Advanced Research in Electrical and Electronic Engineering
Print ISSN: 2349-5804; Online ISSN: 2349-5812 Volume 2, Number 3 January-March (2015) pp. 237-243

http://www.krishisanskriti.org/areee.html

Mechanical Fault Diagnosis in Induction Motor Drives Using Classifiers

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Abstract—*The induction motors are used frequently in industries due to various technical and economic issues. These machines will lead to stresses during the normal operating conditions. These stresses will leads to several modes of faults and failures. The mechanical fault is the one of the most vital fault in all motor systems based on the performances. Mostly all kinds of issues are linked with the mechanical faults only. Based on the dynamic performance of the motor, the accuracy of those instruments and devices which are used to monitor and control the motor systems are dependent. Thus, fault diagnosis of a motor system is inseparably related to the diagnosis of the mechanical parts assembly. In this paper, for the motor fault diagnosis, the mechanical faults frequency features are briefly experimented. The mechanical faults diagnosis of a motor is done using soft computing techniques and the result obtained by this method. It is an excellent choice for diagnosis purposes and it can be a beneficial method for all electrical machine diagnostics using linear support vector machines classifier training and based on discrete wavelet transform.*

Keywords *Induction motor drive, Support vector machines (SVM), HAAR wavelet function, Discrete Wavelet Transform (DWT).*

1. INTRODUCTION

Induction motors are most commonly used electrical machines in all industry because of their low cost, small size, ruggedness, low maintenance and operating with the power supply. There are various kinds of faults occurs during the operation. These faults may be inherent to the machine itself or due to operating condition. The inherent faults may be are due to the mechanical or electrical forces acting on the machine enclosure. If a fault is not detected or if it is allowed to develop further it may lead to a failure. A variety of machine faults have been studied such as winding faults, rotor parameters, and unbalanced stator, broken rotor bars, eccentricity and bearing faults. By using different motor fault parameters are current, voltage, efficiency, speed, temperature and vibration, there are several fault identification methods have been developed and efficiently applied to diagnosis the machine faults. At firstly, fault detection schemes using different neural networks paradigms like artificial neural networks [3]-[6],[13], recurrent neural networks, probabilistic neural networks and k-nearest neighbour are used.

The interpretation of fault which can be employed using the soft computing techniques such as genetic algorithm, expert systems, adaptive neural fuzzy system. When compared with the conventional techniques it has more popularity. These are easy to extend and modify besides their improved performance. The use of above technique increases the precision and accuracy of the monitoring systems. In this paper for the diagnosis of the mechanical faults in induction motor soft computing technique like support vector machines based on discrete wavelet transform are implemented. By using the support vector machines, one can identify the particular fault of the induction motor is determined accurately [1], [2]. Subsequently, a discrete wavelet technique is exploited not only to the detection and location of the faults but also we can know the severity of such faults in an induction motor.

1.1 Basic principle of induction machine

Induction motor works based on the principle of electromagnetic induction. Using a balanced three phase source, each winding are displaced 120 degrees from each other mechanically.

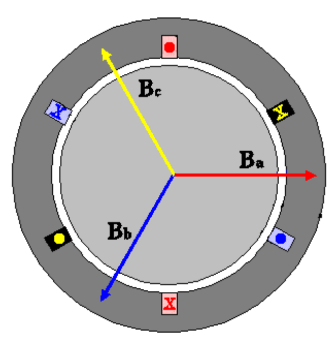

Fig. 1: Mechanically displaced by 120 degree

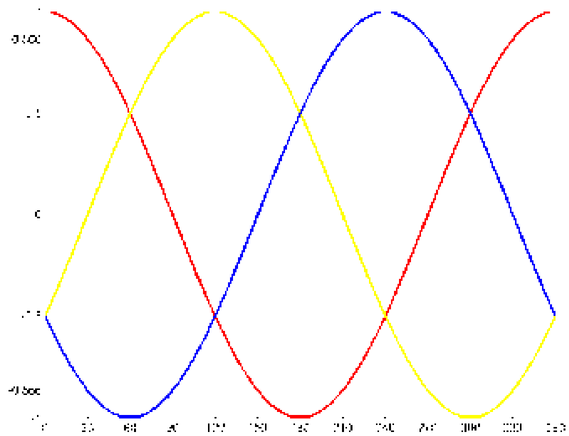

Fig. 2: Rotating magnetic field

A rotating magnetic field with constant magnitude is produced**.** This rotating magnetic field cuts the rotor windings and it produces an induced voltage in the rotor windings due to the rotor windings are short circuited, for both squirrel cage and slip ring rotor and induced current flows in the rotor windings. Another magnetic field is produced by the rotor current. A torque is produced as a result of the interaction of those two magnetic fields.

2. SYSTEM DESCRIPTION

Mechanical faults are one of the most important causes of faults in induction motors. Such faults are caused by several types of stress such as thermal, mechanical, electrical and environmental acting on the insulation system. All these stresses interact with each other in such a way that to degrade in the insulation system. Different types of mechanical faults can develop under such stresses. From that bearing fault is one of the most common types of mechanical fault.

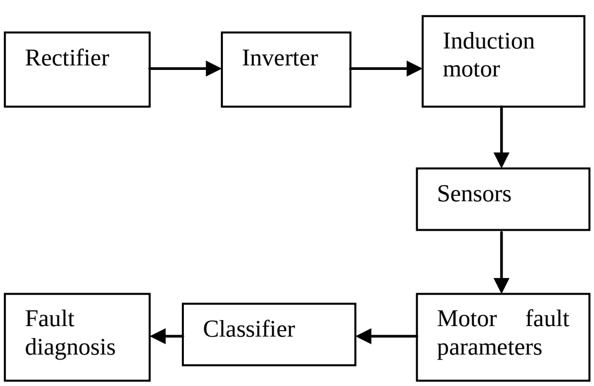

Fig. 3: Block diagram for the fault diagnosis

This chapter presents an experimental set up for the calculation of induction motor parameters such as bearing frequency such as inner raceway frequency, outer raceway frequency, cage frequency and ball frequency. These parameters which are calculated from the experimental set up are used in a model to generate the current in the different level of the frequency and the phase shift between the line currents and phase voltages of an induction motor under fault conditions. The monitoring parameters that can be used to diagnosis the fault for the machine are temperature, magnetic flux, vibration, power, current, induced voltage, instantaneous angular speed, air gap toque, partial discharge, surge current, gas analysis and motor circuit analysis. For diagnosis the faults for an induction motor the procedure can be classified into three classes. Mostly signal based and data based diagnosis is used. [10].

2.1 Data based diagnosis

Data based diagnosis does not require any knowledge of machine parameters and model. It relies only on signal processing and on clustering techniques. Signal processing can be further classed into three main subclasses: spectral estimation techniques, time-domain techniques and time-frequency estimation [12].

2.1.1 Time-domain and frequency analysis:

Time-domain analysis is a powerful tool for a three phase squirrel cage induction motor. In the oscillation of the electric power in time domain becomes mapped in a discrete waveform in an angular domain. Data clustering techniques are used to extract an averaged pattern that serves as the mechanical imbalance indicator. Time-domain technique can track the fundamental frequency and slip of the machine and then compute a diagnosis index without any spectrum analysis.

2.2 Bearing vibrational frequency features:

There are five basic motions that are used to describe the dynamics of bearing elements, with each movement having a corresponding frequency. These five frequencies are denoted as the shaft rotational frequency (Fs), the fundamental cage frequency (Fc), the ball pass inner raceway frequency (Fbpi), the ball pass outer raceway frequency (Fbpo), and the ball rotational frequency (Fr).

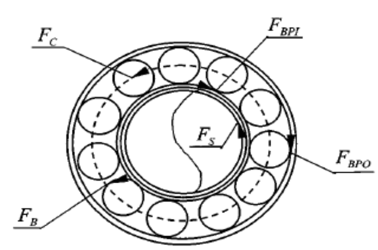

Fig. 4: Variation of frequency bearing components

Based on the above frequency parameters,

The ball rotational frequency is

$$F_B = \frac{D_c}{2D_b} F_s \left(1 - \frac{D_b{}^2 \cos^2\theta}{D_c{}^2}\right) \quad (1)$$

The ball pass outer raceway frequency is

$$F_{BPO} = \frac{N_B}{2} F_s \left(1 - \frac{D_b \cos\theta}{D_c}\right) \quad (2)$$

The ball pass inner raceway frequency is

$$F_{BPI} = \frac{N_B}{2} F_s \left(1 + \frac{D_b \cos\theta}{D_c}\right) \quad (3)$$

The cage frequency is

$$F_c = \frac{1}{2} F_s \left(1 - \frac{D_b \cos\theta}{D_c}\right) \quad (4)$$

Then the components generated for the bearing fault analysis are,

$$f_{cbf} = \left| f_s \pm n f_{rc} \right| \quad (5)$$

$$f_{rc} = \frac{N_b f_s}{2}\left[1 \pm \frac{Db}{Dp}\cos\theta\right] \quad (6)$$

Table 1: Bearing vibration features

Bearing defects	Frequency variations	Observations
Good condition	F_S , F_{BPO} , F_{BPI}	Good condition can have and its harmonics, F_S , F_{BPO} , F_{BPI} amplitude is small and even and no salient frequency stands out.
Bearing looseness	F_S	Looseness condition can have F_S and its harmonics
Rolling elements	$2F_B$, F_{BPO} , F_{BPI}	For severe case these frequency can be modulated by $2F_B$, F_C and the natural frequency can also be excited.
Bearing raceway	F_{BPO} , F_{BPI}	Increased severity of the defects results in higher order harmonics being produced, the frequency for the raceway with defect will stand out, if the clearance is small, $2F_B$, can also be presented.

The components required for rotor fault is,

$$f_{cbf} = f_s\left[n\frac{(1-s)}{p} \pm s\right] \quad (7)$$

The components required for eccentricity fault is,

$$f_{ce} = f_s\left[(nR_s \pm o_{re})\frac{(1-s)}{p} \pm o_{smh}\right] \quad (8)$$

Table 2: Collection of data

Types of faults	Data collected
Bearing fault	Nb =12 Db =0.005 Dp =0.025
Eccentricity fault	Θ =30 Rs =33 Ore =5 Osmh =3
Rotor fault	N =3 S =0.02 P =4

3. SUPPORT VECTOR MACHINES

3.1 Purpose of vector representation

Having represented each sample/patient as a vector allows now to geometrically represent the decision surface that separates two groups of samples.[7],[8],[11].

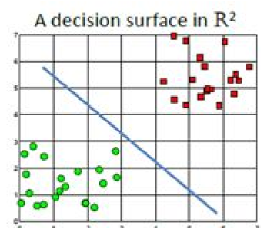

Fig. 5: Hyperplane based on 2D view

3.2 Hyperplane

A Hyperplane is a linear decision surface that splits the space into two parts.It obivious that a hyperplane is a binary classifier.[9].

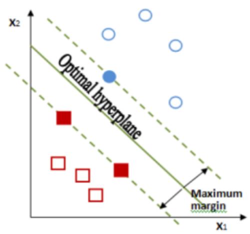

Fig. 6: Diagram of a hyperplane

3.3 Equation of hyperplane

Consider the case of R3, An equation of a hyperplane is defined by a point (P0) and a perpendicular vector to the plane at that point.

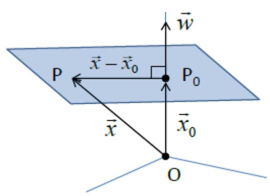

Fig. 7: Vector calculation of hyperplane

3.4 Optimisation

3.4.1 Quadratic programming

Quadratic programming (QP) is a special optimization problem: the function to optimize ("*objective*") is quadratic, subject to linear constraints. Convex QP problems have convex objective functions. These problems can be solved easily and efficiently by greedy algorithms (because every local minimum is a global minimum).

3.5 Linear separable data (Hard margin)

Linear separable data are nothing but the data are linearly separable. i.e. the linear classifier that separates the training data with the largest margin.

$$\gamma_i = \frac{y_i(w \cdot x_i + b)}{\|w\|} \tag{9}$$

3.5.1 Dual formulation

The problems that are caused by the primal formulation can be recast in the so-called *"dual form"* giving rise to *"dual formulation of linear SVMs*" .It is also a convex quadratic programming problem but with *N* variables (α*i*, *i*= 1… *N*), where *N*is the number of samples.

$$\text{Objective function is } \sum_{i=1}^{N} \alpha_i - \frac{1}{2} \sum_{i,j=1} \alpha_i \alpha_j y_i y_j \vec{x_i} \cdot \vec{x_j}$$

$$\text{And subjected to } \alpha_i \geq 0 \, and \sum_{i=1}^{N} \alpha_i y_i = 0$$

3.6 Non-linearly separable data

It is nothing but the data are non linearly separable and we cannot make an hyperplane to find an optimal distance. For such cases Kernal function can be used for separating the non linear data.

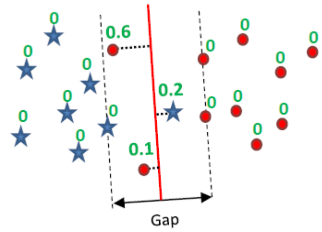

Fig. 8: Non-linear separable data

3.6.1 Kernal function

Nonlinear classification has to be applied by mapping the data into feature space using Kernel function. Mostly radial basis kernel function can be used.

$$K(X_i, X_j) = \exp\left(-\gamma \|X_i - X_j\|^2 \cdot\right), \gamma > 0 \tag{10}$$

4. PRINCIPAL COMPONENT ANALYSIS

PCA identifies an m dimensional explanation of n dimensional data where m < n. Originated as a statistical analysis technique. PCA attempts to minimize the reconstruction error under the following restrictions. They are linear reconstruction and orthogonal factors. Equivalently, PCA attempts to maximize variance, proof coming. Most PCA Neural Networks use some form of Hebbian learning. "Adjust the strength of the connection between units A and B in proportion to the product of their simultaneous activation. Important Note is that neural PCA algorithms are unsupervised. There are three different types of models are used for the PCA with an neural network, they are subspace model, apex model and multilayer model.

5. DISCRETE WAVELET TRANSFORM

Wavelets are a class of functions used to localize a given function in both position and scaling. They are used in applications such as signal processing and time series analysis. Wavelets form the basis of the wavelet transform which cuts up data of functions into different frequency components and then studies each component with a resolution matched to its scale. There are two main types of wavelet transforms: continuous (CWT) and discrete (DWT). The first is designed to work with functions defined over the whole real axis. A wavelet function can be denoted ψ (·). A small wave grows in a finite time period, and decays repeatedly over an infinite time period [10]. For a function ψ (·), defined over the real axis $(-\infty, \infty)$, to be classed as a wavelet it must satisfy the following three properties:

(1) The integral of $\psi(\cdot)$ is zero:

$$\int_{-\infty}^{\infty} \Psi(u)du = 0 \tag{11}$$

(2) The integral of $\psi(\cdot)$ is unity:

$$\int_{-\infty}^{\infty} \Psi^2(u)du = 1 \tag{12}$$

(3) Admissibility Condition:

$$c_\psi \equiv \int_0^\infty \frac{|\Psi(f)|^2}{f} \text{ Satisfies } 0 < c_\psi < \infty \tag{13}$$

One of the oldest wavelet functions is the Haar wavelet (see Fig. 9), named after Haar who developed it in 1910:

$$\Psi^{(H)}(u) \equiv \begin{cases} +1 \; if \; 0 \le u < \frac{1}{2} \\ -1 \; if \; \frac{1}{2} \le u < 1 \\ 0 \; else \end{cases} \tag{14}$$

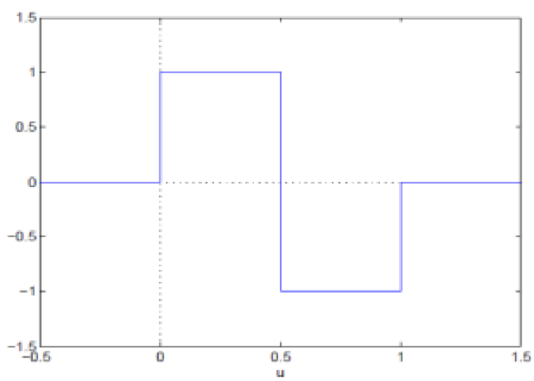

Fig. 9: HAAR wavelet function

The analysis of a signal using the CWT yields a wealth of information. The signal is analysed over infinitely many dilations and translations of the mother wavelet. Clearly there will be a lot of redundancy in the CWT. We can in fact retain the key features of the transform by only considering subsamples of the CWT. This leads us to the discrete wavelet transform (DWT). The DWT operates on a discretely sampled function or time series x(·), usually defining time t = 0, 1, . . . ,N − 1 to be finite. It analyses the time series for discrete dilations and translations of the mother wavelet $\psi(\cdot)$.Then the dyadic scales are used for the different dilations.

It shows the DWT of a signal using the Haar wavelet. In that it can be organized into four plots. The wavelet coefficients account for 896 of the 1024 DWT coefficients. The other 128 coefficients are called scaling coefficients. As with the CWT, the original signal can be recovered fully from its DWT. So, while sub-sampling at just the dyadic scales seems to be a great reduction in analysis, there is in fact not loss of data, then we can recover x(·) from its CWT using the following inverse transform:

$$x(t) = \frac{1}{c_\Psi} \int_0^\infty \left[\int_{-\infty}^{\infty} \langle x, \Psi_{\lambda,t} \rangle \Psi_{\lambda,u}(t) du \right] \frac{d\lambda}{\lambda^2} \tag{15}$$

Where $C\psi$ is defined as in Equation. So, the signal x (·) and its CWT are two representations of the same entity.

The MRA leads naturally to a hierarchical and fast method for computing the wavelet coefficients of a given function. Then it can be written as:

$$x(t) = \sum_k a_k \phi(t-k) \tag{16}$$

6. RESULTS AND DISCUSSIONS

This section describes a generalized model of the three-phase induction motor and its computer simulation using MATLAB. The coding can be performed by the MATLAB software based on the fault monitoring parameters of the three phase induction motor. According to the position of the sensors placing in the motor only the parameters are measured commonly used accelerometers are strain gauge type, capacitive type, and piezoelectric type. Here we use

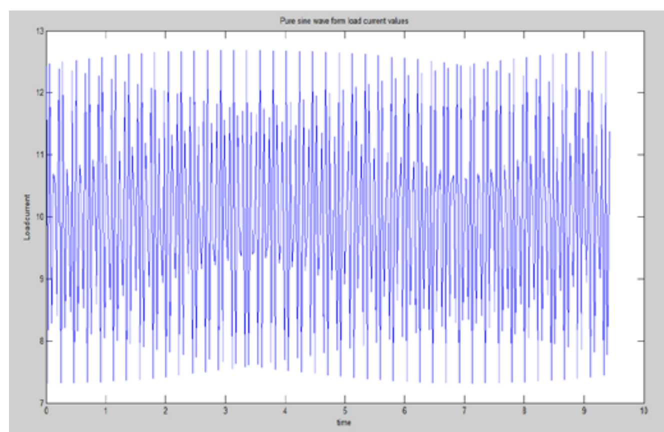

Fig. 10: Without fault current variation

piezoelectric type since it has high natural frequency. For frequency ratios, the ratio between the vibrating member and the natural frequency of the accelerometer greater than 0.4, the response was found to be non-linear for other type of accelerometers; thus piezoelectric type is preferred.

Based on the variation of the time without using the discrete wavelet transform (DWT),

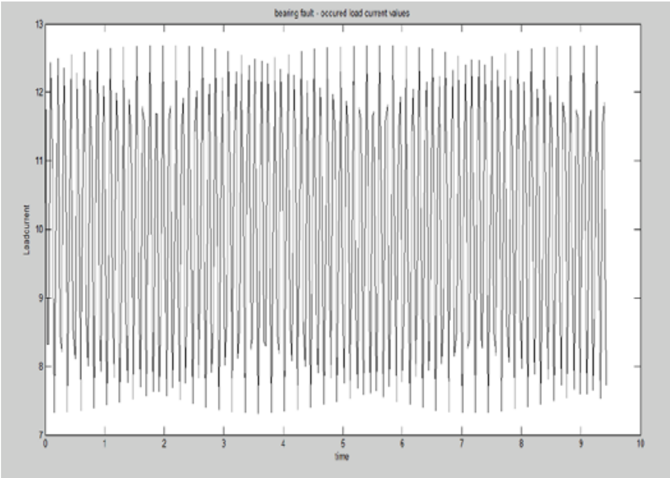

Fig. 11: Bearing fault current variation

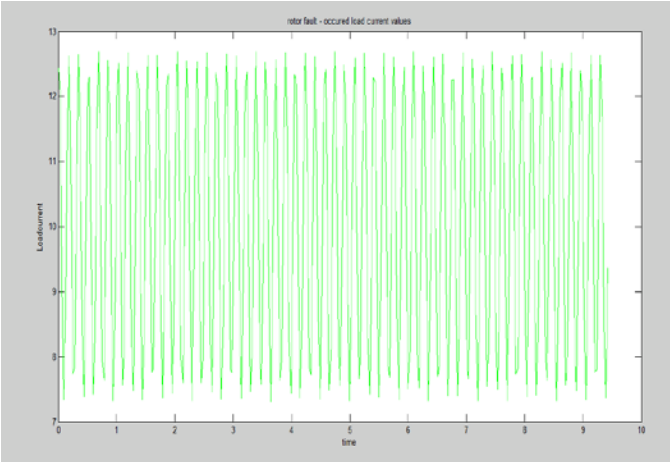

Fig. 12: Rotor fault current variation

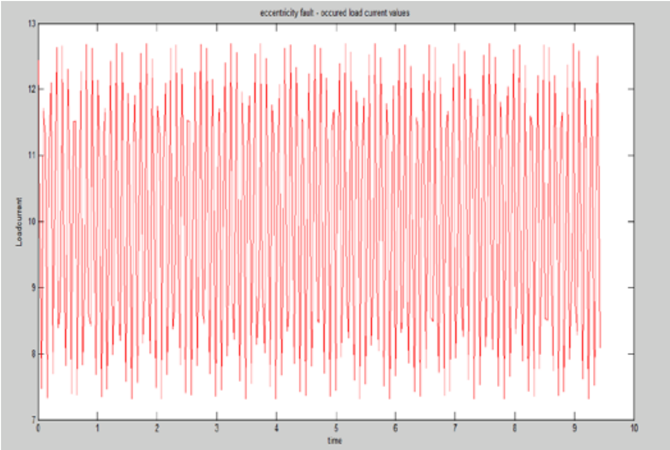

Fig. 13: Eccentricity fault current variation

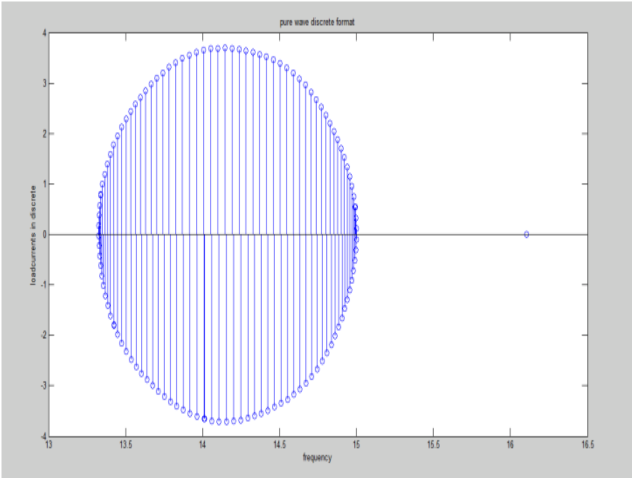

Fig. 14: DWT based without fault current variation

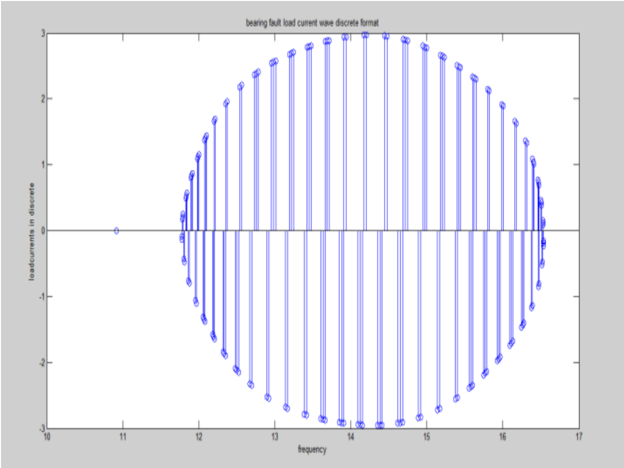

Fig. 15. DWT based with bearing fault current variation

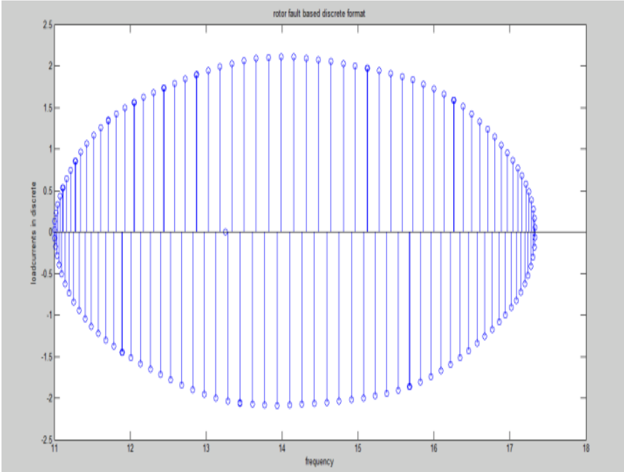

Fig. 16: DWT based rotor fault current variation

Then by using the discrete wavelet transform time domain can be transformed to a frequency domain.

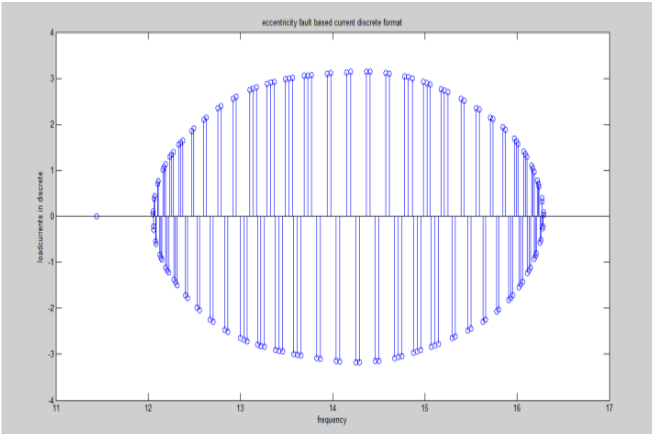

Fig. 17: DWT based eccentricity fault current variation

7. CONCLUSION AND FUTURE WORK

In this chapter, a summary for the work that has been done in this project for achieving the objectives of the study is provided. Also conclusions from this work and suggestions for future work are presented. The objective of this study is to develop a SVM based induction motor for the mechanical faults identifier. This faults identifier detects the bearing fault experienced by the three-phase induction motor. The existing data is can be taken for three-phase squirrel cage induction motor is used to train and test the MATLAB software program is used for implementing the SVM method. A Radial basis Kernel function is used in this project for creating the trained model; also different Kernel functions are introduced in this project to study their effectiveness on the testing accuracy. It is observed that the scaling range has an impact on the prediction accuracy for some Kernel functions in the SVM based induction motor faults identification method considered in this study. One of the testing cases considered used a part of the data for creating the model and the remaining part for testing the accuracy of the prediction. Finally, a fault diagnosis on an induction motor drive using SVM.

The future work of this project attained the goals of this study: developing a SVM based induction motor with practical data and implementing this for the power system protection purpose, and achieving the better performance by using the SVM.

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