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Bearing Fault Diagnosis in 3 phase Induction Machine Using Current Spectral Subtraction With Different Wavelet Transform Techniques



About sixty percent of the power in industries is consumed by induction machines, which implies induction machines are an integral part of industries. Even though these motors are stalwart and rugged in construction, they often experiences faults due to long time usage without maintenance. Bearing damage accounts 40% in the total faults and cause severe damage to the machine if unnoticed at nascent stage. So these faults should be continuously monitored for efficient operation, otherwise may cause severe damage to the machine. Conventional vibration monitoring is difficult due to requirement of high manpower and costly sensors. So motor current signature analysis (MCSA) is widely used for detection and localization of these faults. In this paper, the bearing faults are estimated by means of current frequency spectral subtraction using discrete wavelet transform. In addition to this, the current signature analysis after spectral subtraction is carried out using Discrete Wavelet Transform (DWT), Stationary Wavelet Transform (SWT) and Wavelet Packet Decomposition (WPD) and a comparative analysis is presented to estimate fault severity using statistical parameters. The proposed method is assessed based on current signatures obtained from a 2.2kW induction machine. The experimental results acknowledged the effectiveness of proposed method.

Keywords: Bearing faults; induction machines; current monitoring; motor current signature analysis; spectral subtraction.

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1. Introduction

Induction machines are relatively low in cost; they range from fraction of horse power to thousands of horse power. They do not need external triggering and have high torque, which enables to run much larger machines. Due to the reasons stated, induction machines are used in substantial amounts in industrial process. In fact, they comprise about ninety percent of the machinery used in the industries.

In the end, induction machines are often prone to faults. If these faults go unnoticed, they may cause severe damage to the machine. The varieties of faults that generally occur in an induction machine are

- Rotor faults
- Bearing faults
- Stator faults
- Others

Out of aforementioned faults, bearing fault accounts from 40% to 90% depending on the size of machine as shown in Fig.1.Approximately 40% in higher rating machines and 90% in smaller rating machines [1], [2], [3].

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Conventionally, periodical monitoring is performed to evaluate the condition of the machine. In spite of this, continuous condition monitoring is preferable over conventional periodical maintenance. Condition monitoring implies that monitoring of a specific condition of a machine such as temperature or vibration [4]. The use of vibration sensors and accelerometers are very difficult due to high cost and data is acquired manually by field technicians and then analyzed [5].On the other hand, stator current monitoring uses current signatures that can also be used for detection of other types of faults such as broken rotor bars [6], air gap eccentricity faults [7], along with bearing faults [8]. Therefore use of current monitoring like vibration, chemical and temperature monitoring.



Fig.1. Various types of faults in induction machine

Motor current signature analysis using fast Fourier transform (FFT) is commonly employed for spectral analysis [9]. But FFT technique is inefficient in providing time frequency relation and has spectral leakage and poor resolution etc. So it is impossible to find out time at which the fault has occurred using FFT. Moreover if the magnitude of fault is less compared to noise produced in the machine, it would be impossible to estimate the fault frequency using FFT since the fault frequency would be merged into noise and difficult to discriminate. So we go for window based techniques such as short time Fourier transform (STFT), wavelet transform (WT) [10]. Even using STFT is not recommended because STFT uses fixed window intervals which is a disadvantage because a high frequency signal require a large window and a low frequency signal should be analyzed in a small window. So the concept of using STFT for finding faults using MCSA is not suggestible.

The resolution problems in FFT and STFT are conquered by using multiple signal classification (MUSIC) algorithm [10], [11]. MUSIC uses the concept of extracting fault frequencies from the noise subspace obtained from Eigen vector matrix of faulty signal. MUSIC constructs autocorrelation matrix of the signals and uses signal and noise subspaces to convert the fault detection problem into an Eigen value problem. MUSIC is used to improve the fault detection process in induction machines. However MUSIC is good in extracting fault component from stator current, it is too complex to implement.

Therefore this paper uses another windowed technique i.e., wavelet transform (WT). In [3], [12], [13], [14], and [15] authors using wavelet transform to estimate bearing faults in

induction machine. Compared to STFT, wavelet transform is much better since the size of the windows in wavelet transform can be altered as compared to STFT where fixed length windows are used.

This paper presents the concept of spectral subtraction which is a very good practice for suppressing the effect of healthy components on stator current. By subtracting the obtained faulty current signature from healthy current, the faulty frequency will only remain. Although many papers have discussed the use of MCSA in fault diagnosis of induction motors, this paper provides a novel approach to detect all categories of bearing fault at early stage using various wavelet decomposition techniques namely discrete wavelet transform (DWT), stationary wavelet transform (SWT) and wavelet packet decomposition (WPD) to analyze the stator current after spectral subtraction and compared the performance of decomposition techniques based on fault indexing parameter.

2. Bearing Faults

A bearing is an element used to reduce the friction between moving parts. Faults in bearings occur due to many reasons such as lubricant failure, dust and shaft current etc. The main objective of proposed work is to estimate these faults at incipient stage. Faults that occur in bearing are of two types.

- 1. Cyclic faults (Single point defect).
- 2. Non cyclic faults (generalized Roughness).

Again these cyclic faults are classified into various types depending on the location at which they occur.

- a. Outer race fault
- b. Inner race fault
- c. Ball defect
- d. Cage fault

A cyclic fault creates an impact between bearing and raceway resulting in a detectable vibration [4]. Each fault has its own vibration frequency. So if we are able to detect the faulty frequency in the current signature using spectral subtraction, then it is easily to predict the location of fault i.e., whether the fault is on outer race or inner race or cage or ball.

Outer race:
$$f_0 = \frac{N}{2} * f_r \left(1 - \frac{d}{D} \cos \alpha \right)$$
 (1)

Inner Race:
$$f_i = \frac{N}{2} * f_r \left(1 + \frac{d}{D} \cos \alpha \right)$$
 (2)

Cage:
$$f_c = \frac{1}{2} * f_r \left(1 + \frac{d}{D} \cos \alpha \right)$$
 (3)

Ball:
$$f_b = \frac{D}{2d} * f_r \left(1 + \frac{d^2}{D^2} \cos^2 \alpha \right)$$
(4)

Where f_o is the outer race frequency, f_i is the inner race frequency, f_b is the ball defect frequency, and f_c is the cage fault frequency. N is number of balls in the bearing, f_r is the speed of the rotor, d is the ball diameter, and D is the pitch diameter [4].

All these equations are given by considering ideal conditions. But in real time operations the difference between the obtained frequencies and calculated frequencies would be several Hz. The bearing with cage and outer race faults are shown in Fig.2 and Fig.3 respectively.

The other types of faults that occur are the non cyclic faults. These include

- Deformation of seal
- Corrosion

These faults are progressive in nature and they don't have any characteristic vibrating frequencies available to calculate the fault frequencies and their effects are difficult to predict.

Effect of bearing faults on stator current: Bearings are connected to the rotor in an induction machine. When there is a fault in induction machine's bearing it produces certain vibration which affects the air gap eccentricity between stator and rotor which induces a fault frequency in stator [3].

$$f_p = f_s \pm k.f_v$$

(5)

Where f_p is the predictable bearing frequency, f_s is the supply frequency, f_v is the characteristic vibration frequency generated due to bearing fault and k is a constant. The value of k = 1, 2, 3....



Fig.2. Cage fault in bearings



Fig.3. Outer race fault in bearings

3. Proposed Method

The proposed topology of bearing fault detection is shown in the Fig.4 and explained each step in detail in the following subsection. The proposed scheme involved in five stages stars with acquisition of stator current from the machine, processed for estimation of spectral

components using FFT & Wavelet Analysis of both healthy and faulty currents, reconstruction of signal with new components, frequency domain analysis by DWT, SWT and WPD and finally decision algorithm based on fault indexing parameter.



Fig.4. Block diagram for proposed topology

3.1. Data Acquisition

The stator current is acquired from three phase induction motor using data acquisition systems with suitable sampling frequency such that no data is missing and processed to MATLAB software using proper interfacing system. The acquired stator current is normalized and used for spectral subtraction. In the similar manner stator current is acquired for healthy and faulty condition of the bearing. In addition to this, a stator current with fundamental, harmonic and noise components is modelled for subtraction purpose, which is explained in the following subsection.

3.2. Spectral Subtraction

Spectral subtraction is a tool, which is very widely used for speech enhancement and also in audio data processing for removing acoustic noise [16]-[18]. In this paper this technique is used to reduce the effect of healthy components on the result and also to reduce the impact of noise generated by induction machine. The block diagram of conventional spectral subtraction to remove dominated components from the stator current is shown in Fig.5 (a).

The difference between conventional spectral subtraction and proposed subtraction can be observed from the Fig.5 (a) and 4(b). The procedure followed in this topology is clearly depicted in Fig.5. The steps involved in spectral subtraction are explained in the following.

1. First a healthy stator current is modeled. The modeled stator current contains fifth, seventh and eleventh harmonics along with the fundamental frequency.

$$y(n) = A1 * \sin\left(\omega * \frac{n}{f_s}\right) + A2 * \sin\left(5\omega * \frac{n}{f_s}\right) + A3 * \sin\left(7\omega * \frac{n}{f_s}\right) + A4 * \sin\left(11\omega * \frac{n}{f_s}\right)$$
(6)

Where y(n) is modeled signal, $\omega = 2\pi f_s$, f_s is supply frequency in Hz, F_s is sampling frequency, n is the number of samples and A1, A2, A3, A4 are the amplitudes of fundamental, 5th, 7th, and 11thharmonic frequencies.

- 2. The modeled signal is then normalized and then a signal matrix, on which FFT and WT are applied to get the spectral components.
- 3. Then the faulty signal is taken, normalized and its spectral components are obtained.
- 4. Further the spectral components of modeled healthy components are subtracted from spectral components of faulty signal to get new components.
- 5. Then the resultant coefficients are used to reconstruct the signal.

6. Standard deviation is calculated for new reconstructed signal to estimate the fault severity.

The FFT of both healthy and faulty signals are calculated and subtracted in a real time fashion to extract the fault component from the stator current. In the similar way, the wavelet coefficients of both currents are calculated using daubechis mother wavelet by decomposed into 10 levels. At the 10th level decomposition, 10 detailed coefficients and one approximated coefficient are available for each signal. In this stage, the detailed and approximated coefficients are used to subtract from faulty current to healthy current. The detailed and approximated coefficients are calculated using following expressions [14].



Fig.5. Block diagram of spectral subtraction (a) Conventional, (b) Proposed

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

The wavelet coefficients for level j can be obtained from scaling coefficients form level j-1 using

$$\varphi_{j,k}(x) = \sum_{n \in n-2k} \phi_{j-1,n}(x) \tag{8}$$

$$\left\langle f, \varphi_{j,k} \right\rangle = \sum_{n} g'_{n-2k} \left\langle f, \phi_{j-1,n} \right\rangle$$
(9)

The scaling coefficients for level j can be obtained from the scaling coefficients for j-1 level using

$$\varphi_{j,k}(x) = \sum_{n} h_{n-2k} \phi_{j-1,n}(x) \tag{10}$$

$$\left\langle f, \varphi_{j,k} \right\rangle = \sum_{n} h_{n-2k} \left\langle f, \phi_{j-1,n} \right\rangle \tag{11}$$

Where g and h are high and low pass filters, respectively. The procedure can be initiated by finding first level coefficients and repeat the same until level j is reached using above equations.

3.3. Reconstruction of the Signal

The new components after spectral subtraction using both FFT and WT are used to reconstruct the signal with inverse functions of both cases. It is very important that, the mother wavelet and length of the signals are same which are used to decompose the signal to avoid aliasing problem. After reconstruction of the signal, the wavelet analysis is proposed to analyze the fault components and is explained in detailed in the following subsection.

3.4. Wavelet Analysis

Since three types of wavelets are used to analyze the fault coefficients and are explained in the following.

a. Discrete Wavelet Transforms (DWT):

In this type of decomposition the scaling and dilation parameters sampled instead of signal to get high resolution. Like other wavelet transforms, the key advantage of dwt over FFT is its temporal resolution and gives information in both time and frequency. Different types of mother wavelets include haar's, Daubechies, orthogonal etc of which Daubechies wavelet is most frequently used. In DWT the approximate and detailed coefficients are down sampled by an order of 2 [19], [20]. So a general loss of information occurs. To avoid this SWT is used. In this paper daubechis 32 (db32) wavelet of level 10 is used to decompose and reconstruct the signal. The decomposition procedure for this wavelet is shown in Fig. 6.

b. Stationary Wavelet Transforms (SWT):

The main drawback of dwt is translational invariant. That means even if the periodic signal is extended, the dwt of the signal is not the translated version of signal and due to down sampling there is a general loss of data [19]. So to overcome this problem SWT is used. The main application of SWT is de-noising [21]. In this paper Daubechies (db32) mother wavelet for 10th level decomposition is used to decompose the signal. The decomposition procedure for this wavelet transform is presented in Fig.7.

c. Wavelet Packet Decomposition (WPD):

In WPD signal is passed through more number of filters than DWT and SWT. In dwt the coefficients are down sampled and then approximate coefficients of level 1 are decomposed to get approximate and detailed coefficients of level 2. But in WPD both the approximate and detailed coefficients of level 1 are down sampled and decomposed to get approximate and detailed coefficients of level 2. Since the number of coefficients keep on increasing at the rate of 2^j (j being number of levels), a Daubechies 32 mother wavelet of level 10 is used to decompose the signal. The decomposition procedure for this wavelet is shown in Fig. 8.

The wavelet level at which the signal is to be decomposed is calculated by using the formula [22]

$$j = \operatorname{int}\left(\log\left(\frac{F_{s}}{f}\right) / \log 2\right) \tag{12}$$

The condition that is to be satisfied to use this formula is

$$2^{-(j+1)} f_s < f$$
(13)
Where *Fs* is the sampling frequency [23]



Fig.6. Decomposition of DWT



Fig.7. Stationary wavelet transforms decomposition

3.5. Fault Detection Criteria

For automatic fault detection criteria a ratio of standard deviation of faulty to healthy signal is used. Under normal operating conditions, this ratio is nearer to unity (Ideally 1) and for faulty case increases more than one depending on fault severity. The fault severity can be estimated if the fault indexing parameter reaches threshold value. The expression for fault indexing parameter is given in the following.

$$\sigma = \sqrt{\frac{\sum_{n=0}^{N-1} (y(n) - \mu)^2}{N}}$$
(14)



4. Experimental Setup

The experimental setup is shown in Fig.9 includes a 2.2KW, 415V, three phase, 4-pole, 1435 rpm induction motor. A 3 phase auto transformer is used to supply the motor. LA55P current sensor made by LEM is used to sense the current and the current signature is extracted into PC by using the data-acquisition system NI MY DAQ. The current signal is then normalized and then processed in MATLAB. The sampling frequency is 10 KHz and number of samples N_s =10000. SKF 6206ZZ single row deep grove bearings are used in both driving and non-driving ends of the motor. The test bearing is mounted on driving end of the shaft. The specifications of this bearing are:

Pitch Diameter (D) = 1.83 inches, Ball Diameter (d) = 0.375 inches, Number of bearings = 9 and $\alpha = 0^0$



Fig.9. Experimental setup

In this the outer race fault, cage fault and generalized roughness fault have been tested practically. Fig.2, 3 shows outer race fault and cage fault of the bearing respectively. In addition to these two bearings a generalized roughness fault bearing is also tested and compared using DWT, SWT, and WPD.

Fault type	K = 1 (Hz)		K = 2 (Hz)	
Cage fault	64.961	35.039	79.922	20.078
Outer race	138.85	38.85	227.7	127.7
Inner race	184.64	84.64	319.28	219.28
Ball effect	108.04	8.04	166.08	66.08

Table 1: Fault Frequencies under No load (1495rpm)

5. Experimental results

Several experiments have been performed using the experimental rig shown in figure 9. The same motor type has been used to extract signals throughout the entire paper. The vibrating frequencies at which faults occur are calculated using the equations (1) - (4). The stator current frequencies can be estimated by equation (5) and tabulated in Table.1. Then the decomposition level of the wavelet transform at which the faults may occur can be estimated using equation (8). A sampling frequency of 10,000 Hz is chosen to avoid missing data while acquiring the signal.

Initially the stator current is modeled using healthy components namely fundamental, harmonics of order 5th, 7th and 11th and a white Gaussian noise with low SNR is included in terms of noise due to sensor and EMI. The modeled signal is shown in the Fig.10. Now the modeled signal is used to calculate spectral components using FFT and WT. In the wavelet transform based FSS, signal is decomposed into 10 levels to get wavelet coefficients using DWT. Afterwards the stator current under healthy condition of the bearing is acquired using DAC and processed into PC to perform FFT and WT decomposition. At this moment, the FFT components of modeled stator current are subtracted from acquired healthy current components and reconstructed a new signal using subtracted components. In the similar way, the detailed and approximated coefficients are used to reconstruct new signal using inverse wavelet functions. After that, the standard deviation (SD) of both reconstructed signals using FFT and WT is calculated to estimate proposed fault indexing criteria.

Similarly the cage, outer race and generalized roughness fault bearings are inserted into the machine one after other and acquired the stator current using DAC. The stator current is processed for spectral component evaluation using to perform FSS and estimate the fault indexing parameter. The fault indexing parameters of these faults using FFT and WT based FSS are shown in the Fig.11. From the Fig.11 it is noticed that, the fault indexing is same using both FFT and WT and for minor faults like outer race fault both the analyses will give no fault indication due to direct computation of SD. FFT analysis of reconstructed signal is shown in Fig.12 and noticed that, the fault frequencies of cage fault can be seen clearly but outer race fault is not possible due to less impact on stator current. Similarly generalized roughness fault is also impossible to extract using FFT because it doesn't impose any characteristic frequency and have broad band nature. In addition to this, classification of fault will also be impossible using this type of fault indexing criteria. Therefore fault classification can be done by further analysis of reconstructed signal using DWT, SWT and WPD is proposed.



Fig.11. Fault indexing parameter using FSS for various Faults (1# Cage Fault, 2# Outer Race Fault, 3# Generalized Roughness Fault)

(*a*) *DWT*:

In the DWT based wavelet decomposition signal is decomposed into 10 levels using Daubechies mother wavelet of order 32 to analyze the signal with high resolution. In the 10th level decomposition, signal consist 10 detailed coefficients and one approximated coefficients as shown in the Fig.13. At the each level of decomposition, the signal is down sampled to get better resolution. Stator current with cage fault after spectral subtraction is shown in Fig.13. The standard deviation of each coefficient is calculated and plotted in Fig.14. Similarly the outer race and generalized roughness fault signals are decomposed and the standard deviations are shown in Fig.14. From the Fig.14 it is noted that, the cage fault is clearly indicated in detailed coefficients of 6, 7, 9, and 10, whereas for generalized roughness fault coefficients 1 to 6 have clear indication. But for outer race fault very minor indication

is given by coefficient 5. Therefore for nascent stage fault DWT has shown some better indication compared to FFT.

(*b*) *SWT*:

In the SWT decomposition of stator current, the signal is decomposed into 10 levels and each level consist one detail coefficient and one approximated coefficient. In SWT type of decomposition, down sampling is not employed to avoid missing data and each coefficient is of same length. The approximated and detailed coefficients of stator current with cage fault using SWT is shown in Fig.15. The standard deviations of each coefficient at 10th level decomposition are presented in Fig.16. The SWT has better performance compared to DWT especially for outer race fault. The outer race fault is indicated in detailed coefficients 5 and 8, whereas the cage and generalized roughness faults are indicated by almost detailed coefficients.

(c) WPD:

In the wavelet packet decomposition, the signal is decomposed into 10 levels and has 2^{10} coefficients. The first 10 coefficients are taken for fault analysis and presented in Fig.17. The standard deviation of coefficients are plotted in Fig.18 and observed that, the behavior of WPD in detecting nascent stage faults is similar to DWT. In addition to this, the decomposition process is complex due to more number of coefficients. Especially for generalized roughness faults, implementation of WPD is impossible due to lake of characteristic vibrating frequency.



Fig.12. FFT analysis of stator current after spectral subtraction (a) Cage Fault, (b) Outer Race Fault and (c) Generalized roughness fault..

From the above analysis of stator current with different faults after spectral subtraction has some interesting information i.e. the fault indexing criteria has very good indication using SWT, whereas the DWT and WPD has poor performance for incipient faults. Whereas for faults severe faults like cage and generalized roughness fault DWT has shown better performance compared to WPD. Therefore, detection of bearing faults using current signature analysis has shown better results using SWT based spectral subtraction.



Fig.13. DWT coefficients of stator current with cage fault after spectral subtraction



Fig.14. Fault Indexing Parameters using DWT



Fig.15. SWT coefficients of stator current with Cage fault after spectral subtraction



6. Conclusion

This paper presents an approach to detect the bearing faults in induction motor using current signature analysis by spectral subtraction. The frequency domain analysis is done by using different wavelet transform techniques and is compared. The experimental test is performed on 2.2kW, 3 phase induction motor. Three major bearing faults are considered for

experimental test with different fault severities. The performance of these techniques are assessed through the ratio of faulty signal statistical parameters to healthy signal parameters which concludes that the stationary wavelet transform can assess a signal better than the discrete wavelet transform and wavelet packet decomposition. WPD also gives better performance for severe faults, but includes large number of mathematical calculations at higher decomposition levels.



Fig.17. WPD coefficients of stator current with cage fault after spectral subtraction



Fig.18. Fault Indexing Parameters using WPD

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