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Regular paper

An Intelligent Automated Method to Diagnose and Segregate Induction Motor Faults

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In the last few decades, various methods and alternative techniques have been proposed and implemented to diagnose induction motor faults. In an induction motor, bearing faults account the largest percentage of motor failure. Moreover, the existing techniques related to current and instantaneous power analysis are incompatible to diagnose the distributed bearing faults (race roughness), due to the fact that there does not exist any fault characteristics frequency model for these type of faults. In such a condition to diagnose and segregate the severity of fault is a challenging task. Thus, to overcome existing problem an alternative solution based on artificial neural network (ANN) is proposed. The proposed technique is harmonious because it does not oblige any mathematical models and the distributed faults are diagnosed and classified at incipient stage based on the extracted features from Park vector analysis (PVA). Moreover, the experimental results obtained through features of PVA and statistical evaluation of automated method shows the capability of proposed method that it is not only capable enough to diagnose fault but also can segregate bearing distributed defects.

Keywords— bearing failure, diagnosis, distributed bearing faults, induction motor, park transform, and neural networks.

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1. Introduction

In recent years, the design and construction of stator winding insulation system have been achieved a marked improvement [1, 2]. However, motors driven by solid-state due to fluctuation in the semiconductor switches undergo severe voltage. Moreover, the environment in which induction motors operates is mostly highly corrosive and dusty. Which has vastly spurred to improved and develop insulation material and treatment processes. On the other hand design of rotor has not undergone much improvement. As a result, in induction motor, the larger percentage of failure are due to the bearings deterioration as shown in Fig. 1 [3-6].

The escalating demands of induction motor reliability and efficiency also shade a light on the field of fault diagnosis[7]. In literature, a number of condition monitoring and fault diagnosis methods related to bearing failure are proposed which are based on temperature measurement, vibration measurements, shock pulse method (SPM), and acoustic emission (AE)[8]. Among these the most widely used is vibration measurements [9]. A detailed survey of various vibration and acoustic methods related to vibration measurements, sound measurement, the SPM and the AE technique are given in [10]. In fact, large size motors are equipped with special tools or mechanical sensors. However, most of them are delicate and require a good deal of expertise or expensive tool. If the faults are not prognosticated at the incipient stage, they may increase revenue losses and pose threat to reliability.

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Recently, envelop spectra of vibration is proposed to diagnose and segregate raceways roughness and other bearing faults by P. Kankar et al in [11]. Further, a voltage signal in time domain is used to analyze raceways roughness but it is a complex and require intensive computation. Alternatively I. Y. Önel et al and S. B. Salem et al in [12, 13], Park vector approach is proposed to diagnose bearing faults. But it does not provide any idea about raceways roughness. Later M. Irfan et al in [14], Park vector approach is utilized to diagnose and segregate bearing roughness and other faults. Even though, Park vector approach is a non-invasive and computationally simple and also has contributed to diagnosing raceways roughness. But still, there is demand for more appropriate methods because the recently Park vector approach does not provide any analytical analysis or statistical analysis. Moreover, the characteristic defect frequencies related to raceways roughness are still unknown. Therefore, the instantaneous power analysis and stator current analysis methods could not be used to diagnose bearing roughness defects [13, 15, 16]. Thus, there is demand for simpler approaches that enable even amateurish technicians with the nominal knowledge to estimate the condition of the motor and make reliable decisions [17-19]. Consequently, in this paper, artificial neural network (ANN) is implemented to improve traditional techniques because it is the best solution to analytical and statistical analyze and segregate the faults for all those systems for which there is no mathematical model such as [20]: raceways roughness.

2. Notation

The notation used throughout the paper is stated below.

Indexes:

I_f	fundamental supply current
f_s	fundamental frequency
δ	initial phase angle
I_f	fundamental supply current
$\emptyset$	activation function
W_{xy}	characterized weight
x	preceding input data
z	bias parameter
η	constant learning rate
E	error

3. Theoretical background

The bearing failure is triggered due to a number of factors. Mostly, induction motors are operated in open environment where foreign materials, acid, water and humidity causes bearing failure. But corrosion and contamination are the root cause that frequently accelerates bearing failures [21, 22].

The bearing lubrication and contamination are affected by dust and other foreign materials. The abrasive nature of dust, whose particles hardness relatively vary from soft to the diamond-like, generate sanding and pitting actions that may produce measurable damage to the bearing balls and raceways [3]. The humidity, acids, lubrication deteriorated and even perspiration during installation process can result in bearing corrosion. Similarly, due to build of chemical reaction, the dust particles worn off abrasive damage. In either case, the rotation of balls inside the raceways are affected that eventually rise in temperature. Which break down the grease that reduce the reliability of the motor and accelerates the chances of its failure [13, 23, 24].

During installation of the bearing onto the shaft or into the housing the uneven forcing can result in bearing failure. This results in physically damage of as brinelling or false brinelling of the raceways (surface roughness). Further, Fig. 2 depict all the four ways that are defective due to misalignment of bearing installation.

Even a small fraction in the operation of induction motor due to electrical disturbance can prematurely fail bearing. Because the currents flowing through the bearings potentially prematurely damage the bearings. The fluting pattern on the raceway due to metallurgical damage by the interrupted current is shown in Fig. 3. The increase in the vibration and noise which are typical symptoms of bearing failure [25]. Hence, the main contribution of this paper is to analyze and segregate the raceways roughness of bearing through an automated approaches that even allow unskilled operators to make the decision accordingly with the state of the bearing.

4. Park Vector Transform

A Park vector transformation is two-dimensional representation that is used to describe three-phase induction motor phenomena. It is based on the current that flow through stator winding. Actually, it transforms three phase current into two dimensions and makes the calculation easier. In induction motor, the stator current is represented in three (I_a, I_b, I_c) components. While Park vector approach transforms to obtain I_d and I_q components. From Fig. 4 it is shown that the magnitude of all the phases is same but 1200 shift from each other. The d-q axis is shown rotating with an angular velocity equal to ω, the same angular velocity as the phase voltages and currents. The d axis makes an angle Θ = ω*t with the winding which has been chosen as the reference. The currents I_d and I_q are constant DC quantities [13, 26].

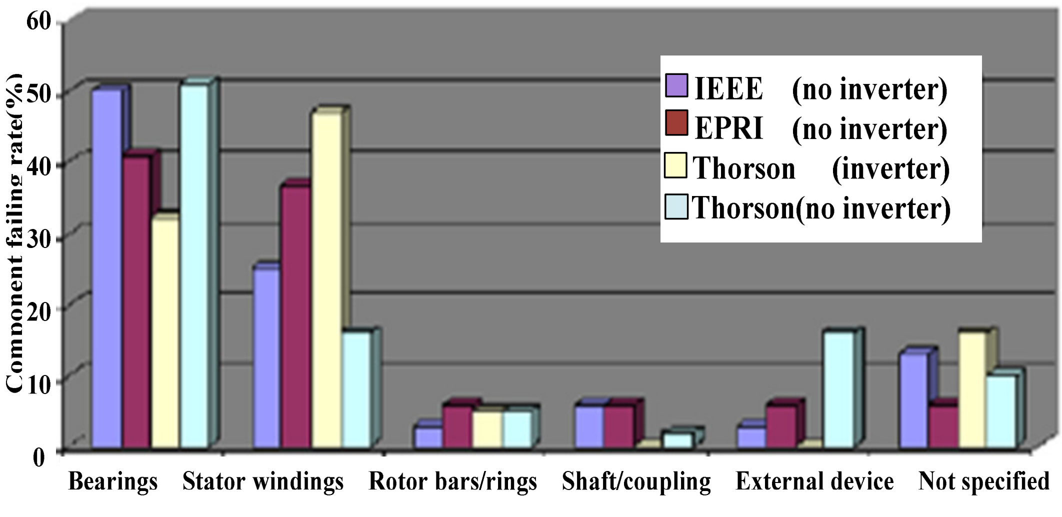

Fig. 1. Failure rate of components

$$I_a(t) = I_f \cos(2\pi f_s t - \delta) \tag{1}$$

$$I_b(t) = I_f \cos(2\pi f_s t - 2\pi/3 - \delta) \tag{2}$$

$$I_c(t) = I_f \cos\left(2\pi f_s\, t + \frac{2\pi}{3} - \delta\right) \tag{3}$$

$$I_d = \sqrt{\frac{2}{3}} I_a - \frac{1}{\sqrt{6}} I_b - \frac{1}{\sqrt{6}} I_c \tag{4}$$

$$I_q = \frac{1}{\sqrt{2}} I_b - \frac{1}{\sqrt{2}} I_c \tag{5}$$

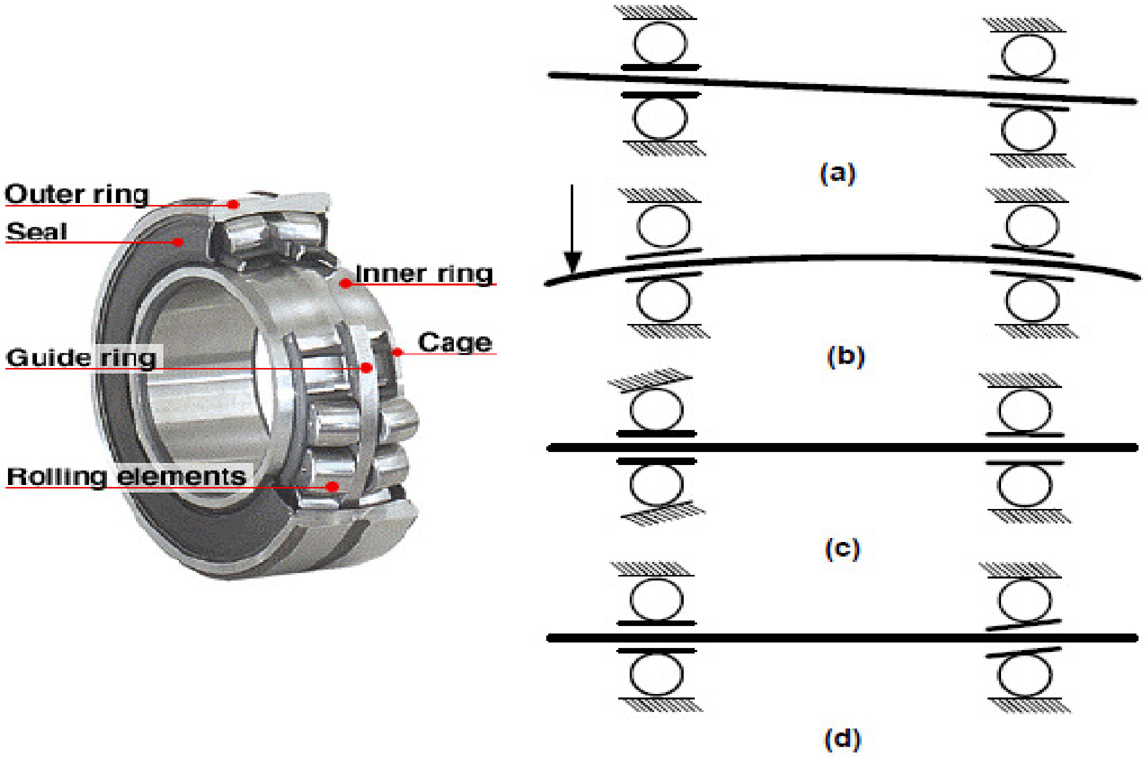

Fig. 2. (a) Misalignment, (b) Shaft deflect, (c) Outer race damage, (d) Inner race damage

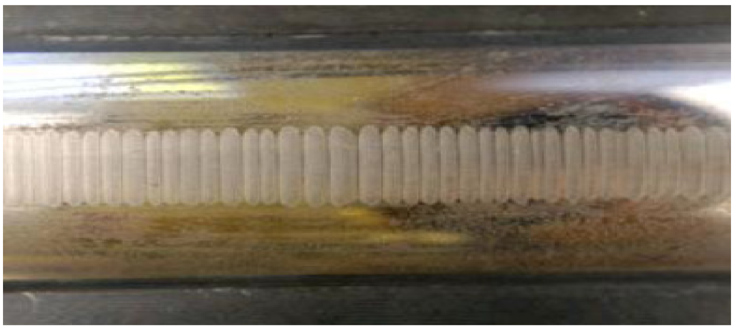

Fig. 3. Roughness of raceways

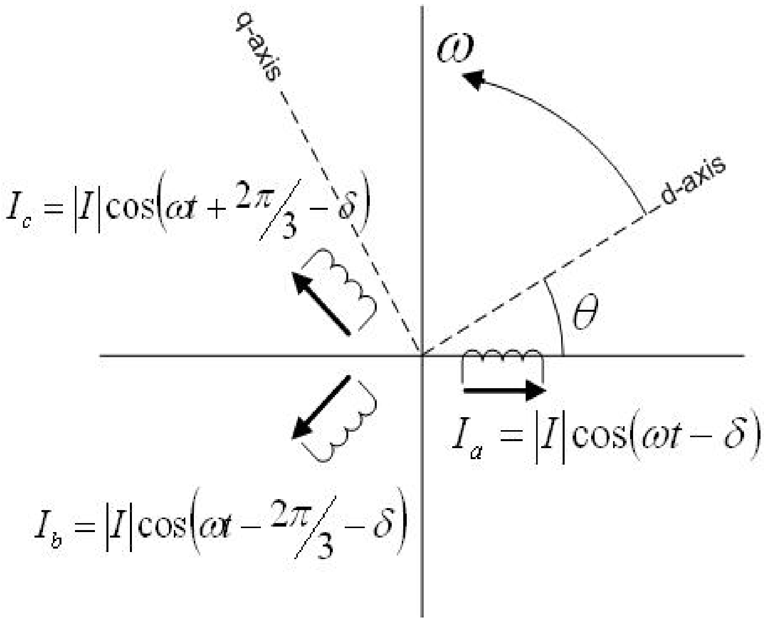

Fig. 4. The Park transformation

Under ideal conditions i.e., in absence of harmonics, the (4) and (5) leads to the (6) and (7).

$$I_d = \frac{\sqrt{6}}{2} I_S \sin 2\pi f_s t \tag{6}$$

$$I_q = \frac{\sqrt{6}}{2} I_S \sin\left(2\pi f_s t - \frac{\pi}{2}\right) \tag{7}$$

The transformation from three (I_a, I_b, I_c) components to I_d and I_q components is a simple approach and for ideal case motor without any fault, the current trajectory of I_d and I_q is a circle as shown in Fig. 5. It is reference pattern that allows the proposed ANN technique to extra the feature for abnormal behavior of the pattern because the occurrence of raceways roughness will manifest the deviation of features and the pattern of the figures.

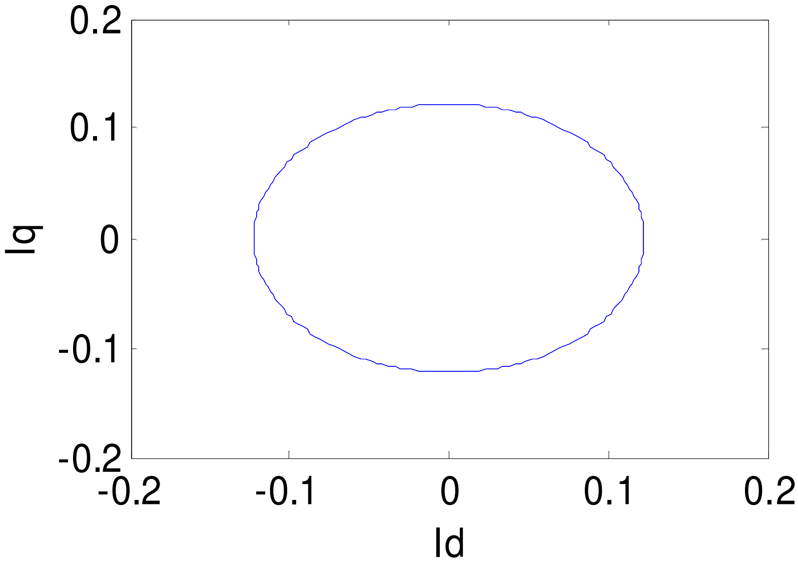

Fig. 5. PV pattern for healthy bearing

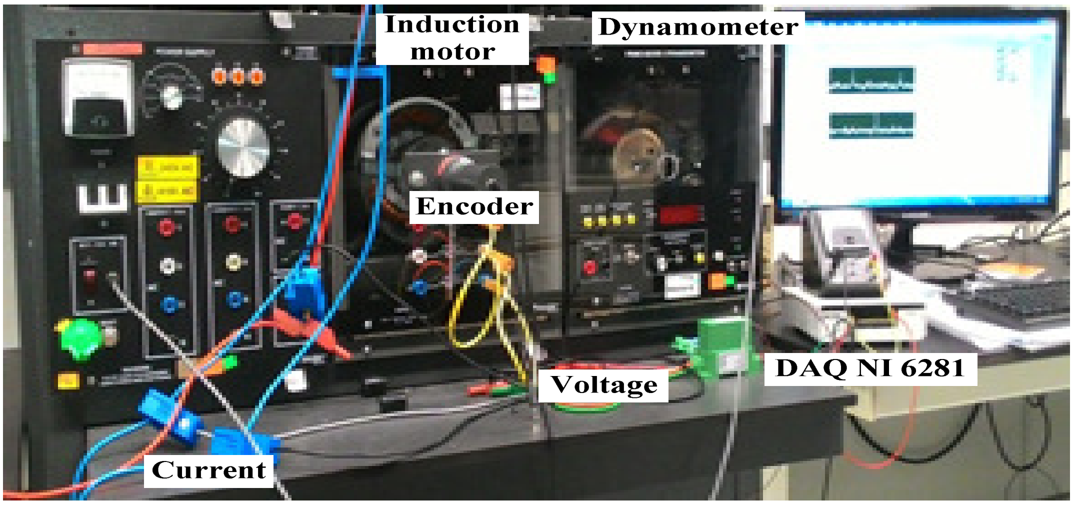

Fig. 6. Test rig

5. Experimental Tests

A. Test Facility Description

The experimental setup is described in Fig. 6. The induction motor, that is installed, has following rated parameters: 0.25 HP, 220/380 V, 1395 rpm, 50 Hz, and 4 poles. The induction motor is further linked with a dynamometer, current transducer (5A/1V), tachometer and the National Instrument data acquisition (NI DAQ) along with LabVIEW® to acquire the

response of the motor. Whereas the specification of NI DAQ card is listed in Table I. The parameter of a bearing are extracted from the datasheet having a pitch diameter of DP = 25 mm, eight rolling balls, each ball of diameter DB = 6 mm, and a contact angle of $\theta = 0^{\circ}$. The bearings are artificially deteriorated as shown in Fig. 7. The total of 1000 samples is acquired in continuous mode with sampling rate of 4 KHz.

6. Artificial Neural Networks

In induction motor, the reliability has also advanced in the approach of fault detection field. This has led to extensive use of artificial intelligence automated techniques, where the results are instantaneously analyzed through input. In ANN, a number of tests are performed against various faults and operating load conditions. Thus, in this paper automated fault detection method is proposed based on ANN due to their numerous advantages over traditional techniques. First, they are feasible for all those systems for which mathematical model does not exist. Second, these can easily be extended and modified, and are adaptable by the incorporation of new data because features are user friendly for general industrial applications. Third, the results obtained not only indicate the type of fault but it is a promising approach to extract the fault and estimate the severity of the faults.

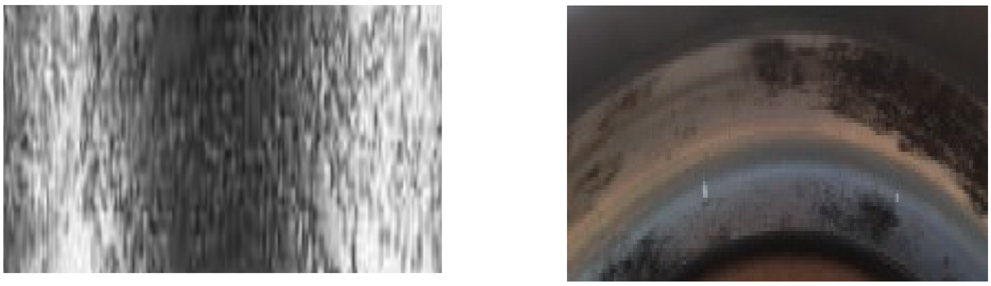

Fig. 7. Roughness in the raceways

7. Experimental Tests Results of PV

The I_d, I_q curves of induction motor with health rotor bearing is shown in Fig. 8. In an ideal case, the pattern of PV (I_d, I_q curves) is circular in the shape. However, in real scenario, there are inherent asymmetries, therefore, the shape of PV pattern is not pure circular. While Fig. 9, and Fig. 10, present the PV pattern against outer and inner raceways roughness.

From Fig. 8 to 10, it is obvious that PV pattern is disfigured with raceways roughness of the bearing as compared to the healthy bearing. The variation in the shape of PV pattern are due to the vibration that is generated by raceways roughness and it causes a modulation in the stator current. The modulations depend on the geometry, speed, and fault location [27]. Apparently, the shape of PV varies with the influence of the bearing faults. The variation in the different shapes indicates that harmonics of inner race roughness are different than outer race roughness defects. Even though, up to certain extent, PV patterns contributes to diagnose raceways roughness but it is really difficult to segregate the fault only through the shapes appearance because the shapes almost resemble each other. Moreover, it depends on individual skills, an angle of vision, noise ratio, and human error that can susceptible the PV approach not be a preferable to segregate the faults. Therefore, automated approaches are required those even allow unskilled operators to make the decision accordingly with the state of roughness. Beside the shapes, there should be other prominent features to diagnose and segregate the bearing faults. Therefore, ANN is proposed to diagnose and segregate the bearing faults.

A. Feature extraction

The ANN networks consist of feed-forward structures, where input layer is locally linked to the neurons of hidden layer which are further fully interconnected with output layer. The architecture of proposed ANN is illustrated in Fig. 11. The ANN are famous due to their classification capacity. In proposed work, the neural network is able to declare the condition of the motor as per the data reception. For this reason, certain stages are processed. The selection of relevant features from PV as an input variables, number of neurons and layers, and output variables. A number of experiments were conducted. Finally, the proposed network is composed of four input as:

TABLE I. SPECIFICATIONS OF THE DAQ

S.r No.	**Specifications**	
1	Analog Inputs	16
2	AI Range	$\pm\mathbf{10}$ Volts
3	Max. Scan Rate	625 KS/s
4	AI Resolution	18 Bits
5	AO	2
6	AO Range	$\pm\mathbf{10}$ Volts
7	AO Resolution	16 Bits

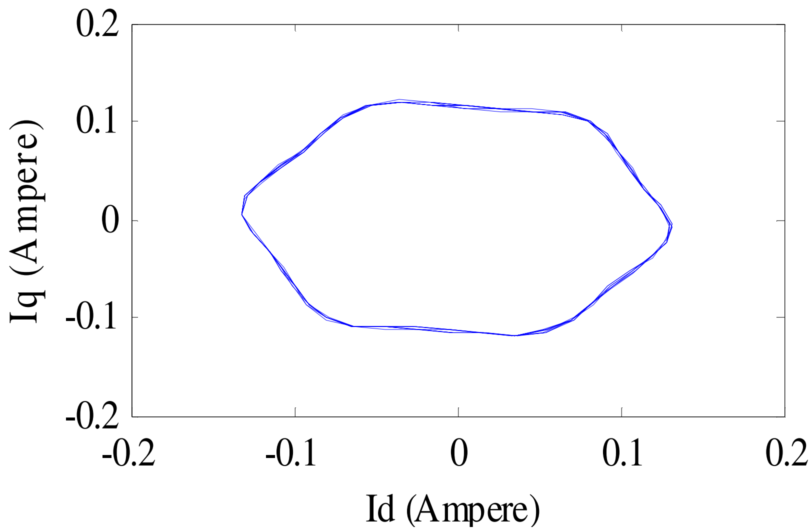

Fig. 8. The *PV* pattern of healthy bearing

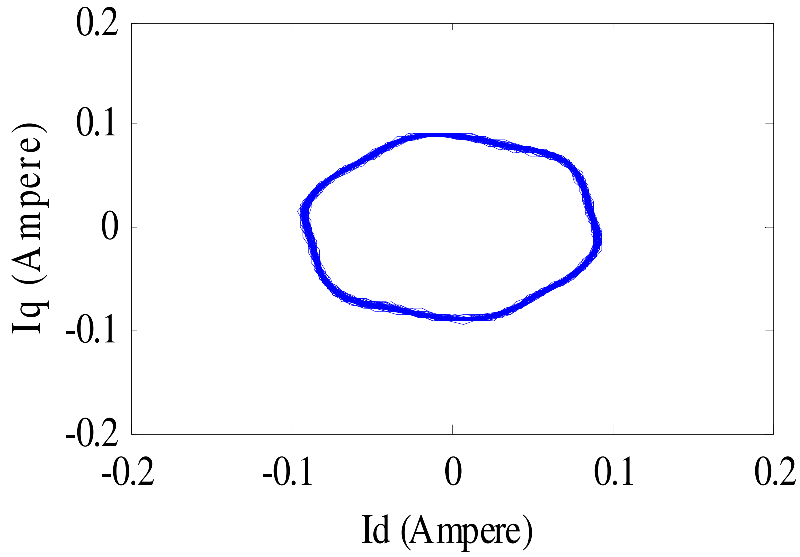

Fig. 9. The *PV* pattern of outer race surface roughness

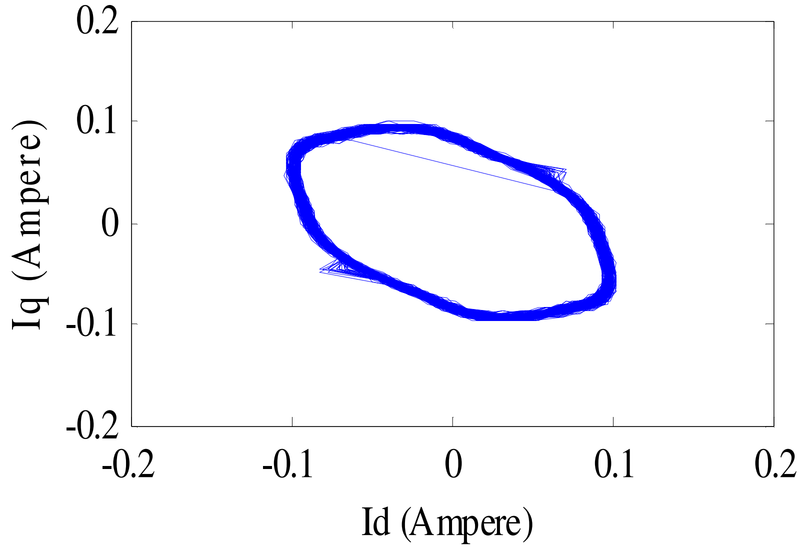

Fig. 10. The *PV* pattern of inner race surface roughness

I_1= Area of the PV pattern
I_2=Circumference of the pattern
I_3=Width of the pattern
I_4= Resultant of the centroid

This is a multilayer perceptron (MLP) with ten neurons in a hidden layer. Where the output attributes to following states:

O_1=1, when bearing of the motor is healthy, otherwise =0.
O_2=1, when bearing inner race has distributive faults, otherwise =0.
O_3=1, when bearing outer race has distributive faults, otherwise =0.

B. Proposed Fault classification

The output y of proposed method are achieved through interaction of activation function Ø, characterized weight W_{xy}, preceding input data x, and bias parameter z. Whereas the weights are calculated through manipulating constant learning rate η and the error E. The ANN is trained by modifying the weights that are accurate enough to recognize any pattern.

$$Y = \emptyset \sum_{i=1}^{n} W_i * x_i + z \quad (8)$$

$$W_{xy}(k+1) = W_{xy}(k) - \eta \frac{\partial E(k)}{\partial W_{xy}(k)} \quad (9)$$

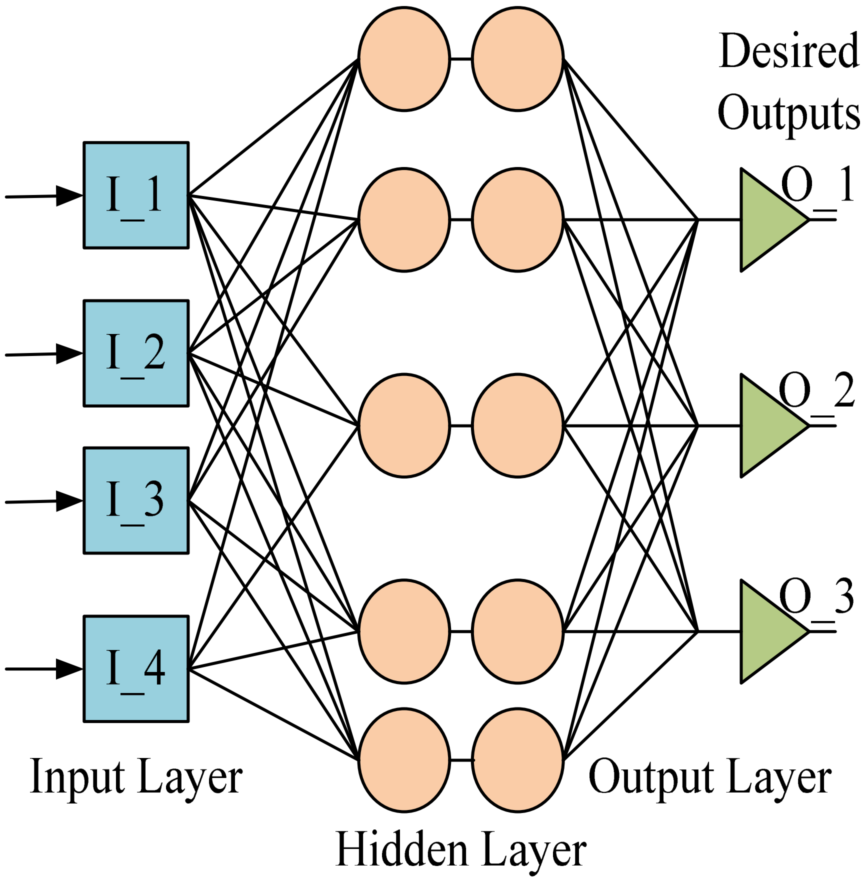

Fig. 11. Architecture of ANN

In proposed method, the fault classification is carried out at two stages i.e., training and testing. Initially, the extracted features of PV pattern are recorded and ANN is trained for healthy, inner race roughness, and outer race roughness. This is achieved through a number of tests performed at the initial stage in order to get distinctive attributes from analyzing PV pattern. During the testing phase, the ANN is tested at a run time to diagnose the bearing fault. In proposed work, tests are performed at full load operating condition. To evaluate the performance of proposed method the results are presented in Fig. 12 to 15, through the analysis from the obtain results it can be obverse that the statistic of all the features that are selected for the classification shows that the bearing surface roughness disfigured the area, circumference, thickness, and resultant centroid. There is significant change in each feature with respect to the reference healthy bearing. The statistic of all the feature varies with the roughness of the bearing race which could not be predicted through PV pattern. Further, it can be analyzed that the statistic of outer race roughness is much higher as compare to the inner race. Which is the indication that the vibration of outer race roughness is much higher than inner race roughness and ultimately higher harmonics will be induced in this case. The results of proposed automated approach are promising for not only diagnose the faults but also are able to segregate the fault type. Thus, the analysis of automated method is useful means for diagnosing and classifying the faults of an induction motor.

Important terms:

HFL= Healthy bearing with full load

DIFL=Distributive Inner race roughness full load

DOFL=Distributive Outer race roughness full load

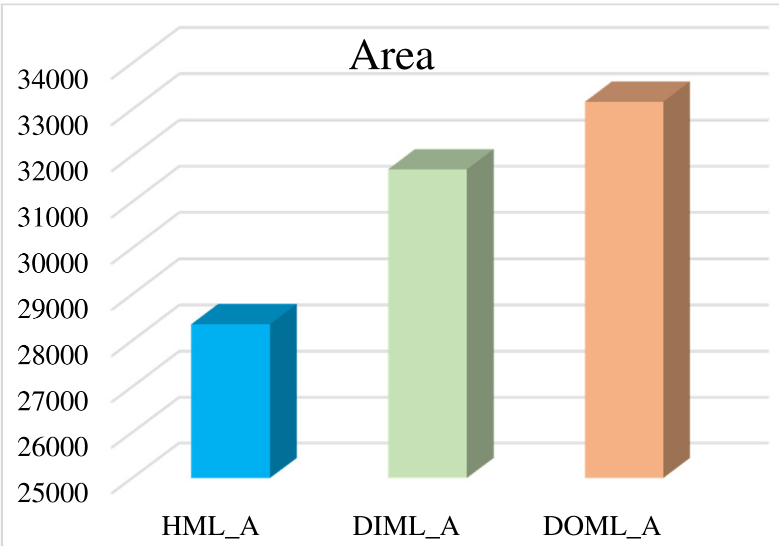

Fig. 12. Deviation in the Area of PV pattern

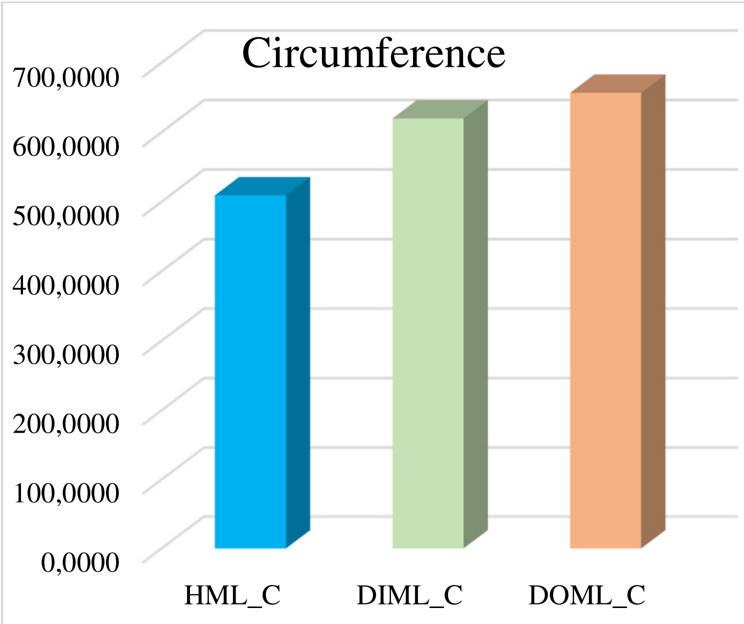

Fig. 13. Impact on the circumference PV pattern

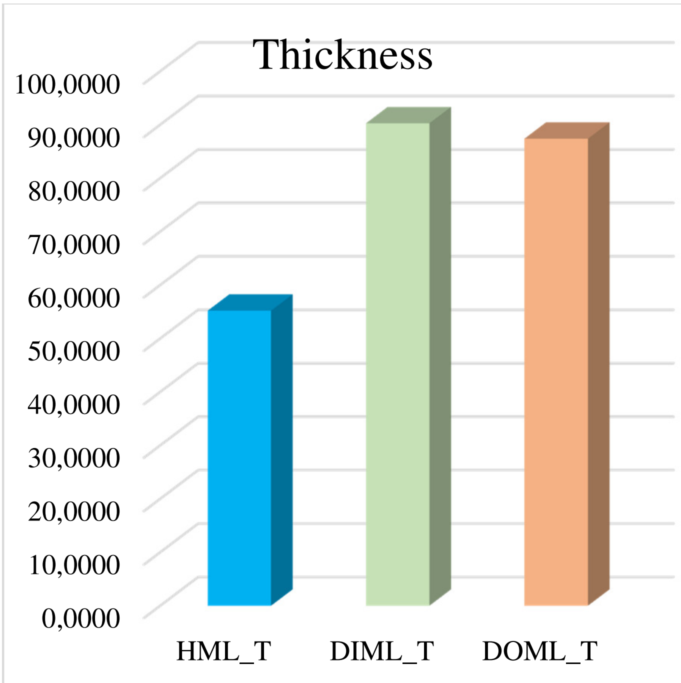

Fig. 14. Influence of the fault at the thickness of I_d and I_q curves

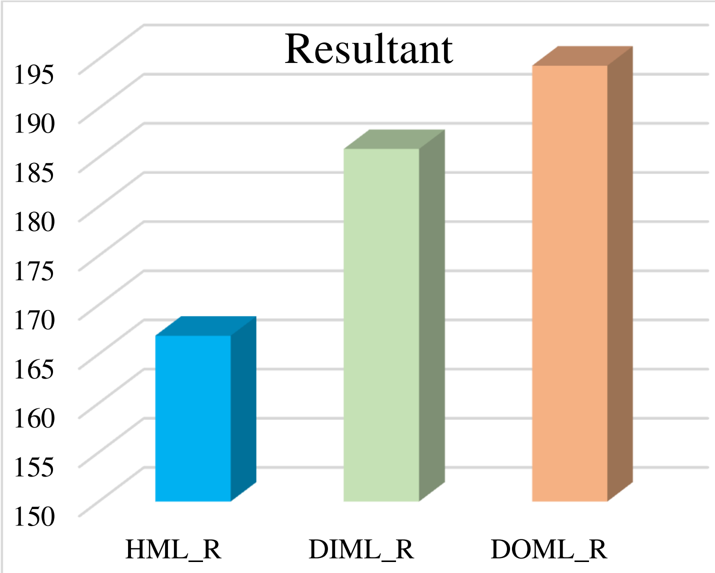

Fig. 15. Influence of the fault at the resultant of I_d and I_q curves

8. Comparison

In literature [28-30], it was suggested that MCSA is more preferable and economical approach to detect bearing defects. Although the MCSA is a non-invasive and economical way to diagnose bearing faults, however, it poses a challenge at no-load conditions where the values of current amplitude do not provide a significant indication of the bearing faults [31]. Later, instantaneous power analysis (IPA) method is proposed to overcome the loading constraint and diagnose localized defects and few other bearing related faults [26]. The bearing distributed defects i.e. surface roughness in inner or outer raceways which are due to irregular or deformed bearing races. The main cause of these defects is grease contamination and improper lubrication of the raceways. Moreover, this category of faults does not have any characteristic defect frequencies model. Thus, MCSA and IPA are not applicable to diagnose distributed defects [13, 16].

Hence, to diagnose the distributed faults and segregate these faults from the localized defects is a challenging task. Therefore, a review presented highlight different models for bearings in presence of bearing localized and distributed faults [32]. Recently, Vibration Analysis method was used to diagnose the bearing distributed defects. The envelop spectra of the vibration signal were utilised to distinguish between bearing localized and distributed defects [33]. The time domain analysis of the voltage signal was used to diagnose bearing distributed defects. Although proposed method has the capability to diagnose distributed defects but it proves to be complex due to an intensive computation of time domain data. Alternatively, Park vector approach was used by [12, 31] to detect bearing localized defects. In the earlier work, Park vector method was used by [13, 26] to diagnose stator voltage unbalanced defects. However, there was no such a method to diagnose and segregate these faults. Which are challenging task and require more efficient non-invasive techniques. Therefore, in this work to overcome existing problem an alternative solution based on ANN is proposed which are also justified through experimental results.

9. Conclusion

In an induction motor, bearing faults account the largest percentage of motor failure. Moreover, the existing techniques are incompatible to diagnose the distributed bearing faults, due to the fact that there does not exist any fault characteristics frequency model these type of faults. In such a condition to diagnose and segregate the severity of fault is a challenging task. Thus, to overcome existing problem an alternative solution based on ANN is proposed. In proposed method, the pattern of PV against healthy, inner race roughness, and outer race roughness are utilized by ANN. The key factor for best classification performance depends upon the identification of more suitable features for inputs, which reflect a good performance at the output. Therefore, a total of four more prominent features are extracted from PV pattern i.e., area, circumference, thickness, and resultant of the centroid. Further, these features are fed to ANN for the training process. The proposed method classify three conditions of a bearing i.e., healthy bearing, inner race roughness, and outer race roughness. The ANN is trained and validated to find the optimum results with least validation errors. From the statistical analysis of the graphs against each feature shows that proposed method is able to diagnose and segregate the faults. The performance of classification of proposed method shows the significance deviation of feature statistic that even allows unskilled operators can make the decision accordingly with the state of the bearing. Moreover, this is a non-invasive method and allow online condition monitoring.

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