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(Review Article)

Artificial Intelligence to detection fault on three phase squirrel cage induction motors subjected to broken bar fault

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Abstract

Induction motors are widely used in various industrial applications due to their robustness, reliability, and low cost. However, they are also prone to various types of faults, such as broken rotor bars, bearing defects, stator winding faults, and eccentricity. These faults can cause performance degradation, energy loss, and even catastrophic failures if not detected and diagnosed in time. Therefore, condition monitoring and fault diagnosis of induction motors are essential for ensuring their safe and efficient operation. In this paper, we propose a novel fault diagnosis method for induction motors based on artificial intelligence, peak variation response (PVR), park vector approach (PVA), and standard deviation (SD). The proposed method consists of four steps:

- Data acquisition and preprocessing,
- Feature extraction using pvr and pva,
- Feature selection using sd, and
- Fault classification using artificial neural networks.

The PVR and PVA are used to extract the amplitude and phase information of the stator current signals under different load conditions and fault types. The SD is used to select the most relevant features for fault diagnosis. The ANNs are used to classify the faults based on the selected features. The proposed method is validated by experimental results on a 1.5 kW three-phase induction motor with various simulated faults. The results show that the proposed method can effectively diagnose different types of faults with high accuracy and robustness.

Keywords: Fault Detection on squirrel cage induction; Park vector approach (PVA); Peak Variation Response (PVR); Standard Deviation

1. Introduction

The rotating electrical machine (motor and generator) and transformer play a vital role from small power application to large power application like power plant. The Figure 1 describes the basic structure of electrical system in power plant

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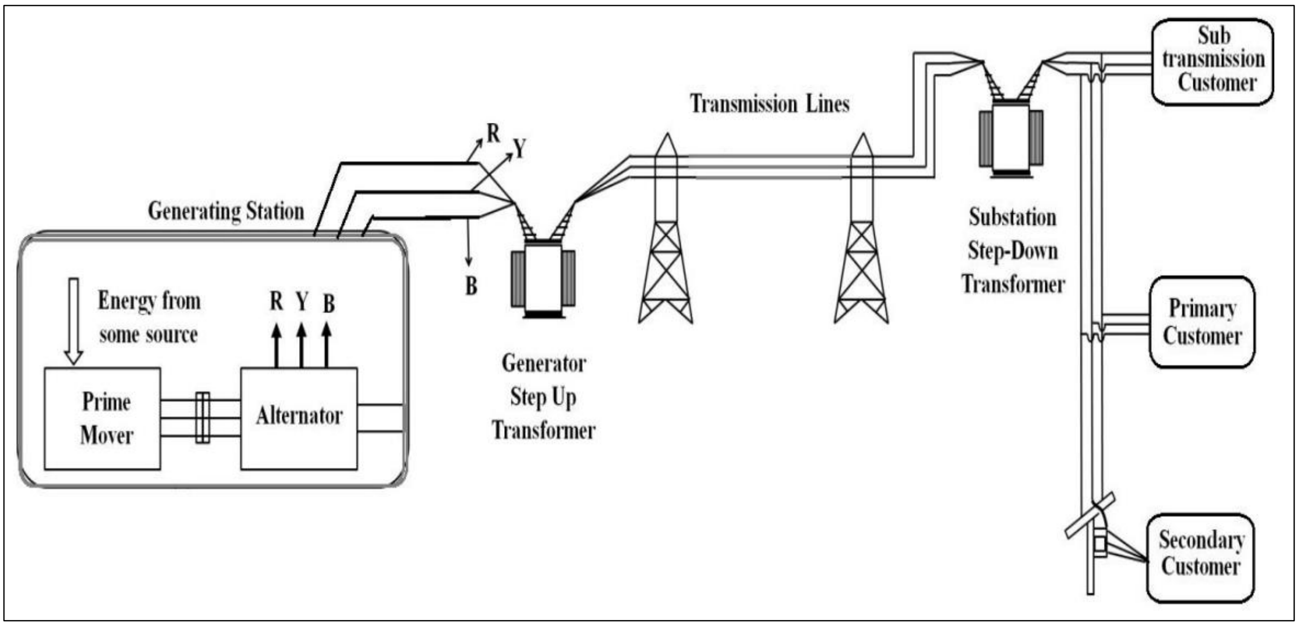


Figure 1 Basic structure of electrical system

Wind turbines are much more expensive than diesel generators, and they also require regular maintenance that can cost up to 2% of their total price. Moreover, some parts of the wind turbines (such as blades, gearbox, tower, braking system etc.) may malfunction occasionally and increase the cost of spare and maintenance. Therefore, it is important to check the system components regularly, either by human-based resources or intelligent systems, to prevent and reduce the number of breakdowns. This leads to research opportunities in the field of condition monitoring of equipment performance and health using intelligent techniques for wind turbine systems operating in grid. By evaluating the conditions of critical system components, the faulty parts can be identified more easily and the time and maintenance cost can be reduced. Furthermore, by analyzing sensor data, implementing fault detection algorithms and using advanced signal processing, the possible faults that may occur can be predicted more accurately. The fault diagnosis of electrical machines has great benefits for both the industries and the environment. Electrical machines are suitable for developing automated equipment's. They have various applications in different fields, from power windows in automobiles to motors and transformers with tap changers used in nuclear power plants. Therefore, electrical machines have a significant role and it is essential to ensure their reliable operation. However, these electrical machines may face many faults during their life cycle. The application of condition monitoring techniques is crucial as it enables asset management, early detection of faults, prevention of severe damage and failure of electrical machines.

1.1. Challenges in Electrical machines

An electrical machine component may face a challenge when its performance falls below a certain standard due to various factors such as aging, improper design, faulty installation, misuse, or a combination of these. If such a challenge is not identified and addressed in time, it may eventually lead to a breakdown. Many researchers have investigated the mechanisms of breakdowns in electrical machines and developed methods to detect them at an early stage. The common internal challenges can be divided into two types.

- Electrical Challenges.
- Mechanical Challenges.

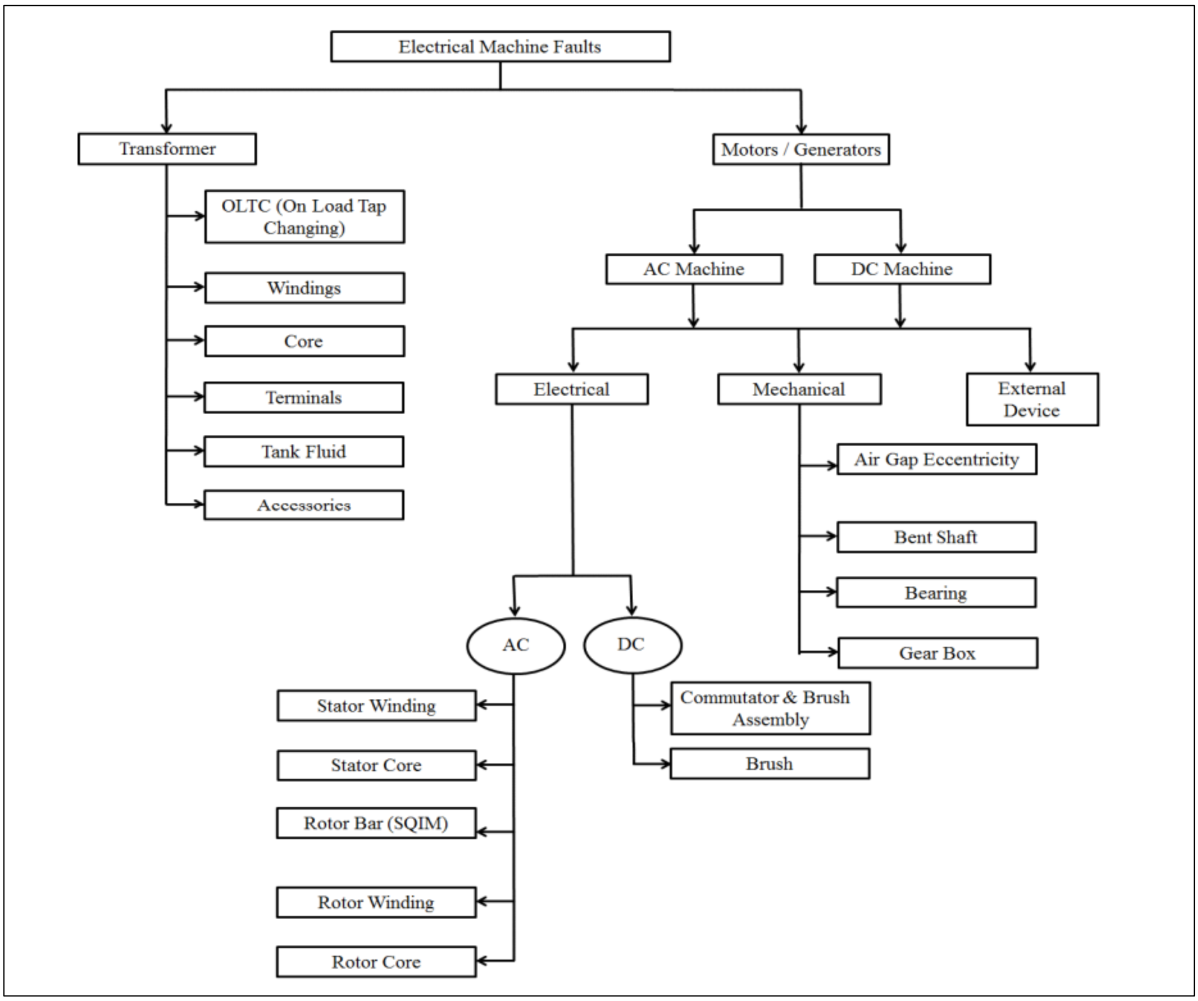


Figure 2 Tree structure representing various failures in electrical machines

1.2. Proposed Electrical Monitoring Techniques

1.2.1. Park Vector Approach (PVA)

To get the Park's vector pattern, the programming is done with signal processing module of LabVIEW software. The induction motor has been initially tested, in the absence of faults in order to determine the reference current Park's vector pattern corresponding to the supposed healthy motor. The Squirrel Cage Induction Motor (SCIM) has been modelled and simulated with unbalanced supply and turn dislocation of pole. The data has been analyzed by Park Vector Approach and compared with the healthy pattern.

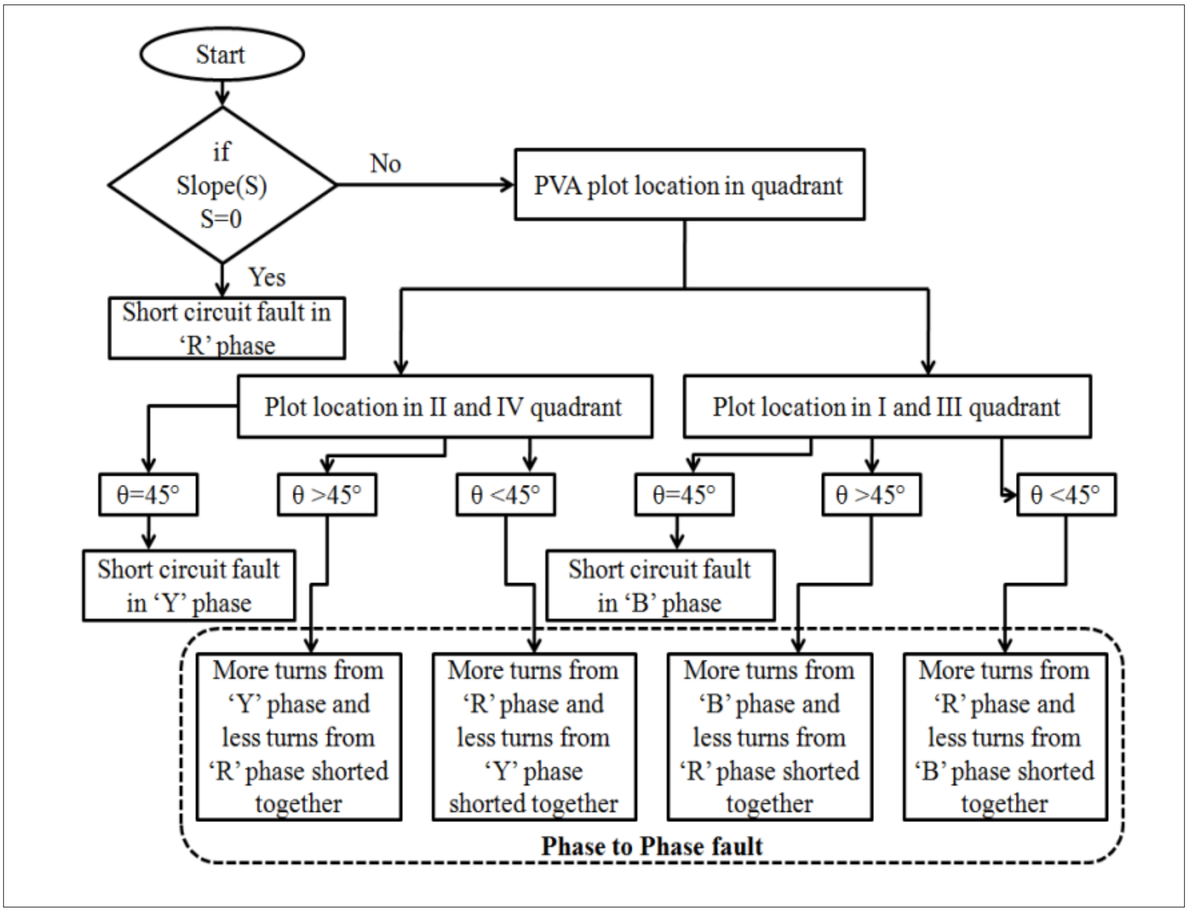


Figure 3 Winding fault detection in electrical machines using PVA

1.2.2. Peak Variation Response (PVR)

In this electrical monitoring technique, fault detection is based on tracing the Peak Variation Response through spectral analysis of electrical signals obtained from electrical machines. In this thesis, the spectrum of current signal and flux signal is analyzed by using peak variations to identify the faults. Generally, oscilloscopes have been used to acquire the electrical signals varying with time. But this information is insufficient to know the fault frequency of electrical signal. To fully understand the performance of an electrical machine or a system, a signal (or signals) must also be analyzed in the frequency domain. In the spectrum analysis the magnitude of an input electrical signals namely, current and flux is measured with respect to frequency.

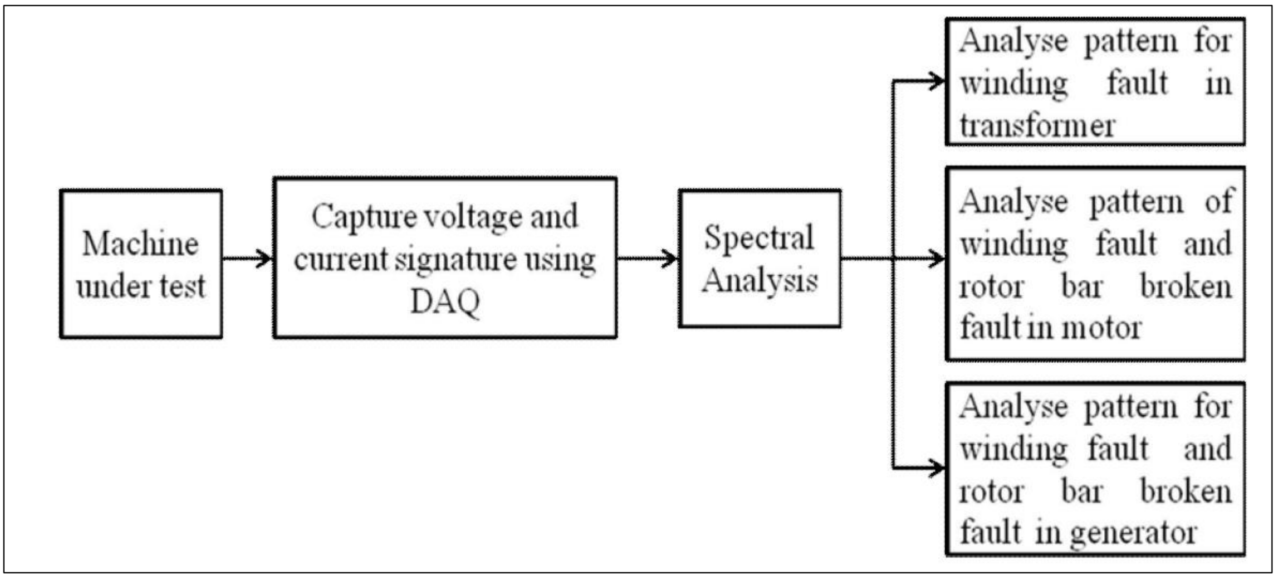


Figure 4 Depicts the scheme for Peak Variation Response (PVR) that is used to diagnose the condition of machine under test

1.2.3. Standard Deviation Technique in Fast Statistics Tool

In Standard Deviation technique, the output electrical signal from faulty machine is collected and given as input into the Fast Statistics tool, where the results of statistical measures such as standard deviation, mean and variance are obtained. These values are compared with the corresponding values of healthy machine and the variation in values with the healthy machine describes the extent of fault occurred in an electrical machine. Among these the standard deviation provides interesting metric of machine fault nature.

2. Techniques used for machine fault detection

The following sections discuss the techniques used in motor fault detection during simulation studies with the magnet software. Here 3ĭ, 415V, 50Hz, 4 pole, 2HP induction machine healthy and faulty condition has been designed using Infolytica MagNet 6.11.2 software. The current data and flux linkage data has been collected from the simulated model and it has been analyzed using Park Vector Approach (PVA), Peak Variation Response and Standard deviation.

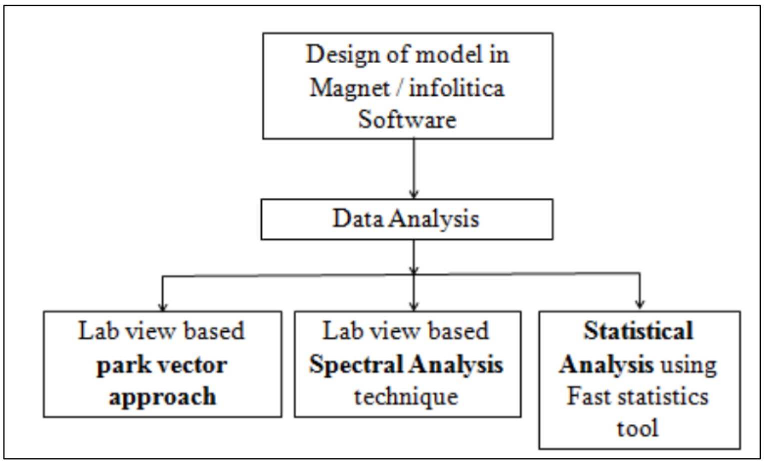


Figure 5 Simplified fault detection block diagram for Induction machine

3. Broken Bar Fault

The 415V, 50Hz, 4 pole, 2HP healthy induction machine and rotor bar broken fault condition has been simulated using Infolytica MagNet 6.11.2 software. The current data and flux linkage data has been collected from the simulated model and it has been analyzed using Park Vector Approach (PVA), Peak Variation Response and Statistical analysis. The experiment has been conducted on machine with same parameters. The current data is collected from the experimental set up and it is analyzed using above mentioned techniques. Rastko Fiser et al (2001) presented a Finite Element Method for predicting the performance of induction motor subjected to broken rotor bar faults. Thomas et al (2002) proposed a new technique - air gap monitoring technique for detecting rotor bar broken fault in squirrel cage induction motor. Cabanas et al (2011) have proposed a wireless sensor network for early detection of rotor bar broken fault.

3.1. Induction Motor Rotor Bar Broken Fault – Simulation

In rotor bar broken fault the rotating part such as rotor has been affected. In rotor bar broken fault four cases have been analyzed.

- One bar broken
- Two bar broken
- Broken bar replaced with iron strip
- Broken bar replaced only with 2 iron strip

The rotor is made up of aluminum casting. The rotor bars were made with split for describing first two cases and the rotor bar is filled with iron material for describing third and fourth cases.

The quarter portion of the healthy and broken rotor bar model is shown in Figure 6. The current data and flux linkage data has been exported to excel file. The Designed Induction Motor mesh diagram has been shown in Figure 8. This Machine has 4 Pole, 12 Slots. The generation of mesh in the designed model is used for dividing a complex problem into small elements. In 2D model, the entire region is subdivided into the triangular mesh, and within each mesh polynomial is used to estimate the true field. This model is simulated by using transient 2D solver.

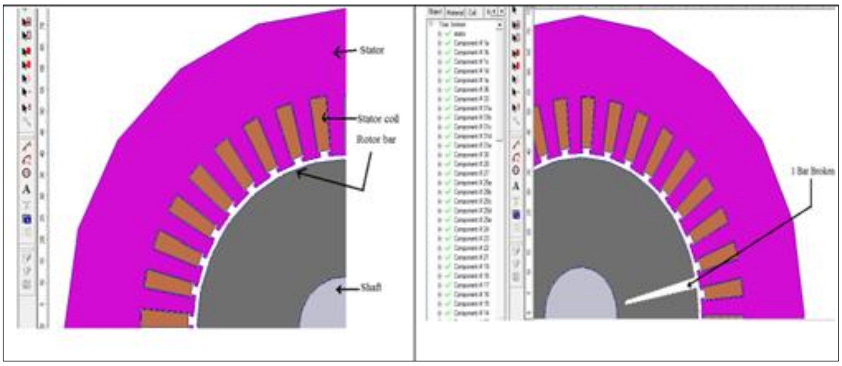


Figure 6 Induction motor simulation model

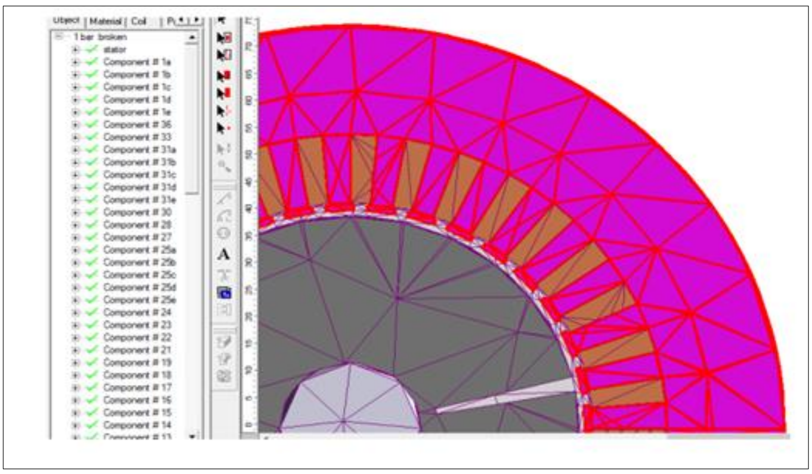


Figure 7 Mesh diagram for rotor bar broken three phase induction motor

3.1.1. Analysis of rotor bar broken fault in Induction motor using PVR–Simulation

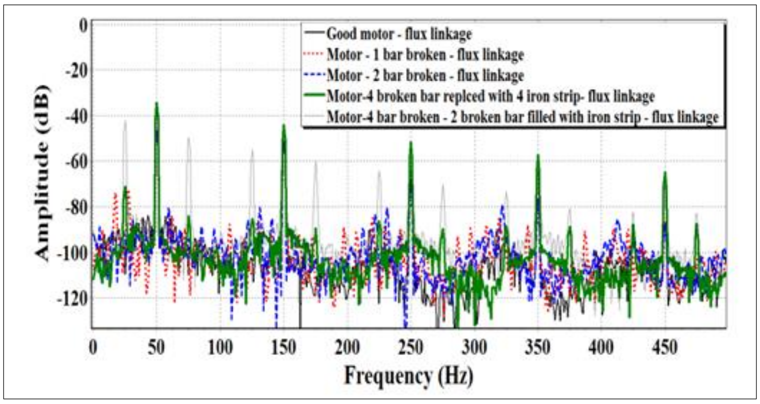


Figure 8 PVR of rotor bar broken in induction motor –flux linkage data

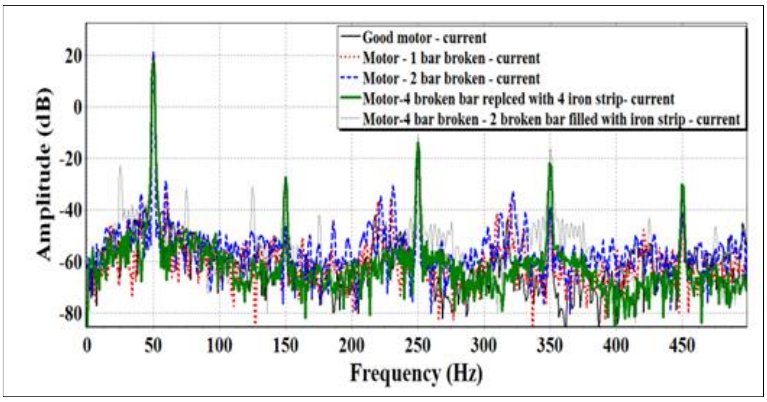
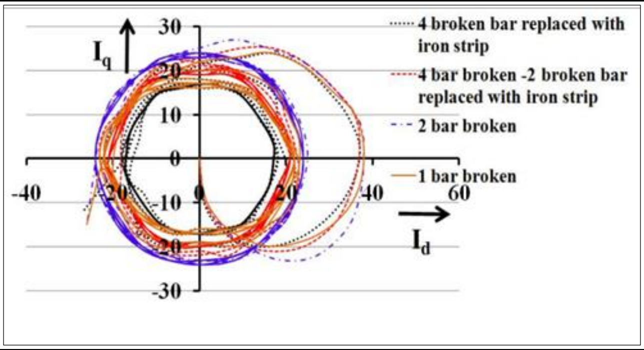


Figure 9 PVR of current data for rotor bar broken in induction motor

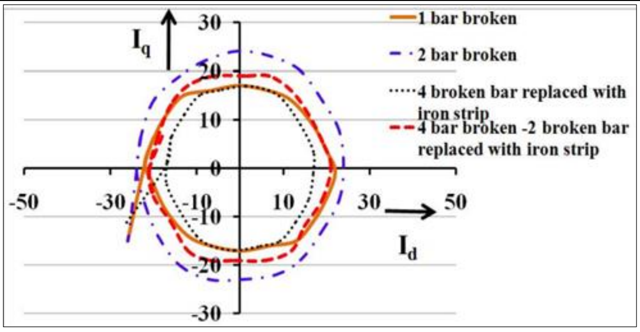
The flux linkage spectral of the rotor bar fault in three phase induction motor has been shown in Figure 8. Among four cases of rotor bar broken fault the third and fourth cases such as the 4 broken bar completely replaced with iron strip and 4 broken bar replaced only with 2 iron strip have their spectral peak at fo±fo/2, fo, 3fo±fo/2, 3fo, 5fo±fo/2, 5fo, 7fo±fo/2, 7fo, 9fo±fo/2, 9fo where, fo is 50Hz. The magnitude of LSB is greater than RSB magnitude. The even harmonics are absent for all four cases. The current spectral of the rotor bar fault in three phase induction motor has been shown in Figure 9. The magnitude of odd odder harmonic is in the odder of f50> f150< f250> f350> f450. The even harmonics are missing. The energy distribution of the 4 broken bar replaced only with 2 iron strip more around their main peak. Which is in the odder of f350> f250 > f150 > f150 . The spectral responses of one bar broken and two bars broken are same at f50, f150, f250, f350 and f450.

3.1.2. Analysis of rotor bar broken fault in Induction motor using PVA -simulation

PVA of the rotor bar fault is shown in Figure 10a. The fault severity is identified as two bar broken>4 broken bar replaced only with 2 iron strip> one bar broken>4 broken bar entirely replaced with iron strip. Hence, it appears that if broken bars are replaced with iron material their failure intensity is comparatively is less as seen from the elliptical Id and Iq PVA plot. Figure 10b shows PVA plot under less data for clarity.



a. PVA for all data



b. PVA for less data

Figure 10 PVA of induction motor with rotor bar broken-simulation

3.1.3. Analysis of rotor bar broken fault in induction motor using standard deviation (SD) – simulation

The fault severity of the std dev using current data is more for broken rotor compared to that of the material replaced bar.

Descriptive Statistics

Variable	N	Mean	Median	TrMean	Std.Dev.	SEMean	Min	Max
good motor - fl	1001.00000	-0.00014	-0.00136	-0.00008	0.00681	0.00022	-0.02885	0.01394
good motor - ct	1001.00000	0.16809	0.65037	0.12137	13.74059	0.43430	-19.52756	31.47367
motor-1 bar broken - fl	1001.00000	-0.00015	-0.00044	-0.00009	0.00680	0.00021	-0.02861	0.01404
motor-1 bar broken - ct	1001.00000	0.16777	0.59637	0.12282	13.77904	0.43551	-19.62128	31.34002
motor-2 bar broken - fl	1001.00000	-0.00018	-0.00041	-0.00012	0.00685	0.00022	-0.03074	0.01406
motor-2 bar broken - ct	1001.00000	0.16679	0.46066	0.12308	13.81847	0.43676	-19.72816	31.27016
motor-4/4 - fl	1001.00000	-0.00009	-0.00003	-0.00007	0.02439	0.00077	-0.04152	0.03072
motor-4/4 - ct	1001.00000	0.17997	0.96285	0.10624	10.10306	0.31933	-17.66831	29.97724
motor-2iron/4 - fl	1001.00000	-0.00011	-0.00075	-0.00004	0.01748	0.00055	-0.03522	0.03066
motor-2iron /4 - ct	1001.00000	0.17366	0.71017	0.11655	11.88994	0.37581	-18.54731	30.18918

Figure 11 Statistical Analysis of rotor bar broken fault in SCIM

Two bar broken>4 broken bar replaced only with 2 iron strip> one bar broken>4 broken bar replaced with iron strip. Standard deviation of flux is less for 1 bar broken< fault free generator < & higher in 4/4broken bar.

3.2. Induction Motor Rotor Bar Broken Fault – Experimental Model

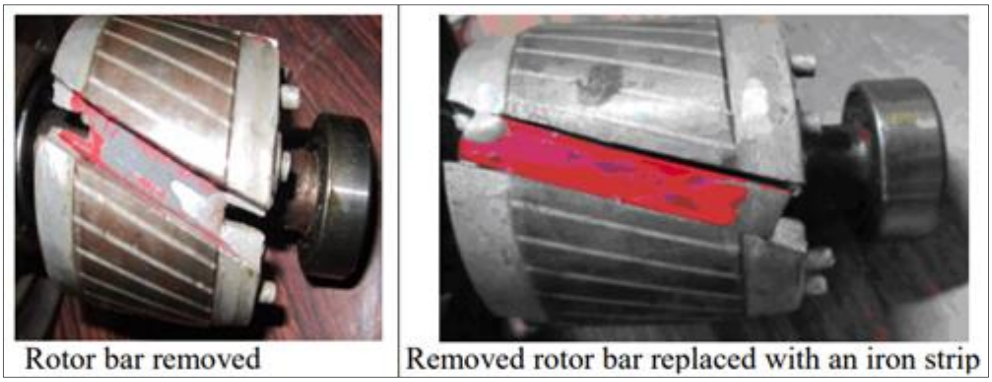


Figure 12 Rotor bar broken fault construction

The broken rotor bar is analytically verified by observing the frequency component of the current due to broken rotor bars. The following predictor equation (Arunava Naha et al, 2016) gives the components in the air-gap flux waveform that are a function of rotor bar broken.

$$fb=(1\pm 2ks)fs \quad (3.13)$$

where,
fb Rotor bar broken fault frequency
k, integer (1,2,3…)
fs Supply frequency
s slip

The experiments were conducted for the following conditions under no-load condition:

- One bar broken
- Two bar broken

Table 1 Rotor bar fault frequency calculation

Machine condition	**N_r rpm**	**s**	**Side lobes**	**Rotor bar broken fault frequency (f_b)**					
				K=1		K=2		K=3	
				comments		Side lobes	comments	Side lobes	comments
1 bar broken	1406	0.062	LSB	43.7	6Hz variation	37.5	12.5Hz Variation	31.2	18.5Hz variation
			RSB	56.2		62.5		68.7	
2 bar broken	1312	0.125	LSB	37.5	12Hz Variation	25	25 Hz Variation	12.5	37.5 Hz Variation
			RSB	62.5		75		12.5	

3.2.1. Analysis of rotor bar broken fault in Induction motor using PVR– Experiment

One bar broken and two bars broken are shown in Figure 14. In one bar broken fault the peak occurs at both odd and even harmonic 83 frequencies (i.e., 50Hz, 100Hz, 150Hz, 200Hz, 250Hz, 300Hz, 350Hz, 400Hz, and 450Hz). In two bar broken fault the peak occurs at odd order harmonic frequencies (i.e., 50Hz, 150Hz, 250Hz, 350Hz, 450Hz) and specific even frequency like 400Hz.

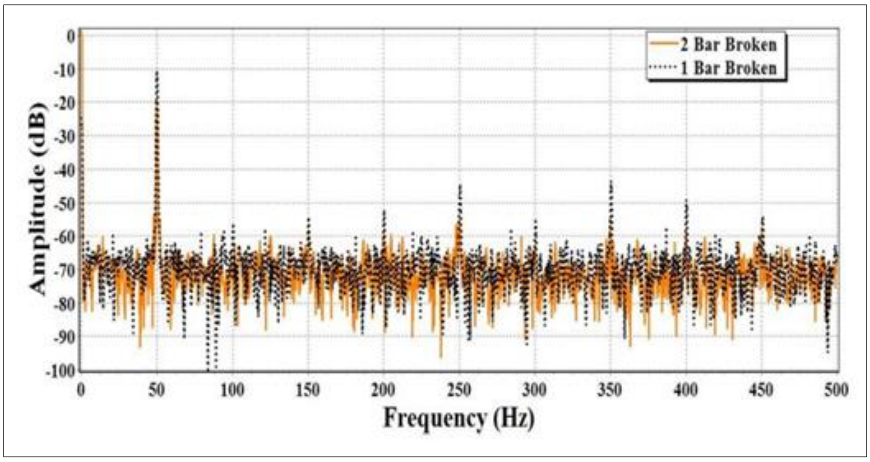


Figure 13 PVR of rotor bar broken in induction motor by experiment

3.2.2. Analysis of rotor bar broken fault of induction motor using PVA– Experiment

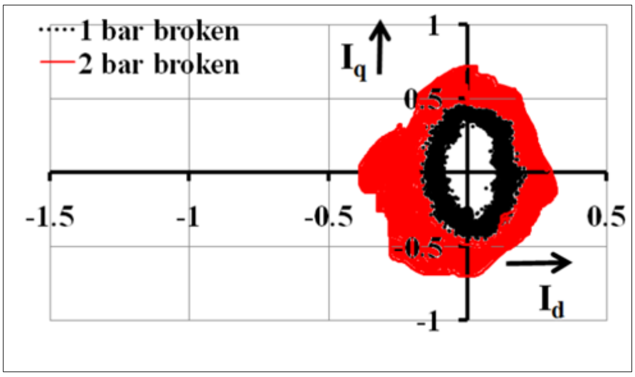
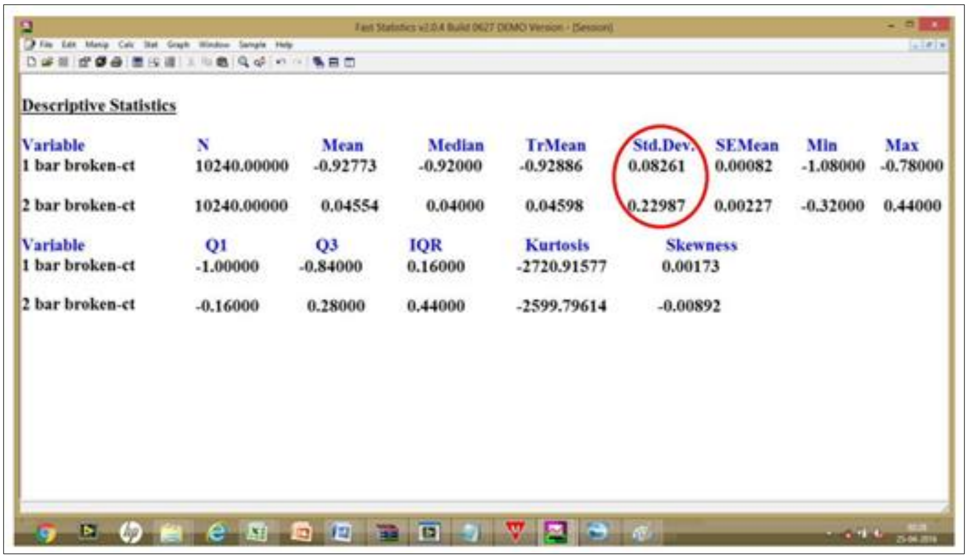


Figure 14 PVA of rotor bar broken

Fault severity of 2 bar broken is higher than that of 1 bar broken fault. In this plot the fault severity reflected in the form of plot dimension.

3.2.3. Analysis of rotor bar broken fault of induction motor using statistical analysis – experiment



Descriptive Statistics

Variable	N	Mean	Median	TrMean	Std.Dev.	SEMean	Min	Max
1 bar broken-ct	10240.00000	-0.92773	-0.92000	-0.92886	0.08261	0.00082	-1.08000	-0.78000
2 bar broken-ct	10240.00000	0.04554	0.04000	0.04598	0.22987	0.00227	-0.32000	0.44000

Variable	Q1	Q3	IQR	Kurtosis	Skewness
1 bar broken-ct	-1.00000	-0.84000	0.16000	-2720.91577	0.00173
2 bar broken-ct	-0.16000	0.28000	0.44000	-2599.79614	-0.00892

Figure 15 Statistical report of rotor bar broken fault

Figure 15 describes the statistical report for the SCIM with rotor bar broken fault. Figure 15 shows that, as the fault severity increases as the standard deviation increases.

4. Artificial Intelligence on finding the fault

Artificial neural network (ANN): This is a technique that mimics the structure and function of biological neurons to learn from data and perform tasks such as classification, regression, clustering, etc. ANN can be used to classify different types of motor faults based on the features extracted by PVR and PVA. E.g. a multilayer perceptron (MLP) network to classify stator winding faults, rotor bar faults, and bearing faults based on the PVR and PVA features of the stator current signals.

Support vector machine (SVM): This is a technique that finds the optimal hyperplane that separates the data into different classes with maximum margin. SVM can be used to classify different types of motor faults based on the features extracted by PVR and PVA E.g. a radial basis function (RBF) kernel SVM to classify stator winding faults, rotor bar faults, bearing faults, and eccentricity faults based on the PVR and PVA features of the stator current signals.

Random forest (RF): This is a technique that combines multiple decision trees to form an ensemble classifier that can improve the accuracy and robustness of the prediction. RF can be used to classify different types of motor faults based on the features extracted by PVR and PVA. E.g. RF to classify stator winding faults, rotor bar faults, bearing faults, and eccentricity faults based on the PVR and PVA features of the stator current signals.

Standard deviation (SD): This is a technique that measures the variation or dispersion of a set of values from their mean. SD can be used to select the most relevant features that can discriminate between different fault types and healthy conditions. E.g. SD to select the best features from PVR and PVA for fault classification using ANN, SVM, and RF.

Results derived between SD, PVR and PVA as follows,

Table 2 Condition Monitoring of Electrical Machines

Faulty condition in Machine New contribution in Machine condition monitoring techniques	**Faulty condition in Machine New contribution in Machine condition monitoring techniques**
Squirrel cage Induction motor rotor bar broken fault	PVA: The plot nature is always circle. As the fault severity increases the plot dimension also increases. PVR: As the fault severity increases, side lobes move away from the main peak Higher energy level is observed at LSB than RSB of every odd order frequency The harmonics of spectral magnitude for flux and current are ordered as 1>3>5>7>9... and 1 >37>9... respectively. SD: As the fault severity increases the SD also increases

5. Conclusion

Condition monitoring (CM) has become a very important technology in the field of electrical machine maintenance, and has attracted more and more attention worldwide. The potential functions of failure prediction, detection, machine fault identification, and aging estimation bring a series of advantage for utility companies by reducing maintenance cost, incorporating early maintenance procedures onto machines, enhancing safety of operators, minimizing accident and the severity of damages, as well as improving power quality. Due to these benefits and the pressure to utilize the existing assets under an environment of multiple machines of various configurations functioning in large scale grids or industries, condition monitoring is now a valuable domain of interest to power system managers and engineers as well as researchers.

This work has focused on condition monitoring and fault diagnosis of three-phase squirrel cage induction machines as generators and motors using signal processing approaches such as analysis of peak variation response (PVR), Park Vector Approach (PVA) and with statistical analysis using standard deviation (SD).

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