearings having natural defects caused by the regular operation of motor were used in experimental study. Motor is fitted with different combination of bearings having inner race and outer race defects. Stator current and phase voltage of the motor for each combination of bearing is then captured in order to compare with healthy bearings. Different experiments were conducted with different combinations of rear side and load side bearings to access the performance of these bearings and its effect on the performance of motor.

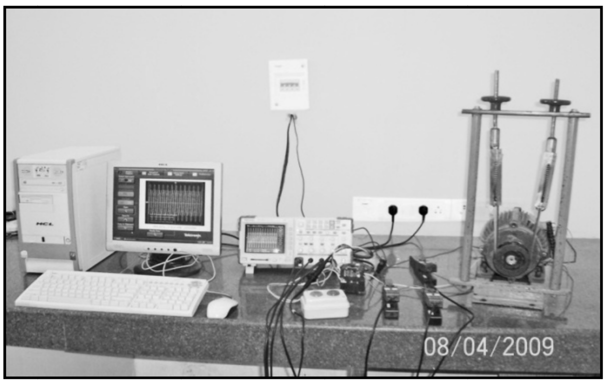


Figure 2. Experimental set up

Three currents I_a, I_b and I_c and voltage V_a were captured using the experimental setup shown in Figure 2. The Tektronix DSO, TPS 2014 B, with 100 MHz bandwidth and adjustable sampling rate of 1 GHz is used to capture the currents. The Tektronix current probes of rating 100 mV/A, input range of 0 to 70 Amps AC RMS, 100A peak and frequency range DC to 100KHz are used.

Figure 3 shows the set of ball bearings used for the study. The bearings used in this study are having natural defects due to their continuous operation. The experimentation was done using the four sets of bearings with different defect in their races. The defected bearings in upper row are of load side and the second row contains the bearings of rear side. A set of load side and rear side bearing has similar defect and are listed below with their age. Load side bearings are numbered as LN, L0, L1, and L2. Bearing LN is new bearing of standard company without any defect, while condition of L0 is similar to LN, but is suspected for incipient fault and its used age is approximately 6-8 months. Used age of L1 is 2.5-3 years and significant play was observed in outer race. In bearing L2, inner race problem was observed and used life of it was approximately 5-6 years.

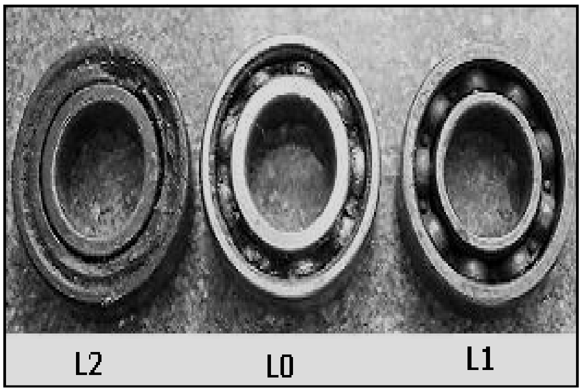
Rear side bearings are numbered as RN, R0, R1 and R2. Bearing RN is new bearing of standard company without any defect, while condition of R0 is similar to RN, but used life of it was approximately 6-8 months. Bearing R1 was having the significant play in outer race and estimated used life of 2-3 years. Bearing R2 is 5-6 years old and has inner race defect.

Some of the bearings are having play in their inner race that causes the rotor eccentricity and some bearings are having pits on the outer race due to which it cannot be fitted properly in the bearing housings, hence making the motion of rotor eccentric. The eccentricities produced may either be static or dynamic depending upon amount of degradation of bearing. As explained, the defect in bearing results in change of amount of current drawn by the motor, the analysis can be carried out in reference with the stator current and phase voltage. Total 500 sets of signals were captured on different load conditions and at different mains supply conditions. This captured data is then analyzed for the faults using discrete wavelet transform for classification of bearing problems.

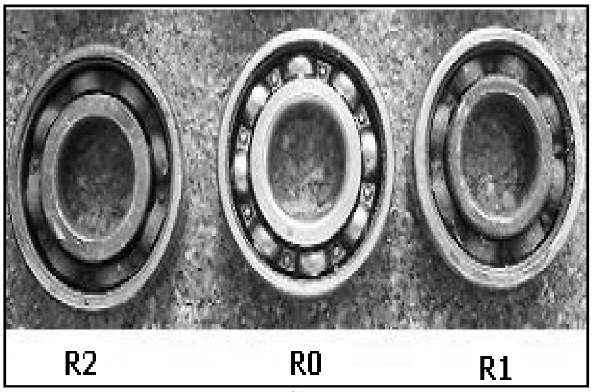
V. RESULTS AND DISCUSSIONS

In the initial phase of study, the effects of defective bearings were observed along the rotor. For this purpose, rotor was painted with washable ink. Rotor marks under the various combinations of rear side and load bearings are observed and studied. The possible combinations and type of eccentricity observed by it is tabulated in Table 1.

A few photographs of rotor marks taken after the experiments are given in the Figure 4(a)-(d), for various combinations of bearings given in Table 1. Figure 4(a) shows the 30% static eccentricity (shown by arrow) observed in machine when motor is fitted with bearings R0-L3. It is important to note that L3 is scrap/obsolete bearing having significant play in inner and outer race. It is used life was approximately 10 years. With this bearing set fitted, motor fails to acquire rated speed and produces loud hissing sound. The eccentricity observed is along the load side of the rotor.



(a)



(b)

Figure 3. Bearings under test:
(a) Load side bearings, (b) Rear side bearings

Table 1. Bearing combinations and observed eccentricity

Sr. No.	Rear and Load Side Bearing Combinations	Type of Eccentricity Observed	Length of Mark Observed in mm
1	RN-L0	Static	4
2	RN-L1	Static	5
3	RN-L2	Both Static and Dynamic	3, 6 and 4
4	RN-L3	Both Static and Dynamic	4,7 and 5
5	R0-L0	Static	6
6	R0-L1	Static	8
7	R0-L2	Both Static and Dynamic	2, 3 and 9
8	R0-L3	Both Static and Dynamic	4, 7 and 5
9	R1-L0	Static	8
10	R1-L1	Both Static and Dynamic	5 and 9
11	R1-L2	Both Static and Dynamic	4 and 7
12	R1-L3	30% Static	30 mm

Figure 4(b) shows the static and dynamic eccentricity observed at the center of rotor in machine when motor is fitted with bearings R0-L1. In Figure 4(c), for combination R1-L2, static and dynamic eccentricity is observed along the rear side of rotor. Minor static eccentricity observed in Figure 4(d), for bearings R0-L0.

After physical inspections of marks on the rotor, it is observed that, minor changes occur in air gap throughout axial length of motor, which fails to appear in current signature. Such minor changes in eccentricity cannot be easily observable in wavelet decompositions of currents under highly polluted supply conditions. Therefore, it is essential to have a sound feature extraction procedure under such conditions.

To understand the behavior of machine under defective bearings, a difference vector of voltage and current is introduced which determines the changes in flux linkages of stator and rotor.

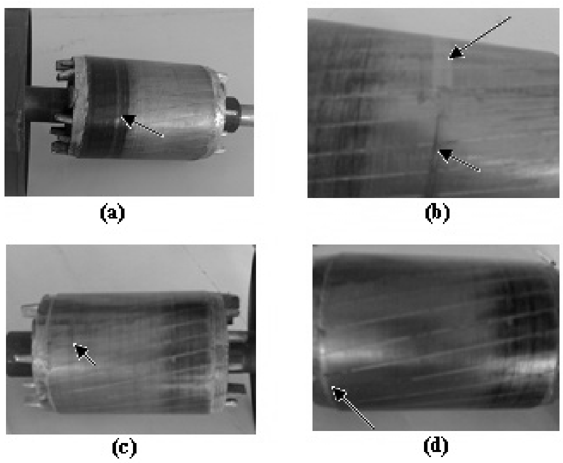


Figure 4. Eccentricity observed for various combinations of bearings: (a) R0-L3, (b) R0-L1, (c) R1-L2, (d) R0-L0

A. Computation of Changes in Flux Linkages of Stator and Rotor: Proposed Strategy

Applying the Kirchoff's voltage law gives the voltage equations for a-b-c stator and rotor windings

$$V_{abcs} = R_s I_{abcs} + \frac{d\Psi_{abcs}}{dt} \quad (16)$$

where, V_{abcs} is the stator voltages for three phases and given by

$$V_{abcs} = \begin{bmatrix} v_{as} & v_{bs} & v_{cs} \end{bmatrix}^T \quad (17)$$

Similarly, I_{abcs} is current vector for three phases and is denoted as

$$I_{abcs} = \begin{bmatrix} i_{as} & i_{bs} & i_{cs} \end{bmatrix}^T \quad (18)$$

while, the stator flux linkages of stator windings is given as

$$\Psi_{abcs} = \begin{bmatrix} \psi_{as} & \psi_{bs} & \psi_{cs} \end{bmatrix}^T \quad (19)$$

The stator winding resistances are represented in matrix form as

$$R_s = \begin{bmatrix} r_{as} & 0 & 0 \\ 0 & r_{bs} & 0 \\ 0 & 0 & r_{cs} \end{bmatrix} \quad (20)$$

Writing equation (16) into component form for a-phase,

$$V_a = R_{as}\ Ia + \frac{d\psi_a}{dt} \quad (21)$$

Therefore, small changes in air gap of induction motor will result into changes in flux linkages in stator winding. Then, rate of change of flux linkage for any one phase can be written as

$$\frac{d\psi_a}{dt} = V_a - R_{as}\ I_{as} \quad (22)$$

Discritizing equation (22), results into a difference equation as given in (23).

$$\psi_a(n) - \psi_a(n-1) = V_a(n) - R_{as}\ I_{as}(n) \quad (23)$$

This difference equation is used to find out small changes in flux linkages of stator windings for small changes in air gap deformations.

B. Algorithm for Proposed Strategy

To classify the incipient, inner race and outer race problems of bearings, the following algorithm is used.

Algorithm:

- Capture a voltage and current of any one phase of induction motor.
- Find difference vector given by equation (23)
- Denoise the difference vector up to second decomposition level using db-4 wavelet.
- Obtain the denoised difference vector.
- Apply DWT to the difference vector.
- Observe the detailed wavelet coefficients at the level 2
- Draw the conclusion from the pattern observed for the inner and outer race defects.

The proposed strategy is applied for various combinations of bearings mentioned in section 4 and obtained results are summarized below.

C. Effect of Mechanical Loading

As the mechanical loading arrangement was used during the experimentation, the first task of the study was to determine the effect of varying load conditions, because mechanical loading can cause rotor misalignment which in turn results into minor changes in air gap length. With this consideration no conclusion can be made until decision regarding the effect of mechanical loading is taken into consideration. For this a machine was fitted with the set of new bearings and voltage and current signals were captured for different load conditions. Wavelet transform coefficients comparison at different load conditions is made and found that level two coefficient remains unaffected irrespective of the loading condition. Thus, a conclusion regarding the type of bearing defect can be derived by the analysis and observation of the second level.

The resulting DWT decomposition of captured signals is as shown below. Figure 5, shows the two dyadic level discrete wavelet decomposition for de-noised difference vector (represented by 'Signal' in figure) formed by taking difference of phase voltage and no load stator current signal captured when motor was fitted with healthy or new bearings considered having no defect. In figure, d1 and d2 are the detailed coefficients obtained at decomposition levels 1 and 2, respectively. While approximate coefficients of decomposed signal are represented as 'a2'. Similar results are shown in the Figure 6 for 75%, of full load conditions.

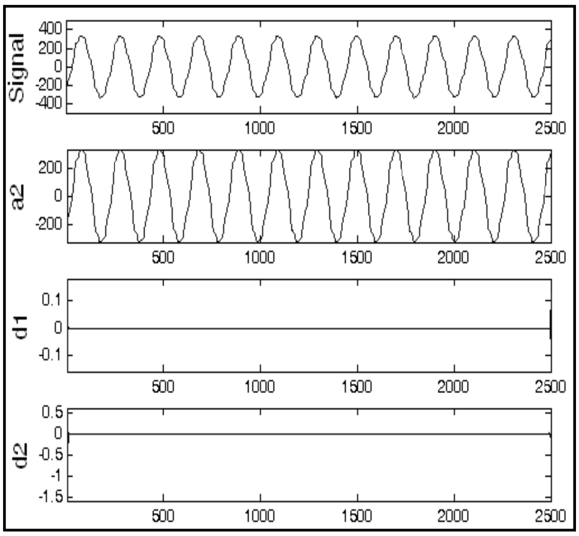


Figure 5. DWT of difference vector for healthy (New) bearing on no load

From Figures 5-8, it can be seen that the nature of second level of decomposition is same irrespective of loading conditions. It is observed in d2 level that pulse appears for the start and end of signal i.e. change in slope of signal. The difference seen is of magnitude for that shows the various loading conditions of the motor. These results show that the nature of second level is not affected due to the change in load, and hence can be considered insensitive to changes in loading conditions. It represents either the machine is loaded or not. Even though the mechanical loading was used there was hardly any effect of unbalance and changing magnitude of load. Hence, as the second level of decomposition is insensitive to changes in load conditions, the comparative analysis can be carried out on this level itself.

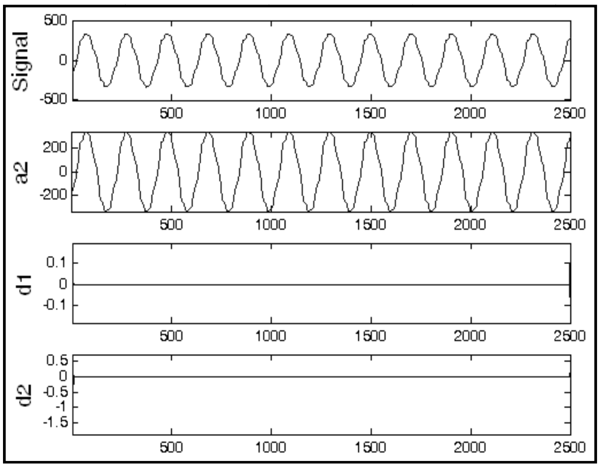


Fig 6: Result of healthy bearing on 75% load

D. Detection of Inner and Outer Race Defects

For the detection of inner and outer race defects, the motor was fitted with different combinations of bearing R1, R2, L1 and L2 with new bearings. Theses bearings with defects were obtained from the repairing workshops. Bearings used in the experimentation were having natural defects and no tampering or an artificial defect is created in the bearings.

A pair of bearings that is load side and rear side having similar defects is used for the analysis. The stator current and phase voltage are the medium of analysis and these signals are captured with the current and voltage probes of Tektronix. The sampling frequency was kept 10 KHz. These captured signals are then processed with same discrete wavelet transform. Both detailed and approximate coefficients were analyzed.

The data sets were prepared for different loading conditions and different defects of bearing and then compared with data sets of new or healthy bearing on different loading condition. A strategy of comparison is adopted throughout the study. The resulting decomposed signals of different bearings with different defects at various loading conditions and their comparison with the decomposed signal of healthy bearing at various loading conditions are shown and discussed here.

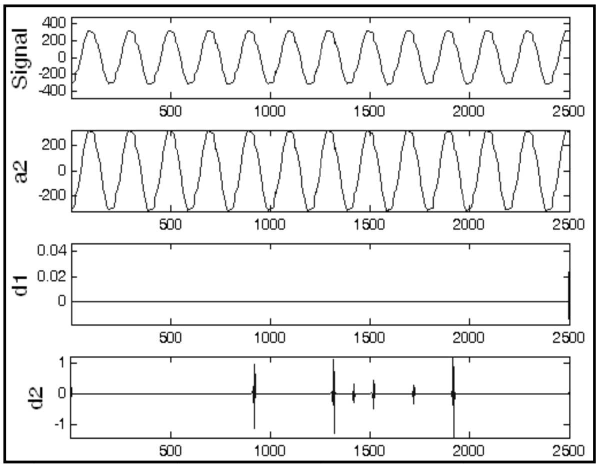


Figure 7. Bearing with inner race defect

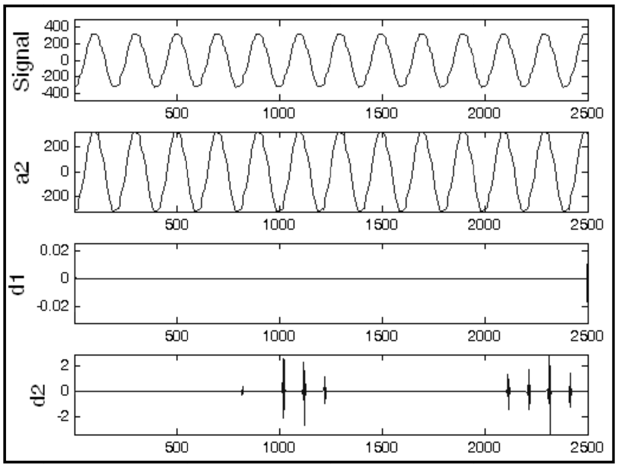


Figure 8. Bearing with outer race defect

Figures 7 and 8 show the decomposition of difference vector signal for motor at no load and equipped with new load side bearing with the rear side bearing having defect in its inner race (R2) and outer race (R1), respectively. Remarkable differentiation can be observed at d2 level of decomposition. As there is no effect of changing load and the unbalance created by mechanical loading on second level the conclusion can be drawn from this level. In the d2 level of decomposition for inner race and outer race defects, the nature of envelope observed is different for either case.

Similar kind of envelope was observed before denoising the signal. The comparative waveforms of second level of decomposition for healthy and defective bearings before denoising are shown in Figure 9. First of the three waveforms is of normal or healthy bearing followed by bearings having inner race defect and outer race defect respectively.

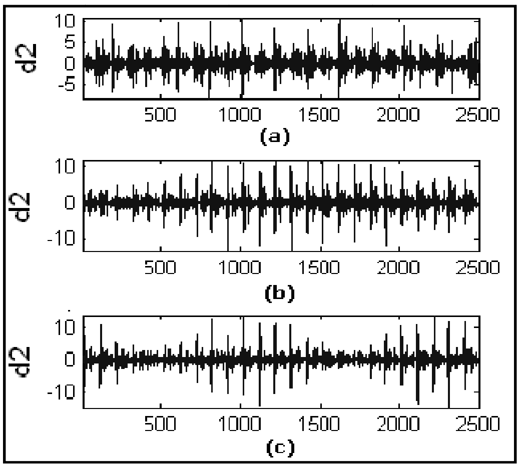


Figure 9. Comparison of DWT coefficients on no load for bearing conditions: (a) healthy, (b) Inner race, (c) Outer race

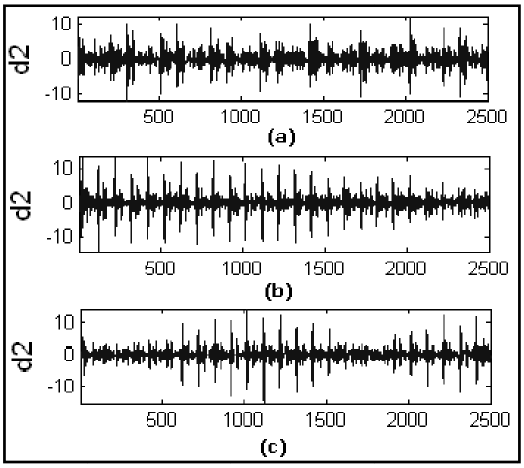


Figure 10. Comparison of DWT coefficients at rated load for bearing conditions: (a) healthy, (b) Inner race, (c) Outer race

Figure 10 shows the comparative waveforms of d2 level for the bearings on rated load condition. The discrimination between the three different bearings can be clearly observed. By comparing Figures 9 and 10, at no load and rated load condition of motor similar nature of waveforms can be observed. The d2 level has a signature nature for the inner race and outer race irrespective of loading condition. Hence, proposed method can be used effectively to detect the inner and outer race defects in the bearings at no load conditions also.

E. Detection of Incipient Defects

Previous sections explain the signature analysis of fully-grown up race defects in the bearings. One of the important observations from sections is that, inner race and outer race defects can be easily classified by carrying out analysis at no load condition.

Detections of slowly growing or incipient defects always posed the challenges to the researchers. Hence, to detect the incipient fault using proposed algorithm, machine was fitted with set of bearings suspected for incipient defects. Decomposition of difference vector at no load condition is shown in Figure 11. From d2 level, the bearing seems to have no defects. But, machine with set of bearing was loaded to 75% of full load condition, and its DWT decomposition of difference vector is given in Figure 12. Observing d2 level, the bearing shows the characteristic or signature of slowly growing inner race defect.

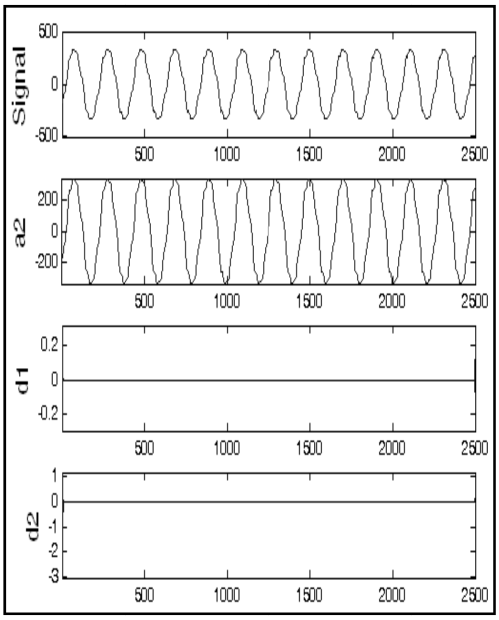


Figure 11. DWT of difference vector for suspected bearing on no load

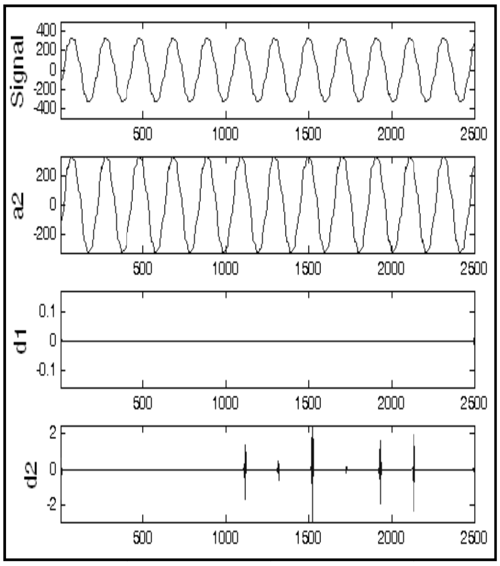


Figure 12. DWT of difference vector for suspected bearing on 75% FL

VI. CONCLUSIONS

In this paper the method based on the discrete wavelet transform of difference vector for the detection and classification of bearing defects is introduced. The method uses stator current and voltage of any one phase for the calculation of difference vector and it is found that difference vector with DWT is an excellent tool for detection of bearing race defects in induction motor. It is found that the defects in inner race and outer race of the bearings have different natures and do not change with the changing load, for the different defects of the bearings the specific nature of envelope is observed. The results obtained shows that, the proposed method can reliably detect and classify the bearing fault even at no load condition of motor. Incipient defects can also be detected easily, using the proposed algorithm.

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