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Research Paper

BEARING FAULT DETECTION OF INDUCTION MOTOR BY ANN METHOD

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Three-phase induction motors are the most-widely used electrical machines and are considered as the workhorses of the industry. About 60% of the electrical power generated is used by induction motors and hence have gained high importance. Their fault-free operation is desired in industrial processes. For this reason, detection of incipient faults has gained significance. Motor current signature analysis is the technique popularly used for the detection of fault in machines. It is non-intrusive and an online method, which analyses the health of the machine through the spectrum monitoring of the stator current. Bearing fault is the most common fault in IM and this paper deals with detection of Bearing fault using Artificial Neural Network (ANN).

Keywords: Induction motor, MCSA, Bearing fault, ANN

INTRODUCTION

Induction motors are workhorses of industrial processes and are frequently integrated in commercially available equipment and industrial processes. There are many published methods and numerous commercially available tools to monitor induction motors to ascertain a high degree of dependability uptime. Despite these tools, many companies are still faced with unforeseen system failures and decreased motor lifetime. The analysis of induction motor behavior during abnormalities and the possibility to diagnose these circumstances have been a challenging issue for many electrical machine researchers.

The literature indicate that majority of the failures in the three-phase induction motors are mechanical in nature such as bearing faults, eccentricity or misalignment faults and balance associated faults (Shashidhara and Sangameswara, 2013; and Allbrecht *et al.*, 1986).

The faults occurring in motor bearing is commonly due to the excessive load, rise of temperature within the bearing, employment

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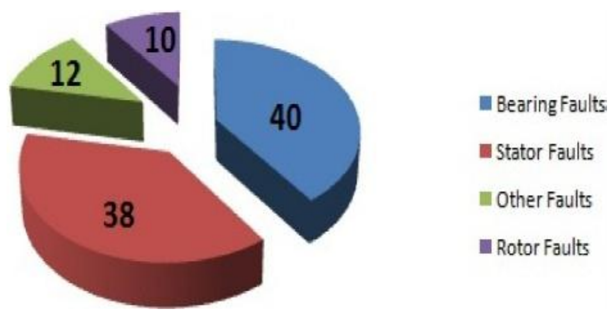
Figure 1: Fault Percentages in Induction Motor



of defective lubricant and so on. The bearing consists of primarily of the outer race, the inner race way, the balls and cage which ensures equidistance between the balls. The different faults that may occur in a bearing can be categorized according to the affected component:

- Outer raceway defect
- Inner raceway defect
- Ball defect

BEARING FAULTS

The bearing faults can be grouped into cyclic faults and non-cyclic faults (Thomson and Gilmore, 2003). Cyclic faults emerge when the rolling component and the rolling element cage of the bearing passes through the point of defect. The deep scratches in a rolling element are a case of cyclic fault. The material abrasion, quality degradation of the lubricant due to contaminants, slither, insufficient lubrication and skid amongst the movable bearing components induce mutilation of the contact areas, which is a non-cyclic fault family. The bearing defects cause non-stationary and fault specific frequency constituents in the stator current and the generated vibrations (Randy *et al.*, 1995; and Benbouzid, 2000).

Ball Defect

The bearing cage in a ball bearing bears on the balls at evenly balanced berths and aids the confined rolling of the balls along the racetracks. While the motor shaft is rotating, the bearing cage rotates at a steady angular velocity that is average of the inner and outer race angular velocities. The cage angular velocity can be exploited to work out the value of dominant fault frequency due to cage defect, fCD as given below (Eschmann *et al.*, 1958):

$$f_{CD} = \frac{\mu_i r_i + \mu_o r_o}{60(D)} = \frac{1}{60D}\left[\mu_i \frac{D - d\cos\text{¤}}{2} + \mu_o \frac{D + d\cos\text{¤}}{2}\right] \quad ...(1)$$

where

μ_i = Angular speed of the inner race in RPM
μ_o = Angular speed of the outer race in RPM
D = Pitch Diameter

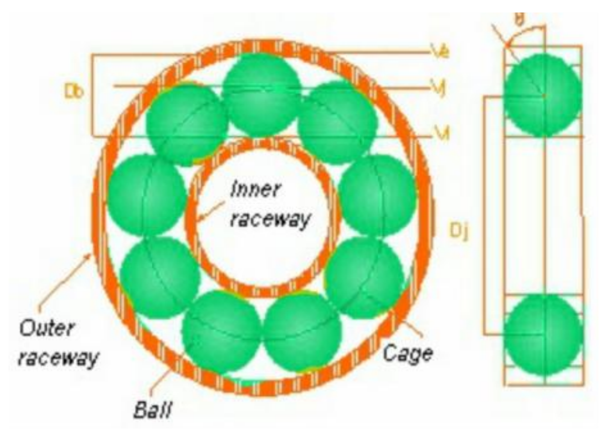
d = Ball Diameter

¤ = Ball contact angle

r_i = Inner race radius, r_o = Outer race radius

The outer race is attached to the casing that is stationary. The shaft and inner race are mounted together and both revolve at the same

Figure 2: Roller Bearing Geometry



angular speed. Consequently, it can be assumed that:

$\mu_o = 0$ and $\mu_i = \mu_r$ ...(2)

where μ_r = Rotor angular speed in RPM

Incorporating the above mentioned assumption as shown in Equation (5) brings Equation (6) as given below:

$$F_{CD} = \frac{\mu_r}{120}\left[1 - \frac{d\cos\text{¤}}{D}\right] \quad ...(3)$$

Empirically, the fundamental frequency due to cage defect for a ball bearing with six to twelve balls in it is given as:

$f_{CD} = 0.4\ \mu_{rs}$ ...(4)

where

$$\mu_{rs} = \frac{Rotor\ angular\ speed\ in\ rpm}{60}$$

The ball defect is simulated in MATLAB using Artificial Neural Network algorithm. In the simulation procedure, the harmonic frequencies generated due to the bearing ball defect fed into the stator current of a healthy machine. Thus the current of phase A obtained is as shown in Figure 3.

Characteristic Frequencies

Each anomaly in the motor operation gets reflected in the stator current as a characteristic frequency. Motor current signature Analysis is a nonintrusive and easy method of finding the fault in the motor. It needs no other input, but, only the stator current. The Characteristic Frequencies can be identified by the frequency spectrum of the current.

In this paper only ball defect is being considered for analysis. Hence, the characteristic frequency of the ball defect is given by

$$f_{bearing} = \left|f_1 \pm m.f_{i,0}\right|$$

where = 1, 2, 3, 4, ..., and $f_{i,0}$ is one of the characteristic frequency based upon the geometry of the bearing shown in Figure 1.

EXPERIMENTAL SETUP

The experimental setup consists of two three phase induction motors 2.2 kw, 440 V, 4 pole,

Figure 3: Stator Current in Phase A

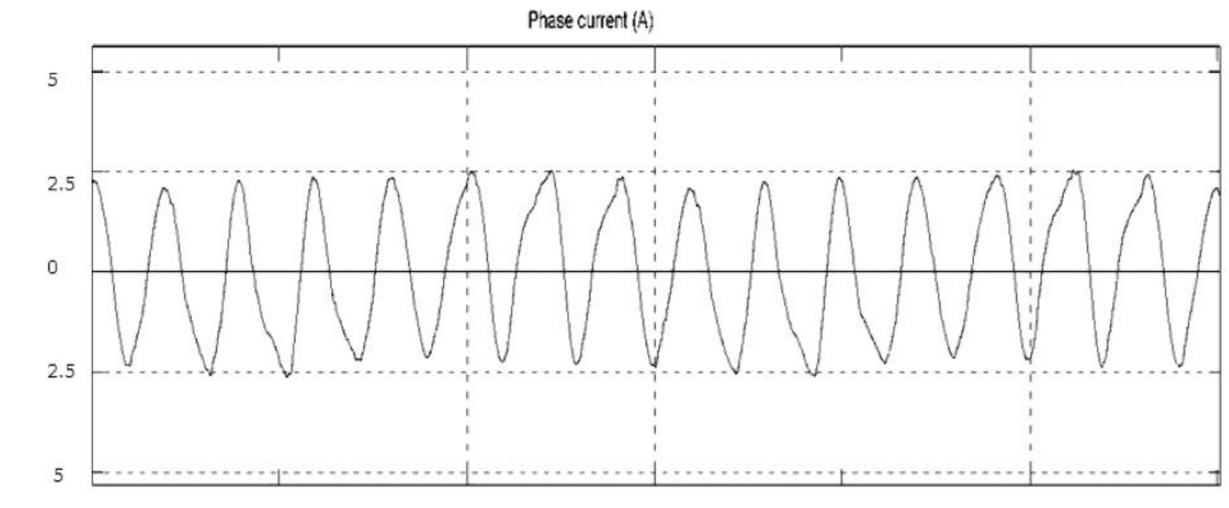


Figure 4: Experimental Setup

50 Hz coupled to a mechanical load. One motor is healthy and the observations were considered as reference to compare with the other motor which has a bearing fault.

The data acquisition and conditioning system was developed and data visualization done on a PC using FFT and Power Spectral Density.

Case 1: Healthy Motor

Experiment was conducted on a healthy motor; the measured current and speed are tabulated in Table 1. Their corresponding waveforms and frequency spectrum are shown in Figures 4 and 5. Interpolation technique was employed to determine the waveforms for the (0.1, 0.2, 0.3, 0.4, 0.6, 0.7, 0.8, 0.9) of the rated load cases to furnish the entire data needed for the Neural Network (NN) to be trained for each case in order to increase its ability of diagnosis.

Table 1: Load Applied on Motor and the Corresponding Speed

Load	Speed
No Load	1440
Half Load	1380
Full Load	1295

Case 2: Faulty Motor

Now, with the defective bearing test results were taken and the results are presented as below:

The above spectrum analysis diagrams show the presence of harmonic components around the fundamental frequency of 50 Hz. The above spectrums show the existence of a harmonic components located around the fundamental line frequency. These constituents are used to be called as lower side-bands and upper sidebands components. It is apparent that their distance

Figure 5: Healthy Motor at No Load (a) Phase Current Signal (b) FFT Current Spectrum

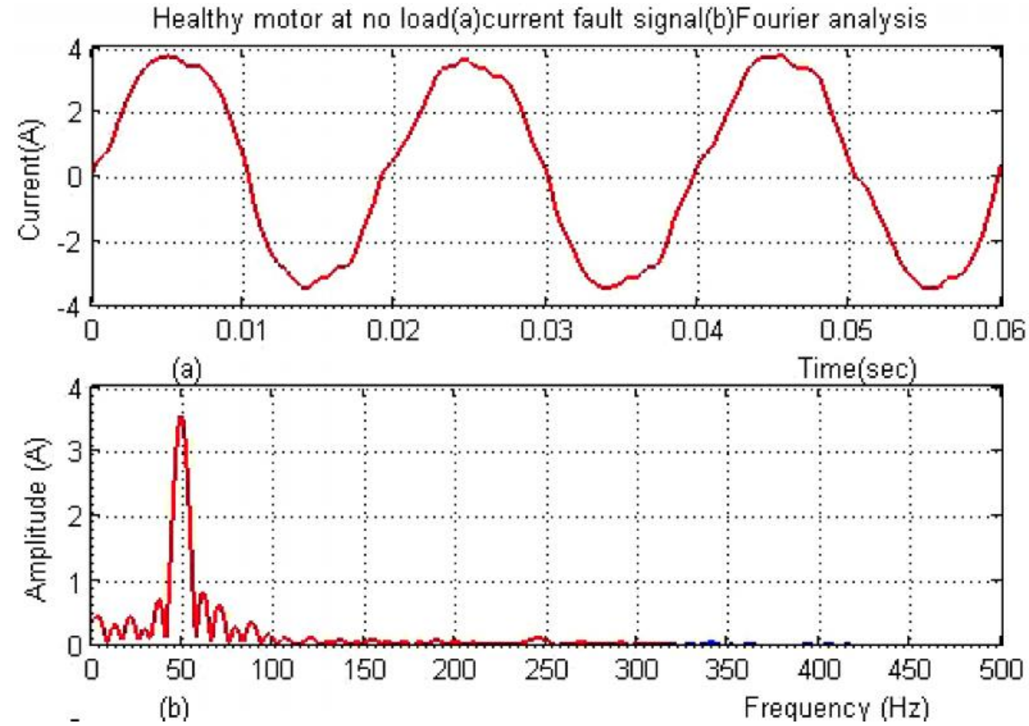


Figure 6: Healthy Motor at Half Load (a) Phase Current Signal (b) FFT Current Spectrum

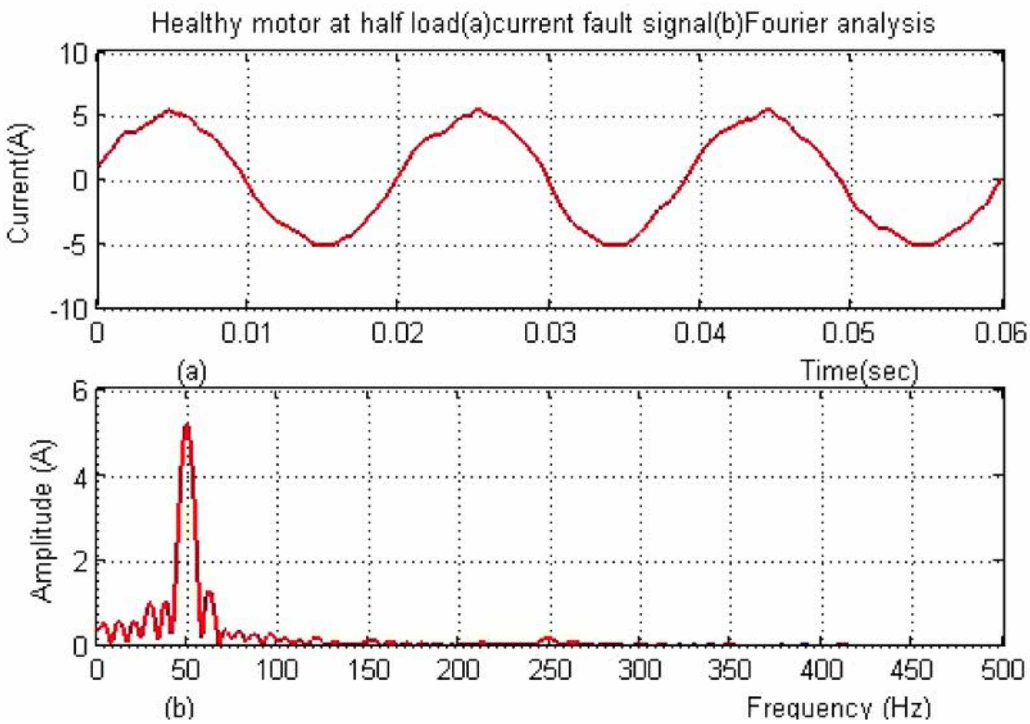


Figure 7: Healthy Motor at Full Load (a) Phase Current Signal (b) FFT Current Spectrum

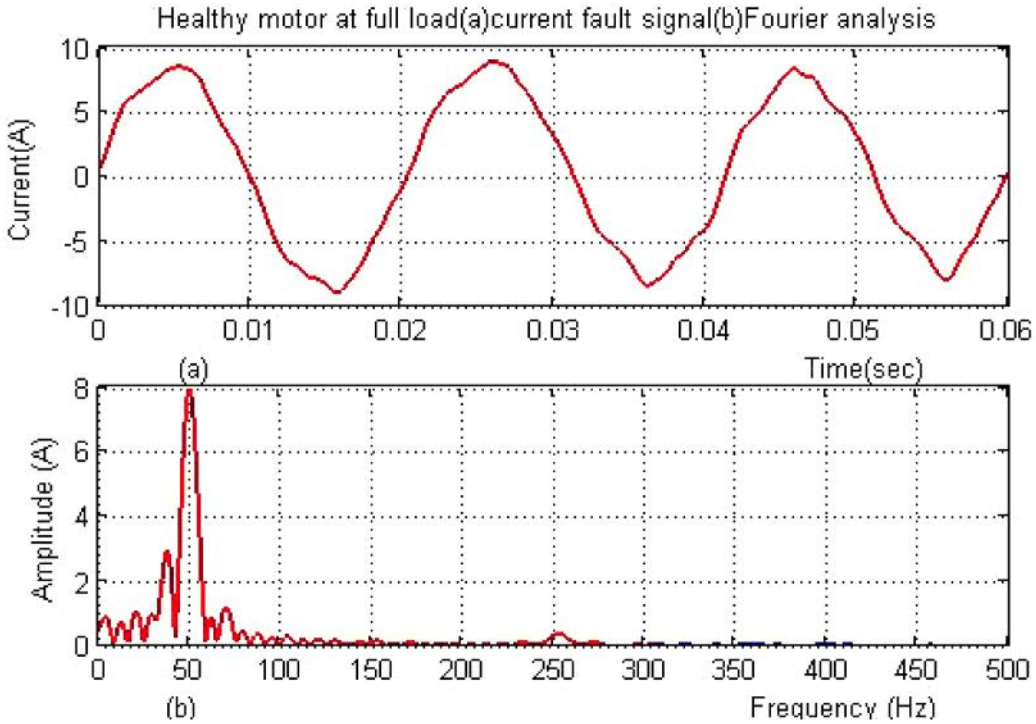


Figure 8: Bearing Fault at No Load (a) Phase Current Fault Signal (b) Fourier Analysis (c) Side Bands at No Load (d) Side Bands at Half Load (e) Side Bands at Full Load

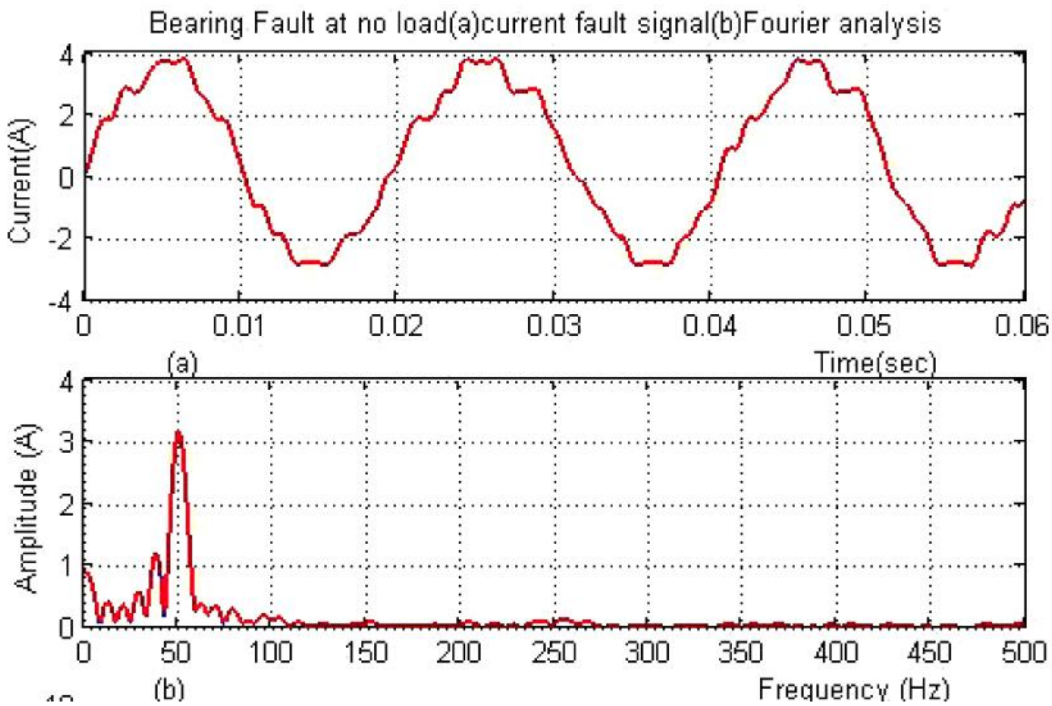


Figure 8 (Cont.)

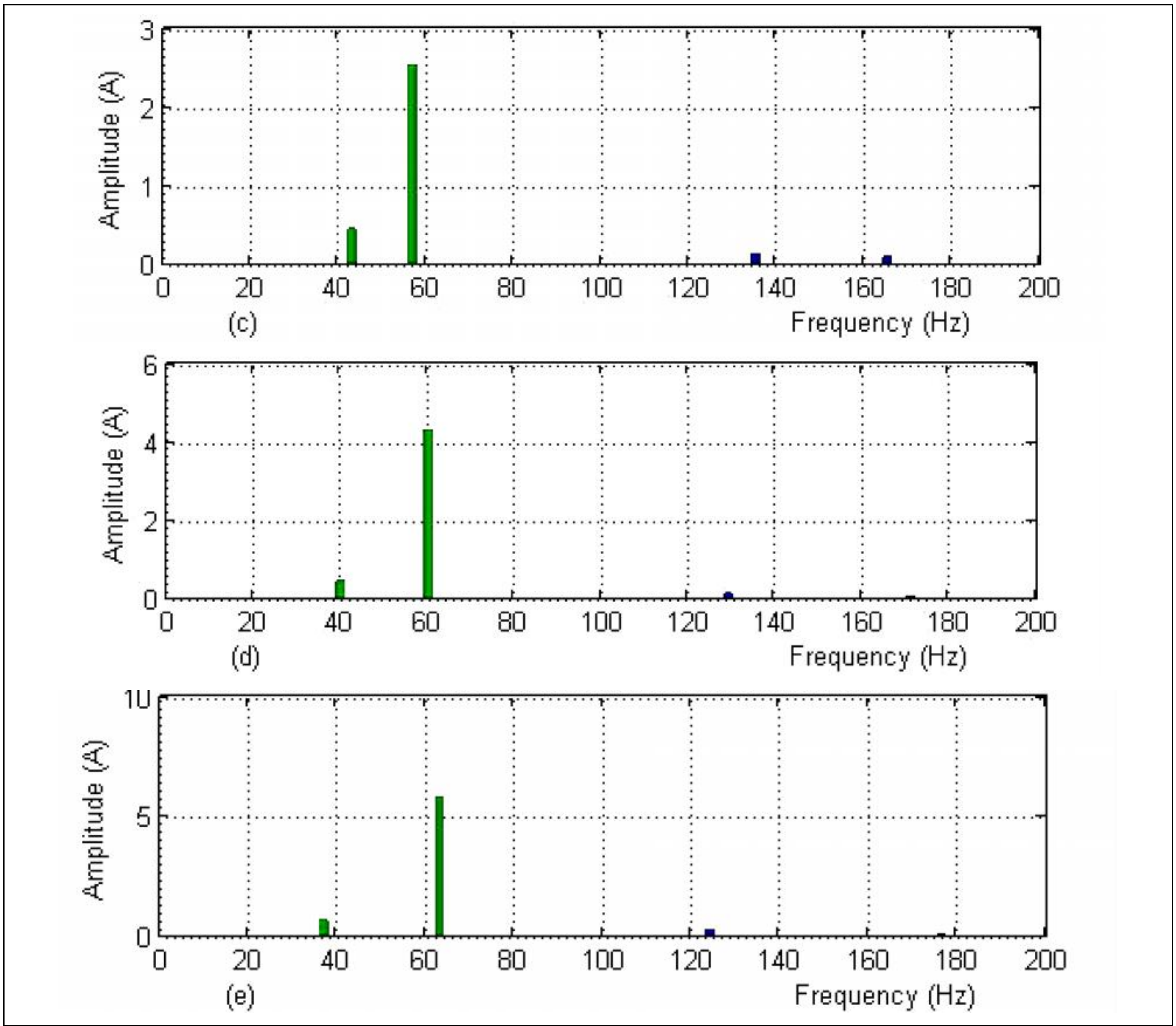
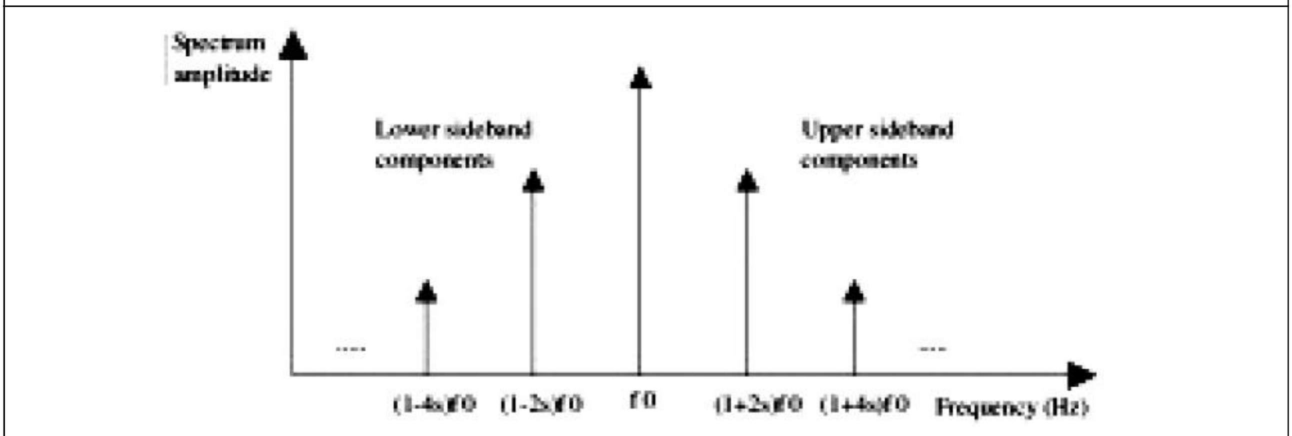


Figure 9: Sideband Frequencies in Stator Current Due to Fault in Motor

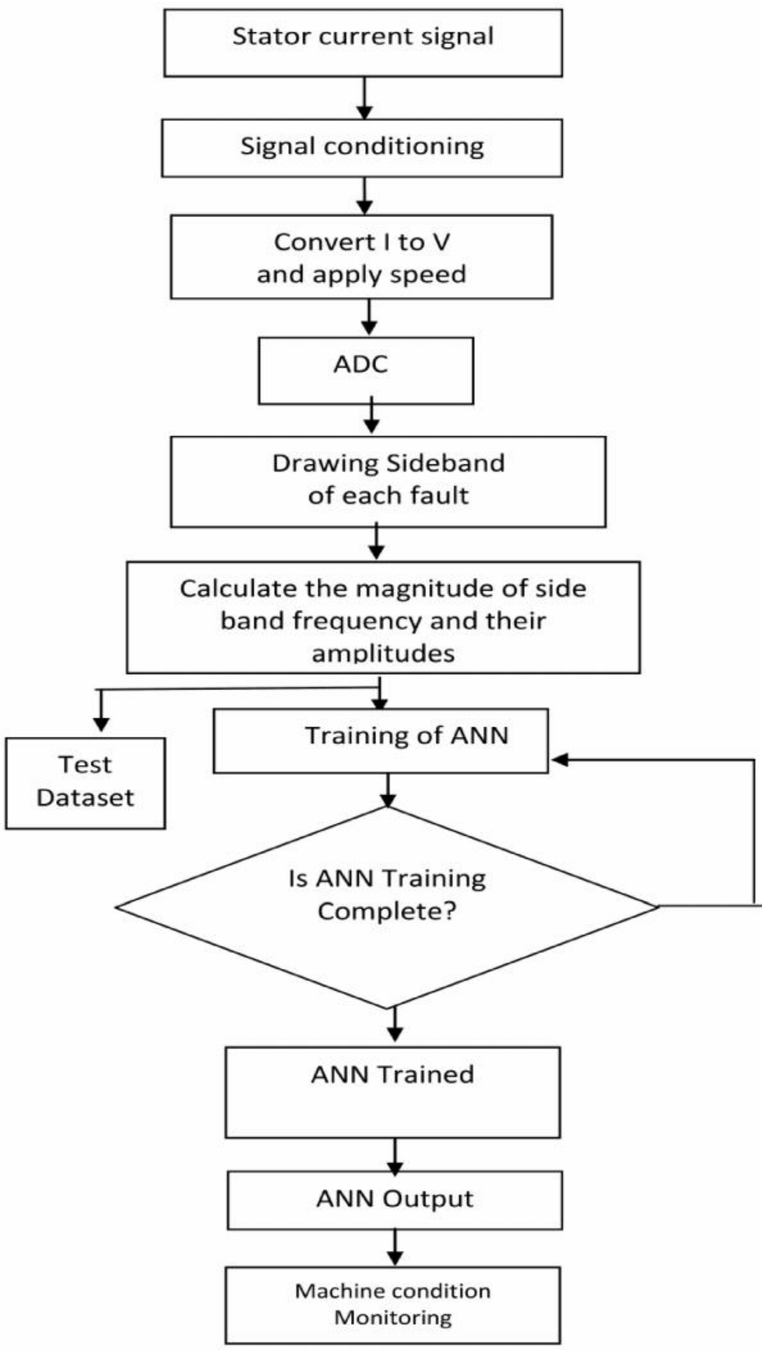


from the fundamental component in the spectrum is increasing with load. Also the magnitude of these sidebands increases as load increases. Figure 9 represents these sidebands clearly in general.

Implementation of Neural Network

Neural Network was simulated using MATLAB Neural Network toolbox choosing Damped Least-Squares (DLS) method, also known as Levenberg-Marquardt Algorithm (LMA)

Figure 10: ANN Algorithm



method. It provides a numerical solution to the problem of minimizing a function, generally nonlinear, over a space of parameters of the function.

CONCLUSION

This paper dealt with the design and testing of the induction motor for the diagnosis of bearing fault. The results obtained experimentally match with the fault signature frequencies derived analytically. It is proved that the MCSA is an effective tool in the detection of bearing fault of induction motor.

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