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NOVEL WAVELET ANN TECHNIQUE TO CLASSIFY BEARING FAULTS IN THREE PHASE INDUCTION MOTOR

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Abstract- Three phase induction motors are the 'workhorses' of industry and are the most widely used electrical machines. For this reason detection of motor failures is very important. Bearing problems is one of the major causes for drive failures. Early detection of bearing faults allows replacements of the bearings rather than replacement of motor. Present contribution reports experimental results for monitoring of bearing faults in induction motor. Motor line currents have been analyzed using modern signal processing and data reduction tool combing Park's Transformation and Discrete Wavelet Transform (DWT). Feed Forward Artificial Neural (FFANN) based data classification tool is used for fault characterization based on DWT features extracted from Park's Current Vector Pattern. An online algorithm is tested successfully on three phase induction motor and experimental results are presented to demonstrate the effectiveness of the proposed method which can reliably distinguish the inner race and outer race defects of the bearing. Experimental results are presented to demonstrate the effectiveness of the proposed method.

Keywords: Induction Motor, Fault Diagnosis, Park's Transformation, DWT, FFANN, Bearing Defects.

I. INTRODUCTION

Induction motors are a critical component of many industrial processes and are frequently integrated in commercially available equipment. Safety, reliability, efficiency and performance are some of the major concerns of induction motor [1]. Induction motor for various electrical applications consumes ample amount of power generated in the world, as it has got a wide range of applications in the industries. Having such a wide application range induction motors are always subjected to various electrical as well as mechanical faults.

These faults can be classified as follows:

- Stator winding fault or inter turn short circuit fault
- Bearing faults
- Air gap eccentricity
- Broken rotor bars
- Misalignment of rotor

Result of recent studies show that bearing problems account for 40% of all machine failures [2]. Therefore this type of fault must be detected as soon as possible to avoid fatal breakdowns of machines that may lead to loss of production. Main reason for triggering bearing faults is dust and corrosion. Induction motors are often operated in hard conditions, so foreign materials; water, acid and humidity are main reasons of bearing deteriorations. Dirt and other foreign matter that is commonly present often contaminate the bearing lubrication. In improper lubrication rolling elements are not allowed to rotate on the designed oil film causing increased level of heating. The excessive heating grease to breakdown, which reduces its ability to lubricate the bearing element and accelerate the failure process [3].

If preventive maintenance is not given due importance such faults can turn into failure of motors. Failure of an induction motor can result into loss of production or it may shutdown the processing units. One cannot afford a loss because of failure of motor. Therefore a reliable monitoring technique is required in order to reduce the loss and the maintenance cost of the motor.

Vibration signal analysis, temperature measurement, shock pulse method (SPM), acoustic emission (AE), motor current signature analysis(MCSA) are the various condition monitoring methods that are used for detection and diagnosis of bearing failure. Most popular amongst these is vibration signal analysis. Large induction motors are often equipped with mechanical sensors, which are primarily vibration sensors such as proximity probes. But these are delicate and expensive and also it is not economically feasible to provide the same for smaller induction motor. Though vibration measurement methods are mostly widely used, but because of economical constraints in small and medium size induction motor, MCSA method for fault detection is overtaking it. Various researchers have suggested that stator current monitoring can provide the same indications without requiring access to motor. These methods do not require costly sensors, using current transformers and data acquisition system currents can be captured.

The wavelet is now becoming more and more popular than other methods of fault diagnosis because it permits systematic decomposition of signal into its sub band levels. If the current signal consists of the non-stationary or transient conditions the conventional Fourier transform is not suitable and the time-frequency or time-scale method has to be adopted. The wavelet was introduced by Jean Morlet a French engineer in 1982. Newland was the one whose work made wavelet transforms popular in engineering field especially in vibration analysis. He has not only proposed the harmonic wavelet but also identified the peaks and packets of the transitory signals [5]. The method based on the wavelet packet for the diagnosis of failure of ball bearings was proposed by B. Liu and S.F. Ling [6]. Loparo used the wavelet transform as tool for feature extraction and fuzzy classifier for detection of fault in bearing [7]. In [8], J.C. Garcia-Prada, C. Castejon, and O.J. Lara have proposed a new condition monitoring technique for detection and classification of bearing faults. They used DWT for the feature extraction and extracted features are then used as input to the neural network for the classification of faults. In [10] bearing fault detection is based on DWT pattern obtained from calculation of flux linkages.

Artificial Intelligence plays a dominant role in field of conditioning monitoring and different techniques such as neural network, fuzzy logic and genetic algorithms are being widely used for feature extraction and classification purpose [9]. Another important tool that is mostly used for fault detection is hidden Markov method (HMM). Its success in speech recognition system causes it to be used in fault detection [4].

In this paper ANN based approach is been proposed and found to be an effective alternative for detecting inner race and outer race defects in induction motor. Artificial Immune system has abilities of learning memory and self adaptive control. In addition ANN can perform continuous nonlinear functions online through the use of inexpensive monitoring devices. These devices obtain necessary measurements in noninvasive manner. Main problems facing the use of ANN are the selection of best inputs and choice of ANN parameters so as to make the structure compact to create highly accurate networks. Many input features require a significant computational effort and thus can result in low success rate.

The present work documents experimental results used for the discrimination of the raceway defects in the ball bearings. The proposed method is an experimental work carried out in the laboratory. The motor is tested with different sets and combination of bearings in different load conditions. Line current signals recorded from motor terminals are processed by Park's Transformation followed by DWT to obtain judicious features corresponding to different fault conditions. Spectral energies contained in detail d_1-d_5 level of Park's current vector (i_d and i_q) are selected as inputs to ANN. The results shows that proposed method can reliably detect and discriminate the defects of bearings.

II. PARK'S VECTOR APPROACH

A two dimensional representation can be used for describing three phase induction motor phenomenon. A suitable one is that based on stator current Park's vector. Park's Transform reduces the number of current components and makes calculation easier. As a function of mains phase variables (i_a, i_b, i_c) the motor current park's vector component i_d and i_q are:

$$i_d = \sqrt{\frac{2}{3}} i_a - \frac{1}{\sqrt{6}} i_b - \frac{1}{\sqrt{6}} i_c \tag{1}$$

$$i_q = \frac{1}{\sqrt{2}} i_b - \frac{1}{\sqrt{2}} i_c \tag{2}$$

Under ideal conditions, three-phase currents lead to a Park's vector with the following components

$$i_d = \frac{\sqrt{6}}{2} I \sin \omega t \tag{3}$$

$$i_q = \frac{\sqrt{6}}{2} I \sin(\omega t - \frac{\pi}{2}) \tag{4}$$

where I is maximum value of the supply phase current, ω_s is supply frequency and t is time variable.

The corresponding representation of i_d-i_q is a circular locus centered at origin of the coordinates under balanced condition. Under abnormal conditions equations 3 and 4 are no longer valid and as a result the observed pattern differs from reference pattern. The philosophy of Park's vector approach is thus based on identifying unique signature pattern, obtained corresponding to the motor current Park's vector representation.

III. WAVELET TRANSFORM

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

$$f(t) = \sum_l a_l \ \varphi_l(t) \tag{5}$$

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

If the expansion (5) is unique, the set is called a basis for the class of functions that can be so expressed. The bases are orthogonal if:

$$\langle \varphi_l(t), \varphi_k(t) \rangle = \int \varphi_l(t) \varphi_k(t) dt = 0 \ , \ k \neq l \tag{6}$$

Then coefficients can be calculated by the inner product as:

$$\langle f(t), \varphi_k(t) \rangle = \int f(t) \varphi_k(t) dt \tag{7}$$

If the basis set is not orthogonal, then a dual basis set $\varphi_k(t)$ exists such that using (7) with the dual basis gives the desired coefficients. For wavelet expansion, equation (5) becomes:

$$f(t) = \sum_k \sum_j a_{j,k} \ \varphi_{j,k}(t) \tag{8}$$

In Equation (8) j and k are both integer indices and $\varphi_{j,k}(t)$ is the wavelet expansion function that usually forms an orthogonal basis. The set of expansion coefficients $a_{j,k}$ are called Discrete Wavelet Transform (DWT).

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

The DWT is implemented using a multi-resolution signal decomposition algorithm to decompose a given signal into scales with different time and frequency resolution. In this sense, a recorder-digitized function $a_0(n)$, which is a sampled signal of $f(t)$, is decomposed into its smoothed version $a_1(n)$ (containing low-frequency components), and detailed version $d_1(n)$ (containing higher-frequency components), using filters $h(t)$ and $g(t)$, respectively. This is a first-scale decomposition. The next higher scale decomposition is now based on signal $a_1(n)$ and so on, as demonstrated in Figure 1.

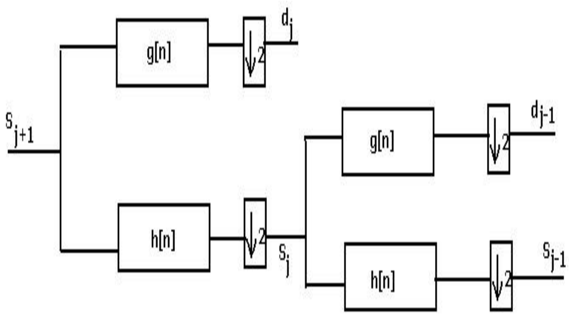

Figure 1. Two band multi-resolution analysis of signal

The analysis filter bank divides the spectrum into octave bands. The cut-off frequency for a given level j is found by:

$$f_c = f_s / 2^{j+1} \tag{9}$$

where f_s is the sampling frequency. The sampling frequency in this paper is taken to be 10 kHz

IV. ARTIFICIAL NEURAL NETWORK

The application of artificial neural network to various decision making, forecasting and classification problems has gained a lot of attention recently. ANN s are able to learn the relationship among past, present and future variables. An ANN is an information processing paradigm, inspired by biological nervous systems. The basic processing element of neural network is called artificial neuron or simply neuron. The key element of it is the novel structure of the information processing system. It is composed of large number of highly interconnected processing elements working in union to solve specific problem.

Artificial neural system functions as distributed computing networks .Their most basic characteristics is their architecture. Only some networks provide instantaneous responses, other networks need time to respond and are characterized by their time domain behavior, which often referred to as dynamics. Neural networks also differ from each other in their learning modes. There are varieties of learning rules that establish when and how the connecting weights changes. Networks exhibit different speeds and efficiency of learning. An ANN is configured for a specific application, such as pattern recognition or data classification, through a learning process. Learning in biological system involves adjustments to the synaptic connections that exist between the neurons.

Neural networks are typically organized in layers. Layers are made up of number of interconnected nodes which contain an 'Activation Function'. Patterns are presented to the network via a system of 'Weighted Connections'. The hidden layer then links to an output layer where the answer is output as shown in Figure 2.

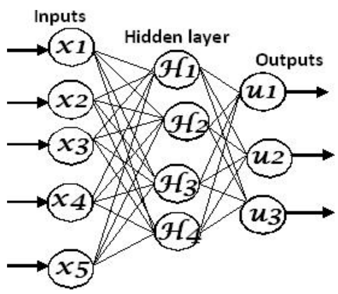

Figure 2. Architecture of Artificial Neural Network (ANN)

Common type of artificial neural network consists of three layers of units, a layer of 'input' unit is connected to a layer of 'hidden' unit, which is then connected to a layer of 'output' units. The activity of input unit represents the raw information that is fed into the network. The activity of each hidden unit is determined by the activities of the input units and the weights on the connection between the input and hidden units. The behavior of the output unit depends on the activity of hidden units and the weights between the hidden and output units. Feed forward ANN allow signal to travel from input to output only. There is no feedback i.e. the output of any layer does not affect the same layer. Feed forward ANN tends to be straight forward networks that associate inputs with outputs.

Prediction with NNs involves two steps: training and learning. Training of FFNNs is normally performed in a supervised manner. The success of training is greatly affected by proper selection of inputs. In the learning process, a neural network constructs an input–output mapping, adjusting the weights and biases at each iteration based on the minimization or optimization of some error measure between the output produced and the desired output. This process is repeated until an acceptable criterion for convergence is reached. The most common learning algorithm is the back propagation (BP) algorithm, in which the input is passed layer through layer until the final output is calculated, and it is compared to the real output to find the error. The error is then propagated back to the input adjusting the weights and biases in each layer.

The standard BP learning algorithm is a steepest descent algorithm that minimizes the sum of square errors. In order to accelerate the learning process, two parameters of the BP algorithm can be adjusted: the learning rate and the momentum. The learning rate is the proportion of error gradient by which the weights should be adjusted. Larger values can give a faster convergence to the minimum. The momentum determines the proportion of the change of past weights that should be used in the calculation of the new weights.

V. EXPERIMENTAL SET UP

Figure 3 shows the set up used for the experimental purpose. Mains fed 2 Hp, 3 phases, 50 Hz squirrel cage induction motor made by the leading Indian Electrical industry has been used for the analysis of bearing faults. The spring and belt arrangement is used for the mechanical loading of the motor. The motor comprises of two bearings numbered as 6204 and 6205. The bearings having natural defects caused by the regular operation of motor were used in experimental study. Motor is fitted with different combination of bearings having inner race and outer race defects. Stator current and phase voltage of the motor for each combination of bearing are then captured in order to compare with healthy bearings. Different experiments are conducted with different combinations of rear side and load side bearings to assess the performance of these bearings and its effect on the performance of motor. Three currents i_a, i_b and i_c are captured. The Tektronix DSO, TPS 2014 B, with 100 MHz bandwidth and adjustable sampling rate of 1GHz is used to capture the currents. The Tektronix current probes of rating 100 mV/A, input range of 0 to 70 Amps AC RMS, 100A peak and frequency range DC to 100KHz are used.

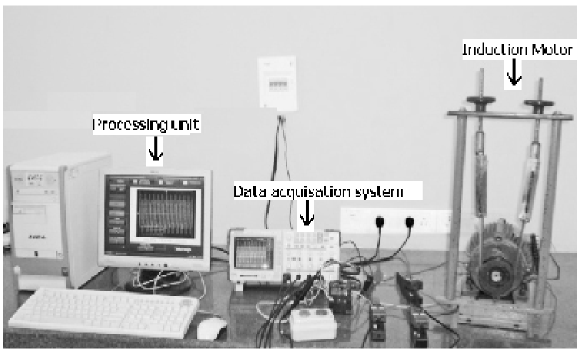

Figure 3. Experimental set up

Figure 4 shows the set of ball bearings used for the study. The bearings used in this study are having natural defects due to their continuous operation. The experimentation is done using the four sets of bearings with different defect in their races. The defected bearings shown in Figure 4(a) are of load side and that shown in Figure 4(b) are the bearings of rear side. A set of load side and rear side bearing has similar defect.

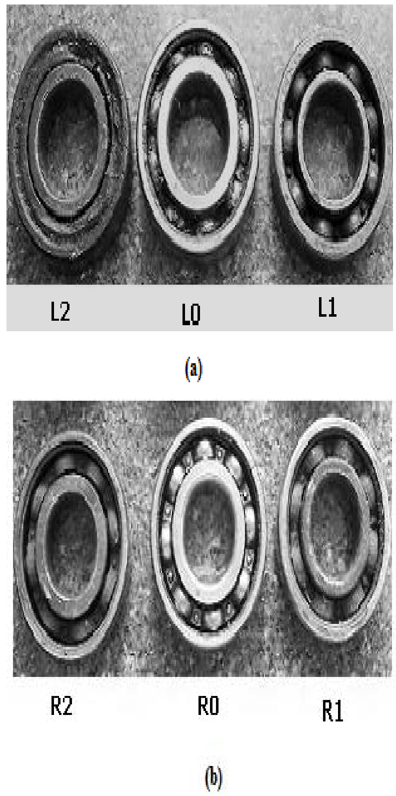

Figure 4. (a) Load side bearings , (b) Rear side bearings

VI. FAULT FEATURE EXTRACTION USING DWT

Three phase line currents fed to induction motor are represented in two dimensional systems by Park's Transformation. For characterizing the faults suitable features need to be extracted from Park's vector pattern .An important step is the selection of mother wavelet to carry out the analysis. Several wavelet families with different mathematical properties have been developed.

These wavelets are Gaussian, Mexican, Hat, Morlet, Meyer, Daubechies, Coiflet, Biorthogonal etc. For extraction of fault components after multiple tests, it is seen that wide variety of wavelet families can give satisfactory results. In the proposed algorithm Daubechies-4 (db-4) is used as the mother wavelet.

When DWT is applied to extract the scaling and wavelet coefficients from a transient signal, a large amount of information in terms of these coefficients is obtained. Although the information is useful, it is difficult for ANN to train /validate that large information. Another alternative is to input the energy contents in the detailed coefficients according to Parseval's Theorem [11].

$$\int f(t)^2 dt = \sum_k c_j(k)^2 + \sum_{x=1}^{j} \sum_k dx(k)^2 \tag{10}$$

where $f(t)$ is signal to be decomposed using DWT, c_j is approximation of the DWT at level j and dx is detail number x of the DWT.

The general meaning of Parseval's theorem is that the energy contained in any signal is equal to the summation of the energy contained in the approximation and details at any DWT decomposition level (j). As only the transients are being focused so only the second part of above Equation (10) is considered. In the proposed strategy Park's current pattern (i_d and i_q) derived from induction motor line currents for healthy and faulty conditions are decomposed up to the fifth level using db4.

Figures 5 and 6 show the Park pattern at no load and full load condition respectively. An insight analysis of Figures 5 and 6 leads to an obvious classification of bearing failures as the patterns observed for faulty bearings deviates from its reference pattern.

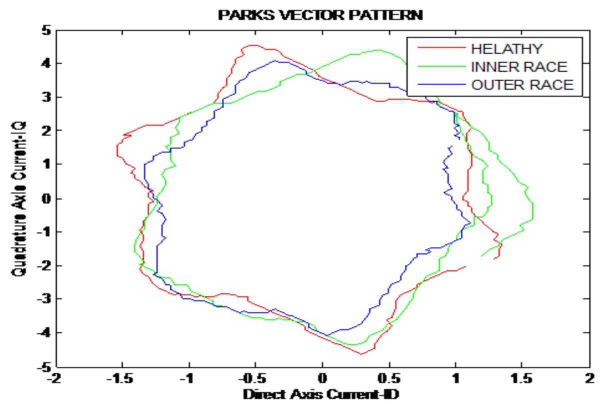

Figure 5. No load condition

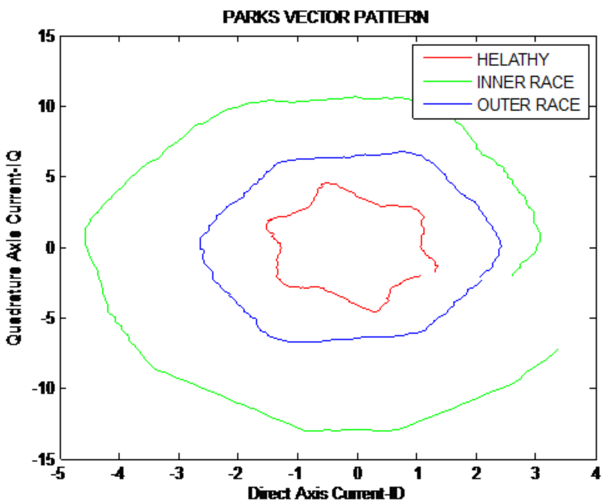

Figure 6. Full load condition

Figures 7, 8 and 9 show the decomposition of Park's current vector for healthy, inner race and outer race conditions, respectively. Energies of the level d_1-d_5 are calculated and are used as inputs to neural network.

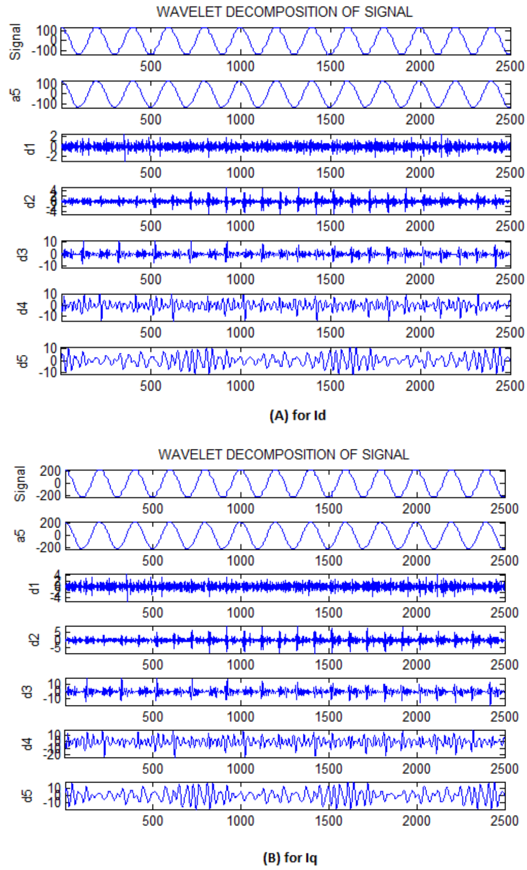

Figure 7. Wavelet decomposition of Park's current pattern for healthy Condition

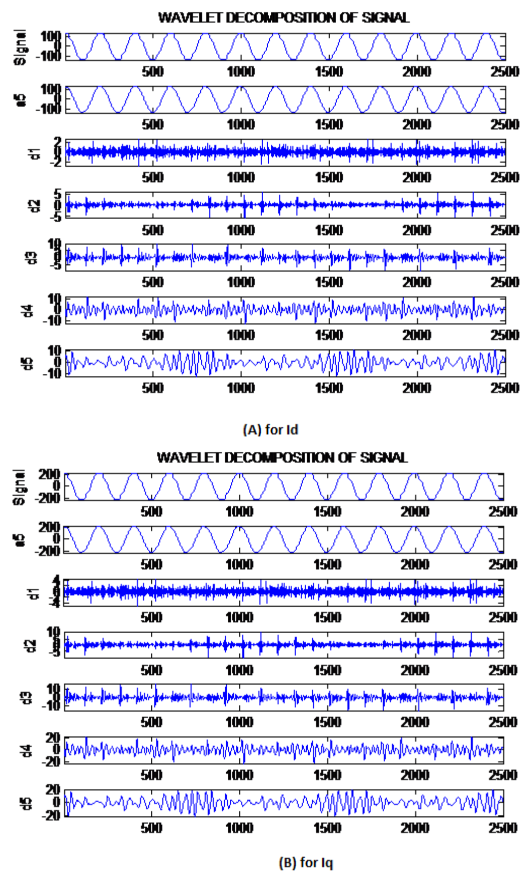

Figure 8. Wavelet decomposition of Park's current pattern for

inner race defect

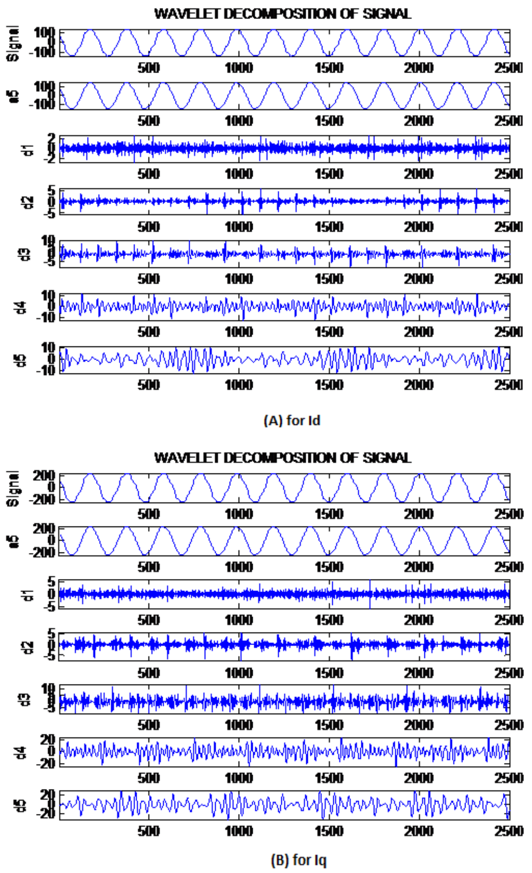

Figure 9. Wavelet decomposition of Park's current pattern for outer race defect

VII. ANN BASED FAULT CLASSIFICATION

Park's Transform approach should be associated with techniques that automate the process of bearing failure detection and diagnosis. For that purpose, two techniques are extensively used: neural networks and fuzzy logic.

Feed Forward Artificial Neural Network is widely accepted classifier .The success of FFANN to distinguish between healthy and faulty induction motor is strongly related to the success in the preprocessing of its input data. The inputs should contain lot of information for the network to properly classify the event.

In this paper three layers fully connected FFANN is used and trained with a supervised learning algorithm called back propagation. FFANN consists of one input layer, one hidden layer and one output layer. Input layer consists of ten neurons, the inputs to these neurons are spectral energies contained in detail d_1-d_5 level of Park's current vector (i_d and i_q). Output layer consists of three neurons representing healthy, inner race defect and outer race defect.

TanhAxon transfer function and Momentum learning rule is used for training the network and average minimum square error MSE on training and testing data is obtained. Momentum = 0.7, data used for training purpose = 60%, for testing = 40%, step size in hidden layer and output layer = 0.1, With these assumptions variation of percentage accuracy of classification for induction motor under healthy, faulty bearing condition with respect to number of processing elements in hidden layer is obtained. Figure 10 shows variations of percentage accuracy with respect to number of processing elements. It is observed that for five processing elements in hidden layer, 100% classification accuracy is achieved for healthy and faulty condition.

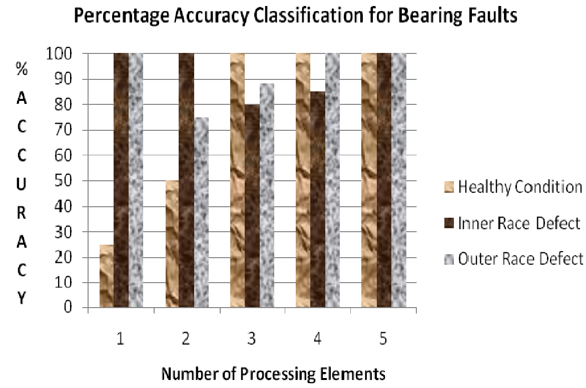

Figure 10. Percentage accuracy classification for bearing faults

VIII. CONCLUSIONS

This paper addresses the issue of bearing fault monitoring in induction motor. Experimental results with inner race and outer race defects in bearings are presented. Line current signals recorded under healthy and faulty conditions are passed through series of signal processing techniques involving Park's transformation. Subsequently DWT is utilized and Park's current are decomposed up to fifth level using db4. To extract the features of faulty condition as against the healthy state of motor energies of d_1-d_5 level are used as input to ANN. Feed Forward Artificial Neural Network with Momentum as learning rule and with five processing elements in hidden layer is then applied to classify the faults based on features obtained by DWT. Proposed methodology is useful in identifying inner race and outer race defects of bearings in induction motor with 100 percent accuracy.

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