PERFORMANCE COMPARISON BASED SELECTING AN OPTIMAL METHOD FOR FAULT DETECTION AND DIAGNOSIS METHODS FOR INDUCTION MOTOR

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Abstract: *Induction motor is one of the most common and basic element involved in large amount of electrical systems. Finding a fault in the earlier stage can prevent the entire electrical system and avoid large damages. To avoid that, it is necessary to find out a best method for fault detection and diagnosis for induction motors. In this study the author compared the performance of various fault detection and diagnosis method and selects the best optimal method for induction motors based on the accuracy. Motor Current Signature Analysis (MCSA), Auto Regressive (AR) model, Discrete Wavelet Transform (DWT) model and Wavelet Packet Distribution (WPD) Model are some of the famous approaches, which are experimented, compared and the performance is evaluated based on various fault indexing parameters. From the obtained results DWT is suggested for the best method using wavelet transforming techniques to predict the severe fault with taking the total power as an indexing parameter in Fault detection and diagnosis for Induction Motor in any electrical Systems.*

Key words: *Induction Motor, Discrete Wavelet Transform, Wavelet Packet Decomposition, Fault Diagnosis Method.*

1. Introduction.

In recent days, various applications under electrical systems are increasing with high demand need to increase the reliability and availability. Some of the famous applications are electrical railway traction, industrial production lines, aircraft and power plant cooling. Unexpected failure in the above system created lot of issues like severe damages to the system, loss, and serious issues to the surroundings and cause other dangerous to human. Even though various methods have been proposed in the earlier approaches, still it is essential to improve the availability and reliability of the fault diagnosis and detection processes in electrical systems.

The components involved in an induction motor is stator and rotor. Stator is a stationary part and rotor is a rotating part. Electric power is transmitted from one component to another component using electromagnetic induction. This induction machine is otherwise called as electromechanical energy conversion device. It is used to convert electrical energy into mechanical energy [1]. Both end of the rotor is supported by bearings. Rotor and stator has two circuits as electric and magnetic circuits. The electric circuit is used to carry out current through a shielded copper insulated aluminum and the magnetic circuit carry out magnetic flux through a plastic-coated magnetic material usually steel. Figure-2 shows the induction motor and the magnetic circuit of stator / rotor of IM.

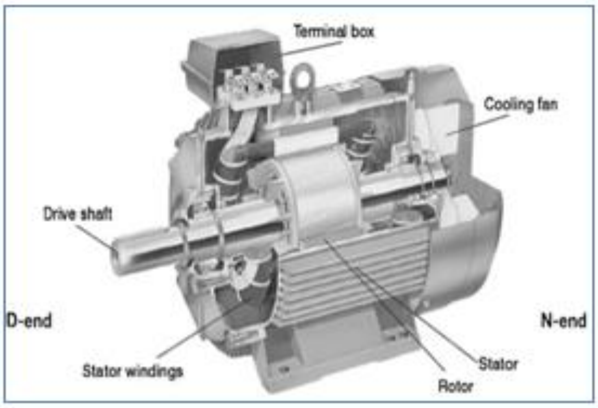


Fig.1. Induction Motor.

Also, some of the various existing methods got failure; henceforth the entire performance of the electrical system is degraded. To avoid this kind of critical scenarios, a potential fault detection method is applied for correcting the maintenance at the beginning stage of the system operations. It leads to avoid sudden and total system failure which may generate profound consequences. Electrical machines are the main components of the electrical systems. Induction motor is one of the famous electrical motors used frequently in electrical systems due to simplicity of creation, high efficiency and robustness. Some of the common faults occur in induction motor is electrical fault and mechanical faults. Electrical faults are created due to short circuit, breaks in rotor bar, end-ring and inverter. Rotor eccentricity, shaft misalignment, bearing faults and load faults are considered as mechanical faults.

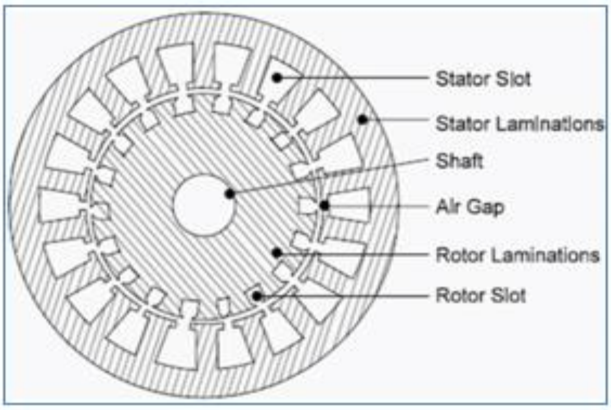


Fig. 2. Magnetic circuit of stator/rotor of IM.

Most of the electrical systems are using induction motor as the main component. Hence, this paper focused on diagnosing, identifying and detecting faults in induction motor. Also, it concerned with the electrical as well as the mechanical fault detection in the great concern in electric drives. The entire contribution of the paper is listed as:

- Design a sample electrical system involving induction motor
- Diagnose and detect faults using Motor Current Signature Analysis (MCSA)
- Diagnose and detect faults using Auto Regressive (AR) model
- Diagnose and detect faults using Discrete Wavelet Transform (DWT) model
- Diagnose and detect faults using Wavelet Packet Distribution (WPD) Model
- Finally, the performance analysis is carried out among the above said methods and the best method suggested.

2. Background Study.

To understand the induction motor and the associated applications some of the recent earlier research works are studied given here. It helps to understand the issues and challenges faced by earlier research works. Author in [1] stated that total number electrical machines used throughout the world are 16.1 billion in 2010 to 2011 and it is increased about 50% in 2011 to 2012. Authors from [2] said that the bearing faults occur from 50% to 90% due to the size of the machine and focused on continuous monitoring on bearing faults in medium voltage machines. In [3], author presented about temperature and vibration monitoring is used to verify the condition of the machines. The cost of the vibration sensors is costly and it needs high man power for data collection and filed technician for analyzation [4]. Monitoring the stator current using current signatures is also used to detect different kinds of faults like break in rotor bars [5], bearing faults [6] and air gap eccentricity faults [7]. Inappropriately, the induction motor may flop because of other methods, such as bearings [8], the rotor due cracks in short-circuiting rings or broken bars [9], and eccentricity in the air gap [10]. In [11-12], some of the methods generally used for this purpose are explained.

3. Limitations of Existing System and Problem Statement.

Several earlier research works used Fast Fourier Transform (FFT) method often for MCS analysis. But FFT has some drawbacks like spectral leakage, inefficiency in providing time-frequency relation and poor resolution etc. Because of the above said reasons and the magnitude is lower than the noise formed in the machine, it is very difficult to obtain the time of fault occurrence and the component of the fault occurred respectively using conservative FFT. So that, to overcome these kinds of issues and improve the fault detection accuracy, various signal processing methods has been implemented. For example, ZFFT [10-11] is proposed for improving the frequency resolution in FFT. MUSIC algorithm is proposed in [12-14] for finding the frequencies from the noise subspace gained from faulty signal by computing Eigen vector matrix from the signal. But implementing MUSIC algorithm is too difficult, to overcome this drawback MUSIC algorithm is integrated with ESPRIT algorithm discussed in [15]. Even though the frequencies are obtained using MUCIS, ESPRIT and ZFFT, still the problem spectral leakage is a challenging one in induction motor based electrical systems. To solve this problem, FFT using windowing-based transform method like STFT [16] and WVD [17] were used in spectral analyzation of stator current. Though STFT and WVD were providing better results, they are not considered as better approaches since they are using fixed size window intervals whereas it is difficult to manage the cross terms. Hence the problems such as, frequency resolution, spectral leakage and time-frequency relations this paper motivated to analyze various approaches and selects a better approach by implementing and verifying their results.

4. Principle of operation of MCSA.

In this paper, MCSA method is described initially to experiment and verify the performance and develop a Modified MCSA. The temperature of stator windings is analyzed using double frequency tests. Similarly, the rotor position is obtained by signal injection on IM. MCSA method is a well-known method largely used for identifying various faults in induction motor also it uses spectral analysis on stator current. Some of the faults occur in IM are break in rotor bars, damages in bearing and eccentricity of the rotor axis are detected frequently. Among various methods MCSA is one of the famous methods mainly used in IM. The procedure used in MCSA is evaluating the relative amplitude of the current harmonic as:

$$f_{brb} = f_1\left[m\left(\frac{1-s}{\frac{p}{2}}\right) \pm s\right] \quad \text{.............} \quad (1)$$

In the above equation, $\boldsymbol{m}$ represents the harmonic order like 1, 2, 3…. When the harmonic values of $\boldsymbol{m}$ is comparing with harmonic values of $\boldsymbol{f_1}$, if the value becomes lesser than a limit value then the machine is considered as healthy, else it is considered a faulty one. First harmonic is $\boldsymbol{m}$ and the second harmonic is f_1. MCSA uses $\boldsymbol{m}$ for fault finding near $f_1(1 \pm 2s)$, whereas other methods use fifth harmonic for fault finding near $f_1(5-4s)$ *and* $f_1(5-6s)$. In the earlier works certain faults like damage in bearing [1] and dynamic and static eccentricity [2] due to air gap, thermal bend and incorrect position of the stator or rotor. Frequency associated with fault variations in IM like air gap eccentricity is depicted in Figure-1. Also, the air gap eccentricity and the damage in bearing are expressed in equation -2 and 3.

$$f_{ecc} = f_1\left[1 \pm m\left(\frac{1-s}{p}\right)\right] \quad f_{airgap} = \left|f_1 \pm mf_i\right| \quad (2)$$

$$f_{i,o} = \frac{n}{2} f_r\left[1 \pm \frac{bd}{pd}\cos\beta\right] \quad (3)$$

To provide an efficient, speedy and easy fault identification method this paper motivated to experiment and verify motor current signal analysis method. Which includes: Broken rotor bars, abnormal level of airgap eccentricity, short circuit in stator windings and other mechanical problems. Due to the fault in the broken rotor bars, the rotating flux got change which is directly related to stator windings and the motor failure can be detected by the mechanical vibration spectrum. The voltage and current induce by rotating magnetic field in the rotor at slip frequency, which produce three phase magnetic field at two cases: one is symmetric, and another is asymmetric, in the first case, there will be a forward rotating field, later backward rotating field will be result. Current and voltage is induced in the stator winding when backward rotating.

$$f_{sb} = f_1(1 \pm 2s)Hz \quad (4)$$

Due to injured rotor bars a twice slip frequency sideband is occur, with a torque pulsation in accordance to speed oscillation and inertia functions. The speed oscillations may reduce the magnitude of $f_1(1-2s)$ sideband amplitude, but an upper sideband of $f_1(1+2s)$ is then induction in the stator winding.

Various automatic and diagnosis and analysis system has been developed by using MCSA's. The injured motor with rotor eccentricity and ruined rotor bars on the side band frequencies. A slip frequency is 5% at the full load motor. Rotor eccentricity effect is larger than the effect of injured bars. Moreover, for medium and large power motor the slip frequency is very slow. To identify the faulty harmonics there are various methods are illustrated. The methods illustrated are very expensive, but the industry needs low budget methods for the various applications with less complexity. Hence, we proposed the modified MCSA method for low cost with less complexity.

5. Modified MCSA.

Modified MCSA is very useful to the low power machines and as well as high power machines with less slip frequency with reduced cost. The test signal is applied to the stator for a specific time interval to analyze the working condition of the motor by comparing the main and applied test frequencies. The serial transformer is used to insert the test signals with different effects.

To analyze the effect of the injured rotor bars in the spectrum of the machine, flux variations in machine, mechanical variation frequency, and also the speed variation also considered. Due to the various test signals inserted in the stator, there are different magnetic fields generated and hence the different mechanical speed occurred in the machine. And then if we inserted a rotor, it can be easily analyzing the relative speed between the rotor and the stator. If there is an injured bar then it has the effect on the stator current. The injured rotors are the non-ideal effect and it will cause the different effect of faulty marks in the current spectrum for the different test signals inserted. There are various flows in the machine and it is capable to generate connection for linking the flows, rotational speed of the rotor, and the faulty marks caused by the rotor fault because of the injured bars in the rotors.

By considering the frequency of the rotor, synchronic speed, electrical speed, rotor's speed it is probable to find the fault's mark in under the spectrum in the frequency test side band as mentioned in the following equation.

$$f_{fault} = f_{test} + f_1\left(\left(1-s\right) \pm ps/2\right) \quad (5)$$

The present harmonic components outcome from the rotating magnetic fluxes compositions are as follows:

$$f_{c1} = 2f_1 + f_{test}\,; \quad f_{c2} = 2f_{test} + f_1 \quad . (6)$$

Though the amplitude of these new components is very low, the proportion between the faulty frequency and the generating frequency is bigger than the proportion found in the standard components used in the classical MCSA. The test frequency is monitored for the long period of time, if there is harmonic amplitude increment but the load torque has not changed, then the fault will be detected. Applying the test signals is the main drawback of this method, but various researchers inserted the test signal for the sensor less control. Selecting the suitable test signal is an important factor in this research. This can be suggested to identify the injured rotor bars and also to detect the other motor faults.

6. AR Model.

Then Autoregressive Model is described here to verify the performance. There are N samples are taken from three phase induction motor's stators current $i_a, i_b, and\ \ i_c$ denoted as:

$$\begin{bmatrix} i_a \\ i_b \\ i_c \end{bmatrix} = \begin{bmatrix} i_{a1} & i_{a2} & \cdots & i_{aN} \\ i_{b1} & i_{b2} & \cdots & i_{bN} \\ i_{c1} & i_{c2} & \cdots & i_{cN} \end{bmatrix} \tag{7}$$

And these currents are comparing and mapping with the $\alpha - \beta$ stator fixed reference frame using Concordia transformation method, then:

$$\begin{bmatrix} i_\alpha \\ i_\beta \\ i_o \end{bmatrix} = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 & cos\left(-\frac{2\pi}{3}\right) & cos\left(\frac{2\pi}{3}\right) \\ 0 & -sin\left(-\frac{2\pi}{3}\right) & -sin\left(\frac{2\pi}{3}\right) \\ \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \end{bmatrix} \begin{bmatrix} i_a \\ i_b \\ i_c \end{bmatrix} \tag{8}$$

Each $\alpha - \beta$ samples of the current are obtained by applying ISP module, and the coefficients of the p-order AR model are estimated. The AR model is a finite impulse response filter which can be described as:

$$ISP_n = \sum_{k=1}^{p} A_k ISP_{n-k} + \varepsilon_n, n = 1, 2 \ldots N \tag{9}$$

Where,

A_k denotes the coefficients of the AR model

ISP_{n-k} is the value of the ISP module delayed k samples.

ε_n represents uncorrelated random noise.

Regardless of the used method, it is necessary to define the model order that best fits the signal of interest (3). The chosen order selection criterion was the FPE which was evaluated for a p-order AR model by

$$FPE = log\left(R_{22}^2\right) - log\left(\frac{N(N-p+1)}{N+p+1}\right) \tag{10}$$

Finally, the fluctuations in FPE values for different cases with and without fault are compared with the other methods.

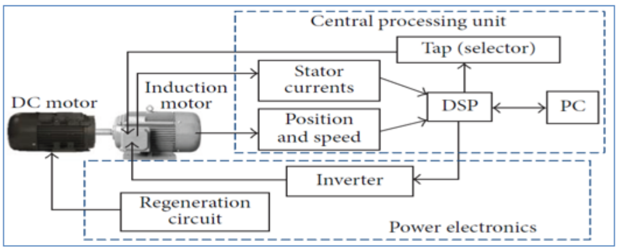


Fig. 3. Block Diagram

The stator current retrieved from the induction motor in healthy and faulty situations of the bearing and functioned for spectral subtraction with various wavelet decomposition methods in the subscribed bearing fault detection method. After processing the spectral subtraction, the stator current is utilized for fault indexing parameter computation. The step by step procedure is illustrated in the figure 4. Spectral subtraction, wavelet decomposition methods and fault indexing parameters are described in the subsequent subsections.

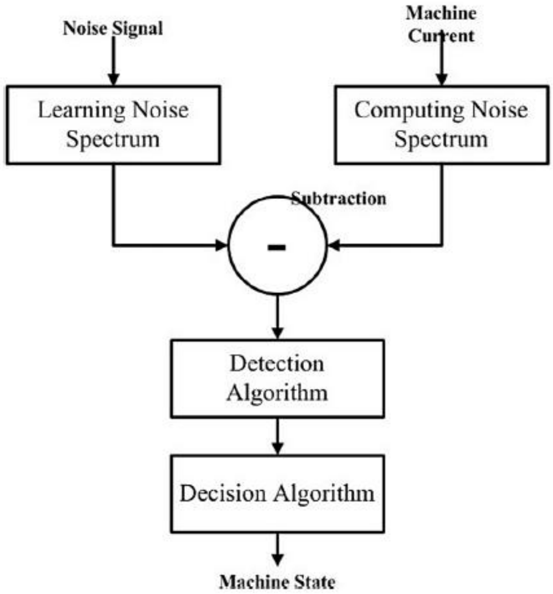


Fig. 4. Bearing Fault Detection

7. Spectral Subtraction.

Spectral subtraction method is used in [24-26] for enhancing speech signal using signal processing by removing acoustic noises. Spectral subtraction tool is mainly used. Here we utilized this for cancelling the pre-fault mechanism in the stator current and to decrease the force of the noise. In this work, healthy condition stator current is designed and decayed in to wavelet coefficients using DWT, SWT and WPD.

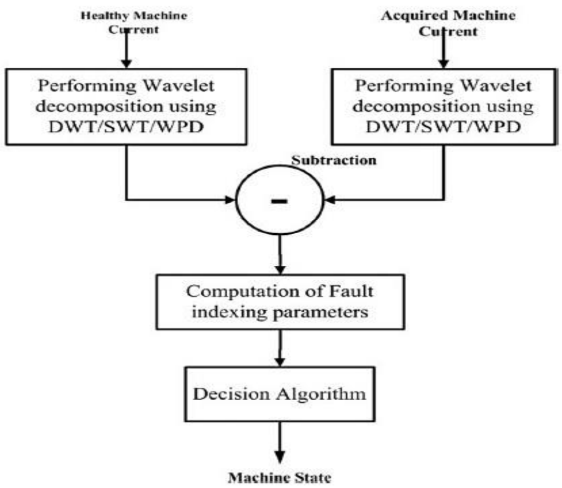


Fig. 5. Steps involved in detection of bearing faults using frequency spectral subtraction.

Then the healthy stator current coefficients received from the induction motor are subtracted from the wavelet coefficients of designed stator current. After subtracting the obtained coefficients are utilized to rebuild a signal which is used to guess the fault constituent by manipulating the fault indexing parameters. By the way after putting faulty bearings into the motor and decayed into wavelet coefficients, the faulty stator current is taken from the machine. Thus, the all process is repeated these faulty current coefficients are subtracted from the wavelet coefficients of designed stator current. Accordingly, the healthy and faulty indexing parameters are compared together to find the fault severity. Spectral subtraction using wavelet coefficients is shown in Figure 5.

8. Modeling of Stator Current

Mathematical modeling of healthy stator current of the bearing contains primary constituent, its harmonics and noise due to measuring devices and electromagnetic interference (EMI). The primary constituent with 50 Hz and its 5th, 7th and 11th harmonics with frequencies 250 Hz, 350 Hz and 550 Hz are measured for designing using the following equation. The noise due to measuring devices and EMI is modeled using white Gaussian noise (WGN).

$$Y = A_1 \sin(\omega_0 n/F_s) + A_2 \sin(5*\omega_0 n/F_s) + A_3 \sin(7*\omega_0 n/F_s) + A_4 \sin(11*\omega_0 n/F_s) \quad (11)$$

Where Y is modeled signal, $w_o = 2\pi f_s$, f_s is supply frequency in H_z, n is the time integer, A_1, A_2, A_3, A_4, are the amplitudes of fundamental, 5^{th}, 7^{th}, 11^{th} frequencies.

9. Wavelet decomposition.

There are three different decomposition methods for the wavelet decomposition of both modeled and acquired signals and it is processed. They are discrete wavelet transform (DWT), stationary wavelet transforms (SWT) and wavelet packet decomposition (WPD), which are discussed in detail in subsequent subsections. In general, in decomposition the mother wavelet for these three types of techniques are taken as Daubechi's with resolution 8 (db8) and decomposed into 10 levels.

10. Discrete Wavelet Transform (DWT).

In this wavelet transform, the wavelets are discretely sampled. The main benefit of DWT over Fourier transform is its temporal resolution, it provides information in both time and frequency when compare to others. In our work by using DWT, the stator current is decomposed into 10 levels. After this, DWT will provide 10 thorough (cd1-cd10) coefficients and 1 approximated coefficient (ca10). In the same way, the stator current taken from machine is also decomposed into 10 detailed and 1 approximated coefficients. Then the coefficients are subtracted from designed to acquire signal and a new rebuild signal is developed with the modified coefficients. The flowchart for this wavelet is shown in Figure 6. The approximate and detailed coefficients are down sampled by an order of 2 in DWT [27, 28]. Then the common loss of information occurs, so to keep away from this SWT is used.

11. Stationary Wavelet Transform (SWT).

One of the main drawback of DWT is translational invariant. DWT of the signal is not a translated version and it will make data loss because of down sampling [27], even if the periodic signal is unlimited. To eliminate this issue, SWT is used. The major application of SWT is de-noising [29]. In this work, the new rebuild signal is produced by subtracting the received signal coefficients from designed signal coefficients as explained in the previous section. The flowchart for this wavelet is shown in Figure 7.

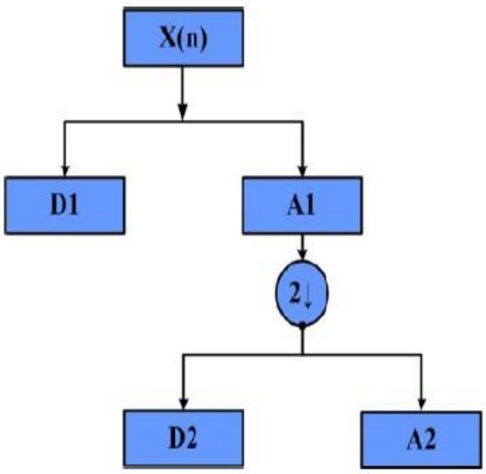


Fig. 6. Wavelet Decomposition using DWT.

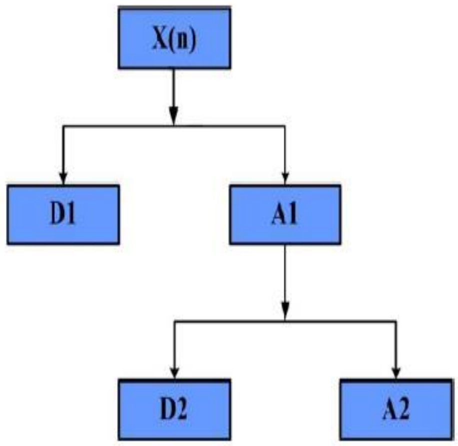


Fig. 7. Wavelet Decomposition using SWT.

12. Wavelet Packet Decomposition (WPD).

In this method, the signal is passed through more number of filters than DWT and SWT. The coefficients are down sampled and then estimated coefficients of level 1 are decomposed to get estimated and detailed coefficients of level 2 in DWT. But in WPD both the estimated and detailed coefficients of level 1 are down sampled and decomposed to get estimated and detailed coefficients of level 2. Because the number of coefficients continue rising at the rate of 2j (j being number of levels), a Daubechis of order 8 is taken as mother wavelet decomposed into 5th level to decrease the difficulty in coefficients and a new signal is rebuild after FSS. The flowchart for this wavelet decomposition is illustrated in Figure 8. The wavelet level at which the signal is to be decomposed is computed by using following expression [30].

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

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

$$2^{-j+1} f_s < f \tag{13}$$

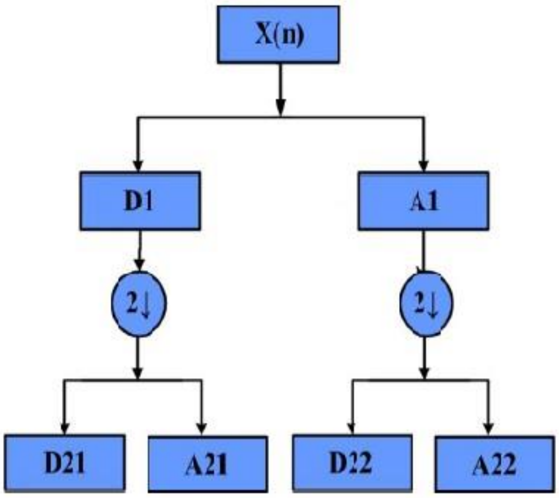


Fig. 8. Wavelet Decomposition using WPD.

13. Fault detection criteria

By using the altered wavelet coefficients, the signal is rebuilt, the fault index parameters are computed to estimate the fault severity. The fault indexing parameters are chosen as standard deviation (SD), simple square integral (SSI) and total power of the rebuild stator current. In both healthy and faulty circumstances of the bearing, these parameters are computed. Here the ratio of faulty values to healthy values is treated as fault severity. The SD, SSI and total power expressions are mentioned below.

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

$$SSI = \sum_{n=0}^{N-1} |y(n)|^2 \tag{15}$$

y(n) is the noise canceled stator current, μ is the mean value of y(n) and n is the time integer.

$$P = \sqrt{\frac{1}{N} * \sum_{n=0}^{N-1} |y(n)|^2} \tag{16}$$

$$R = \frac{Faultyparameters}{Healthyparameters} \tag{17}$$

14. Experimental Setup.

A 2.2 KW, 415V, 4-Pole, and 1435 rpm with a full load speed three phase induction motor used to experiment and to choose the best optimal method of various fault detection and diagnosis method such as Motor Current Signature Analysis (MCSA), Auto Regressive (AR) model, Discrete Wavelet Transform (DWT) model and Wavelet Packet Distribution (WPD) Model. A three-phase auto transformer is used to supply the motor and by using the data-acquisition system (NI MY DAQ), the current signature is extracted into system which is sensed by the LA55P current sensor. MATLAB software is used to process the normalized current signal. Three phase inverters is used to adjust the motor rotating speed and an optical encoder used for getting the rotor angular position and speed shaft. The sampling frequency is 10 KHz, N_S = 10,000 for DWT &WPD, but for SWT the sampling frequency it is 10240. Single chain deep grow bearings are used in the both ends of the motor. In this setup, the outer race faults have been experimented for the above said methods. In this bearing fault detection method, the stator current is obtained from the motor for both healthy and faulty conditions of the bearing are processed for the spectral subtraction using various wavelet decomposition techniques.

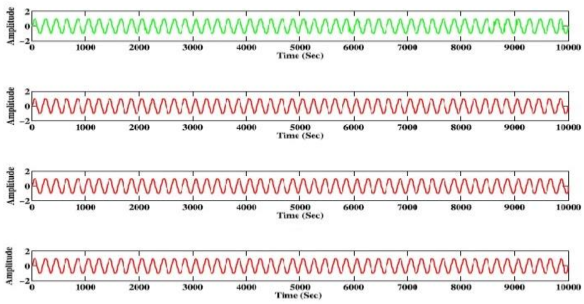


Fig. 9. Stator Current under healthy and Faulty Conditions.

15. Results & Discussion

Various experiments had done by the experimental set up to evaluate the performance of the discussed fault detection methods. The stator current obtained for both healthy and faulty bearings is used to process in MATLAB for the further analysis. It is very tedious to differentiate the healthy and faulty currents at early stage and it is shown in the figure 9. Hence the spectral analysis using the wavelet decomposition techniques experimented and described below.

(a) Discrete Wavelet Transform (DWT)

Decomposition using DWT of the modified signal up to 10 levels has the 10 detailed coefficients and one approximation coefficient. Down sampling of these coefficients in each level and hence it reduced the length in the further levels. This method is processed for the healthy and outer race faults using DWT. The detailed coefficients and approximated coefficient are subtracted from the modeled signal coefficients and the new signal is rebuild using the modified coefficients. The rebuild signal for outer race fault is shown in figure 10 and it shows that the fault is in the initial stage. To discover the early fault, total power is the important parameter to be compared to other valid parameters. Some of the data might loss due to down sampling in each level of DWT; the indication of fault might fail in the analysis.

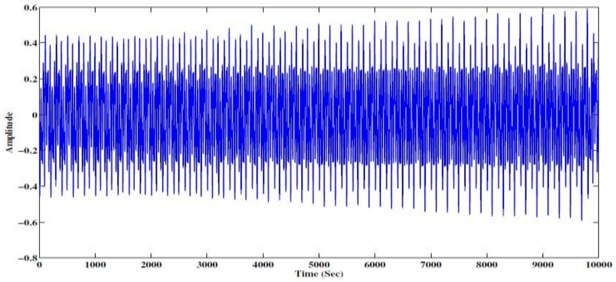


Fig. 10. Stator current after spectral subtraction with outer race fault using DWT.

(b) Stationary Wavelet Transform (SWT)

This method is same as that of DWT except that length of the coefficients in each level are same as the sampling frequency, but in DWT it down sampled by 2 at each level. Due to the same length of the wavelet coefficients it is tedious to discover the fault. From the figure 11 it shows that SWT will give better warning to outer race fault but not for severe fault. As discussed in DWT, in SWT also the total power is the best fault indexing parameter.

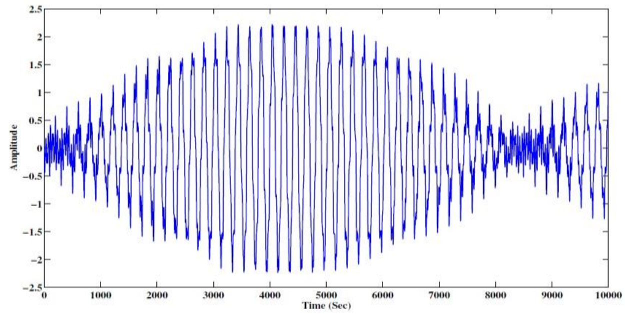


Fig. 11. Stator current after spectral subtraction with outer race fault using SWT.

(c) Wavelet Packet Decomposition (WPD)

In this method, unlike the methods DWT and SWT, WPD generates more coefficients and it is tedious to perform, so the signal is decomposed at level 5 rather than at level 10 to perform the execution easy. The rebuild signal obtained from the subtraction of healthy and faulty signal coefficients. Using the fault indexing parameters, the different faulty signals are analyzed, and it observed that the WPD is not suitable to indicate the early stage of outer race fault such as DWT and SWT and it is shown in figure 12.

(d) AR Model

In the AR model most of the earlier works were discussed about bearing faults, few of the works discussed about bearing faults and some of the works were focused in detecting faults in gearbox coupling systems. But in this paper, the AR model focused on estimating the power spectral density, harmonic analysis and frequency analysis. To predict the fault, Akaike Final Prediction Error (FPE) value is calculated from the Induction Motor operational condition. Various tests are evaluated on validating the auxiliary voltage, testing signal and analyzing the harmonic for fault detection in Induction Motor. In this experiment, running of the motor at various speeds like low and high based motor conditions are analyzed.

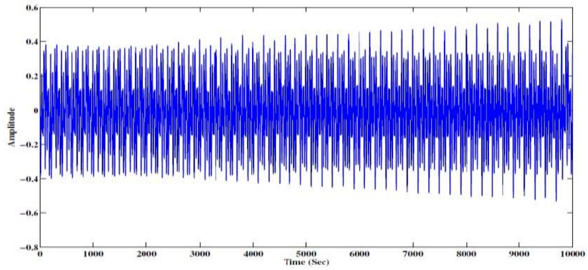


Fig. 12. Stator current after spectral subtraction with outer race fault using WPD.

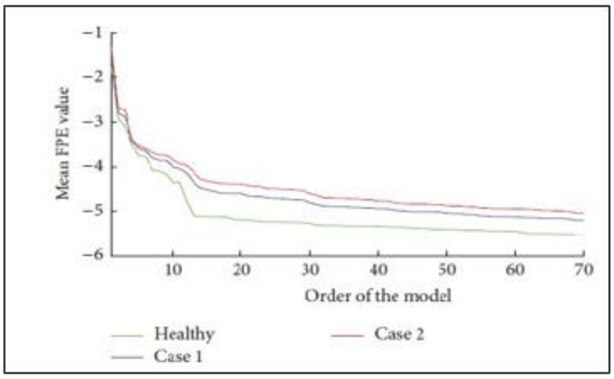


Fig.13. Mean FPE value for three fault scenarios at a speed of 1800 rpm.

For the obtained stator current, there are 4096 samples processed for the sampling frequency $f_s = 4000Hz$. For the various speeds 1200rpm, 1500rpm, and 1800rpm the load torque applied to all experiments. From the three different cases, the mean of the FPE value of the ISP module validated for the various orders (p= 2, ..., 70) and it is shown in the figure 13. For the order (p=3, ... , 8) the space between the values are lesser, but the space increases for the order p=11 and the order keep on goes up. For the three various speeds in 35 order AR model, the mean of FPE value and the rate of change Δ% among various fault degrees with reference to the healthy case and it is summarized in the Table 1.

Table 1
Mean FPE value of order p = 35 for three fault scenarios at different speeds

f_i (Hz)	Healthy	Case 1 Δ%	Case 2 Δ%
60	0.045	583.59	858.21
50	0.033	568.77	856.36
40	0.047	511.59	756.01

From the experiment it is tested for various loads like full load and no load. Stator current is verified and the obtained results are shown in Figure-14. The figure shows that the healthy and faulty conditions of the induction motor are given for static eccentricity.

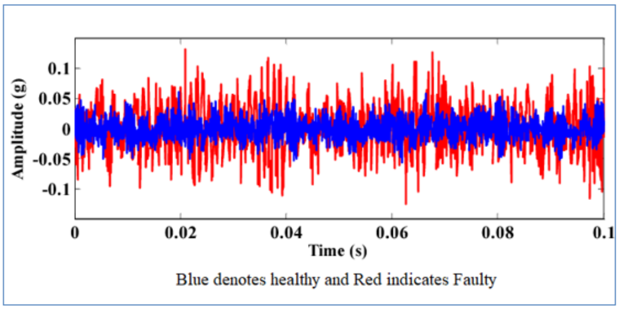
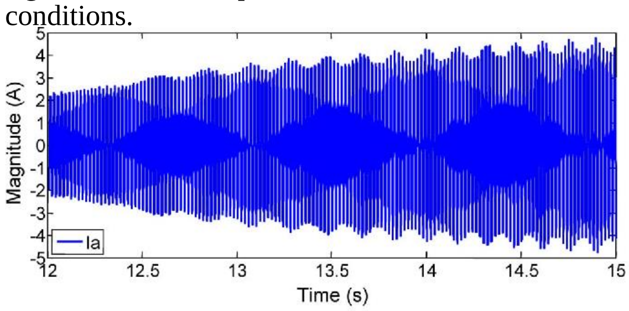
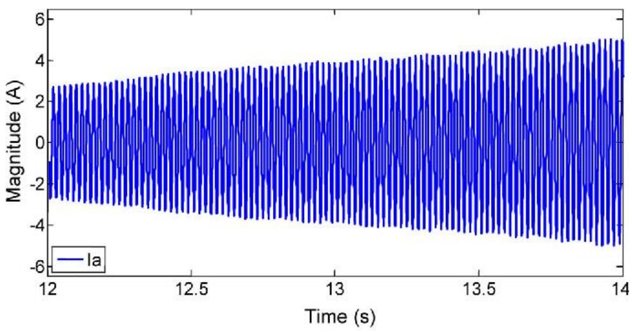


Fig. 14. Stator Current Characteristics.

It is essential to distinguish the induction motor at various frequencies for enumerating the level of damage without manipulating the transfer function of the AR model in the frequency domain. Here the 3-sigma rule was performed for various treated conditions.



(a)



(b)

Fig. 15. Stator current for an induction motor with torque variation
(a) Broken rotor bars (b) Stator shorted turns.

(e) Modified MCSA

Various experiments are carried out and validated the design of auxiliary voltage test signal and analyzing the side band harmonics for the discovery of faulty induction motor. Figure 15 shows the current spectra with broken bars and stator shorted turns. It is used to show the aim of positioning and discovering new current components that effect of motor failures namely broken rotor bars but also eccentricities and other faults.

16. Conclusion.

In this work, we experiment the various methods such as DWT, SWT, WPD, AR model and modified MCSA for finding the bearing faults in induction motor and analyzed the results of all the methods. We understand that DWT can produce the better indication for the severe faults in total power, but SWT predicts some of the faults at early stage only. WPD also performed like DWT and it is suitable only for the cyclic faults. Hence the fixed wavelet transform based spectral subtraction of stator current has superior warning for any type of faults whereas remaining are appropriate for few types of faults. In future, the wavelet transform based spectral subtraction technique may experimented for more types of bearing faults and may also tested for stator and rotor faults. In the AR model, the Gaussian distributions does not overlie in their consequent 3-sigma rule period for a assurance level of more than 99.7% is endured on the detection and 95% in the recognition of stator faults. The AR model approach, the worth and effectiveness for fault discovery and quantification of initial short circuit stator faults by considering low AR model orders for various faulty conditions, were established considering a 3-sigma rule. In the MCSA method, identification of the components which depends on the frequency of the auxiliary voltage inserted in the stator windings and on the motor load, which determines the slip frequency of operation. Thus we concluded that DWT is better for predicting the severe faults at early stage. The AR model approach, suitable only for discovering the initial short circuit stator faults in the low AR model orders. In the MCSA method, discovering the faults depends on the load and the tested signal inserted in the stator windings. Each method is showing its own characteristics for the various faults predicted at early stage and depends upon the type of faults.

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