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Fault Diagnosis System for 3-Phase Induction Motor using Nature Inspires Tools

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***Abstract*—** Fault diagnosis of induction motor is gaining importance in industry because of the need to increase the reliability and to decrease the possible loss of production due to machine breakdown. Due to environmental stress and many other reasons different faults occur in induction motor. Many researchers proposed different technique for fault detection and diagnosis. However, many techniques available presently require a good deal of expertise to apply them successfully. Simple approaches are needed which allow unskilled operators to make reliable decisions without a diagnosis specialist to examine data and diagnose problems. In this paper we use different techniques like neural network, fuzzy logic and many other nature inspiring tools. The use of above techniques increases the precision and accuracy of the monitoring systems.

***Keywords*—** *STFT; FT; WT; VS and AVIS*

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I. INTRODUCTION

Induction motors are most commonly used in industry because of their low cost, reasonably small size, ruggedness, low maintenance, and operation with an easily available power supply. Although these are very reliable, they are subjected to different modes of failures/faults. These faults may be inherent to the I.M .itself or due to operating conditions. 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 in the literature such as winding faults, unbalanced stator and rotor parameters, broken rotor bars, eccentricity and bearing faults. Several fault identification method have been developed and been effectively applied to detect machine faults at different stages by using different machine variables, such as current, voltage, speed, efficiency, temperature and vibrations. Thus, for safety and economic considerations, it is essential to monitor the behavior of motors of different sizes such as large and small. Traditionally maintenance procedures in industry follow two approaches as follows. The first one is to perform fixed time interval maintenance, where the engineers take advantage of slower production cycles to fully inspect all aspects of the machinery. The second is to simply respond to the plant failure as and when it happens. However, making use of today's technology, new scientific approach was becoming possible for maintenance management. One of the key elements to this new approach is predictive maintenance through condition monitoring, which depends upon the condition of the plant. Condition monitoring is used for achieves performance of machinery, reducing consequential damage, increasing machine life, reducing spare parts inventories and reducing breakdown maintenance. An efficient condition-monitoring scheme is one that provides warning and predicts the faults at early stages. Monitoring system obtains information about the machine in the form of primary data and through the use of modern signal processing techniques; it is possible to give vital diagnostic information to equipment operator before it catastrophically fails. The problem with this approach is that the results require constant human interpretation. The logical progression of the condition-monitoring technologies is the automation of the diagnostic process. Recently soft computing techniques such as expert system, neural network, fuzzy logic, adaptive neural fuzzy inference system, genetic algorithm etc. have been employed to assist the diagnostic Task to correctly interpret the fault data. These techniques have gained popularity over other Conventional techniques. These are easy to extend and modify besides their improved Performance. The neural network can represent any non-linear model without knowledge of its actual structure and can give result in a short time. From the early stages of developing electrical machines, researchers have been engaged in developing a method for machine analysis, protection and maintenance. The use of above technique increases the precision and accuracy of the monitoring systems. The area of condition monitoring and faults diagnostic of electrical drives is essentially related to a number of subjects, such as electrical machines, methods of monitoring, reliability and maintenance, instrumentation, signal processing and intelligent systems.

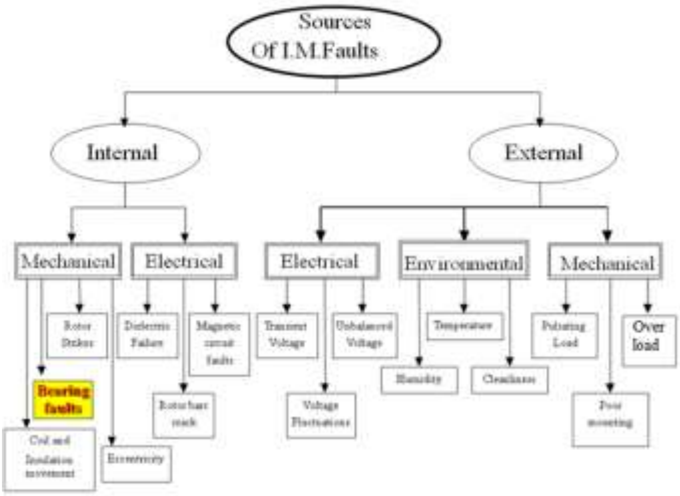

Fig: 1 Source of I.M. Faults

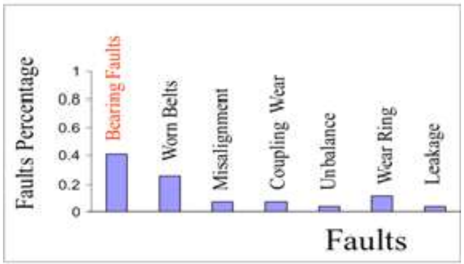

Fig: 2 Industrial Drives Fault in Statistical Prospective Report

II. BRIEF REVIEW OF THE WORK

Various fault monitoring techniques for induction motors reported in literature can be broadly categorized as shown in Fig.3

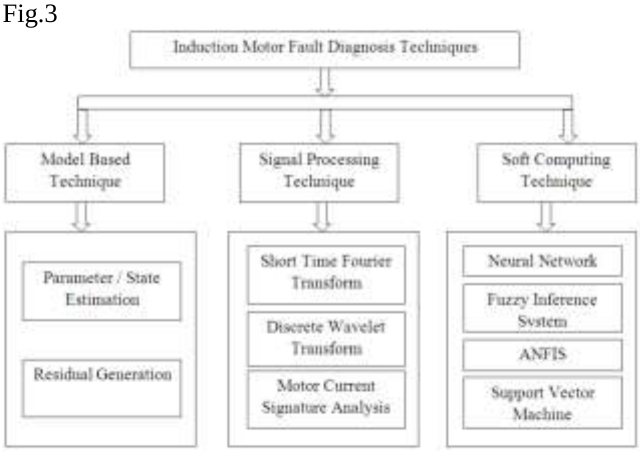

Fig: 3 Induction Motor Fault Diagnosis Techniques

A. Model Based Technique

Isermann [1] has presented a novel, unified model-based fault detection and prediction (FDP) technique is developed for non linear multiple-input-multiple-output (MIMO) discrete time systems. The proposed scheme addresses both state and output faults by considering separate time profiles. The faults, which could be incipient or abrupt, are modeled using input and output signals of the system. The fault detection (FD) scheme comprises online approximate in discrete time (OLAD) with a robust adaptive term. An output residual is generated by comparing the fault detection (FD) estimator output with that of the measured system output. A fault is detected when this output residuals exceeds a predefined threshold. The asymptotic stability of the fault detection and prediction (FDP) scheme enhances the detection and time to failure accuracy. The effectiveness of the proposed approach is demonstrated by using a fourth-order MIMO satellite system.

Arkan, Kostic-Perovic and Unsworth [2] have presented two orthogonal axis models of a three phase induction motor. From these two models first one having asymmetrical windings and the other one having inter-turn short circuits on the stator winding. The machine is modeled by using classical two axis theory, and the equations are modified to take into account the stator inter-turn faults. A state space form of the system is presented for dynamic simulations. The simulation results from the models are compared with experiment carried out on a specially wound motor with taps to allow different number of turns to be shorted. The above models have been successfully used to study the transient and steady state behavior of the induction motor with short circuited turns.

Sahraoui, Ghoggal, Zouzou, Aboubou and Razik [3] have proposed a new mathematical model of the induction motor operating under stator inter-turns short circuits. The model is based on the multiplied coupled circuit approach. The inductances calculation is performed an extension in 2- D of the modified winding function approach (EMWFA), which was able to take into account the space harmonics in addition to the effects of rotor bar skewing and to the linear rise of MMF across the slots. From the results it is shown that the inter-turn short circuit gives rise to some spectral components which appear in the current line spectrum.

Bachir, Tnani, Trigeassou and Champenois [4] have suggested a new model of squirrel cage induction motors under stator and rotor faults. First, they study an original model that takes into account the effects of inter-turn faults resulting in the shorting of one or more circuits of stator phase winding. Then, they propose a new faulty model dedicated to broken rotor bars detection. The corresponding diagnosis procedure based on parameter estimation of the stator and rotor faulty model is proposed. The estimation technique is performed by taking into account prior information available on the safe system operating in nominal conditions. In this paper the output error (OE) identification technique is used to estimate the parameters.

B. Soft Computing Technique

Nejjari and Benbouzid [5] have used the Park's vector patterns for detecting different types of supply faults, such as voltage imbalance and single phasing. In addition a neural network based back propagation algorithm is used to obtain the machine condition by testing the shape of the Park's vector patterns. Two neural network based approach have been used, these are classical and decentralized. The generality of the proposed methodology has been experimentally tested and the authors claim that the results provide a satisfactory level of accuracy. Fillippetti [6] has introduced a comprehensive study about the application of artificial intelligence in machine

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monitoring and fault diagnosis. Here, expert system has been used as a tool for the fault diagnosis. The authors show the validity of using neural network along with fuzzy logic for fault identification and fault severity evaluation. The paper also covers a diagnosis of the inverter system, which is used to drive the motor.

Awadallah [7] has introduced a comprehensive adaptive neuro-fuzzy inference system for identification of stator short circuits in brushless DC motors, where the diagnosis of the fault was done through two independent ANFISES, first one is used to find out the shorted turns and the second one is used to identify out the faulty phase. The inputs to the first ANFIS are the diagnostic indices to determine the number of shorted turns, while the output was taken zero during the normal operation and integers under fault conditions. Input to the second ANFIS were the three phase identification indices and its output was an integer indicating the faulty phase. Tan and Huo [8] have suggested a generic neuro-fuzzy model based approach to the detection of rotor broken bar faults in an induction motor. In this paper the data for training the neuro fuzzy system to model the generic static torque-speed relationship of the class of induction motors used in the practical evaluation of the fault detector. Modeling error was found by comparing the output speed of the neuro-fuzzy model and the speed which is obtained from the experimental torque-speed equation. This approach overcomes the practical limitations of model based strategies as it reduces the amount of experimental data that are needed to design the fault detector. This method is also able to identify the absence/presence of cracked rotor bars under varying load conditions.

Makarand, Zaffer, Hirallal and Ram [9] have been applied an adaptive neural fuzzy inference system for the detection of inter-turn insulation and bearing wear faults in induction motor. Here, the authors have given five inputs to the ANFIS; these are motor intakes current, speed, winding temperature, bearing temperature and the noise. The neural fuzzy architecture takes into account both ANN and fuzzy logic technology. They have used multilayer feed forward network as the ANN and sugeno type fuzzy rules as fuzzy inference systems. First they have developed both the detectors with two input parameters. Then the remaining three parameters are included. In case of the two inputs for insulation detector the training error was 0.068 and the accuracy was 94.03%, for bearing condition the training error was 0.0905 and the accuracy was 90.5%.In case of the five inputs, for insulation detector the training error was 0.001209 and the accuracy was 96.67%, for bearing condition the training error was 90.000945 and the accuracy was 98.77%. It was observed from the performance results that the five inputs ANFIS technique provides more accurate results in comparison with two input system.

Rodriguez and Arkkio [10] have used a methodology using for detection of stator winding fault in induction motor. In this paper, the stator three phase rms values of currents and the variance have been used as the input to the fuzzy logic system. The input data are generated with the motor working in different load conditions by using the FEM analysis. The fuzzy logic method was able to detect the motor condition with high accuracy for both with noise and without noise. The drawback of the method is that a current unbalance originating from the supply source may be identified as a fault condition of the motor.

Abiyev [11] has integrated both fuzzy logic system with a wavelet neural network for identification and control of an uncertain system. In this paper he has used the gradient decent algorithm for the parameter updating. Two examples have been presented for identification and control performance studies. It has been demonstrated that the fuzzy wavelet neural networks can converge faster and is more adaptive to new data.

Bouzid [12] has suggested a neural network approach for the detection and location automatically of an inter-turn short circuit fault in the stator windings of an induction motor. In this paper they have used a feed forward multi layer perception neural network which is trained by the back propagation technique. The phase shift between the phase voltage and line current of an induction motor is used as the input to the neural network. The desired output is set to either ‘one’ or ‘zero’. If a short circuit is detected and located on one of the three phases, the corresponding neural network output is set to ‘one’; otherwise, it is ‘zero’

III. METHODOLOGY OF RESEARCH WORK

We take AVI signal from Induction motor at different-2 condition through voice recording by the voice recorder then apply on MATLAB tool

- FFT analysis(in progress)
- Wavelets
- Neural network
- Fuzzy logic system

The summery of our work is given below-

- Firstly we choose different type of induction motor according the ratings of motors.
- After choosing the rating we take the voice recording according to our specification that we are required.
- This sound getting in .amr signal.
- We convert this .amr signal to .avi signal by using convertor.
- We apply .avi signal on MATLAB tool and we get the result by using FFT.
- Time domain analysis.

IV. FAULT DIAGNOSIS CONSTANTS

Most of the signals in practice are time-domain signals in their raw format. That is, whatever that signal is measuring, is a function of time. In other words, when we plot the signal one of the axes is time (independent variable), and the other (dependent variable) is usually the amplitude. When we plot time-domain signals, we obtain a time-amplitude representation of the signal. This representation is not always the best representation of the signal for most signal processing related applications. In many cases, the most distinguished information is hidden in the frequency content of the signal. The frequency spectrum of a signal is basically the frequency components (spectral components) of that signal. The frequency spectrum of a signal shows what frequencies exist in the signal.

A. ROOT MEAN SQUARE (RMS)

The square root of the average of the squares of a set of numbers. In root mean square or rms is a statistical measure of the magnitude of a varying quantity. It can be calculated for a series of discrete values or for a continuously varying function. The name comes from the fact that it is the square root of the mean of the squares of the values. It is a power mean with the power t=2.The rms for a collection of N values {x1, x2, ..., xN} is:

$$x_{\mathrm{rms}} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2} = \sqrt{\frac{x_1^2 + x_2^2 + \cdots + x_N^2}{N}} \quad \text{.......[A]}$$

and the corresponding formula for a continuous function f(t) defined over the interval T1 ≤ t ≤ T2 is:

$$x_{\mathrm{rms}} = \sqrt{\frac{1}{T_2 - T_1}\int_{T_1}^{T_2} [f(t)]^2\, dt}. \quad \text{.......[B]}$$

The RMS value can be calculated using equation (2) for any waveform, for example an audio or radio signal. This allows us to calculate the mean power delivered into a specified load. For this reason, listed voltages for power outlets (eg. 110V or 240V) are almost always quoted in RMS values, and not peak-to-peak values.

B. CREST FACTOR

It is defined as the ratio of maximum amplitude to rms value of vibration signal, which is also used in determination of health of ball bearing.

C. SKEWNESS

Skewness is a measure of symmetry, or more precisely, the lack of symmetry about its mean. A distribution, or data set, is symmetric if it looks the same to the left and right of the center point. The skewness of normal distribution is zero, and any symmetric data should have a skewness near zero. Negative values for the skewness indicate data that are skewed left and positive values for the skewness indicate data that are skewed right. By skewed left, mean that the left tail is heavier than the right tail.

$$c\,(\text{skewness}) = \frac{\frac{1}{N}\sum (x_i - \mu)^3}{\sigma^3} \quad \text{... ...[C]}$$

D. KURTOSIS

A more recent development in the state of art of bearing fault detection is statistically based parameter called Kurtosis. It is a measure of whether the data are peaked or flat relative to a normal distribution. That is, data sets with high kurtosis tend to have a distinct peak near the mean, decline rather rapidly, and have heavy tails. Data sets with low kurtosis tend to have a flat top near the mean rather than a sharp peak. A uniform distribution would be the extreme case. Positive kurtosis indicates a "peaked" distribution and negative kurtosis indicates a "flat" distribution

$$k\,(\text{kurtosis}) = \frac{\frac{1}{N}\sum_{i=1}^{N} (x_i - \mu)^4}{\sigma^4} \quad \text{....[D]}$$

The Kurtosis technique has the major advantage that the calculated discriminate takes a value, which is independent of load or speed conditions. It has been found that the Kurtosis factor for undamaged bearing is 3. In general, the initial appearance of flaws is marked by an increase in the value of Kurtosis.

E. STANDARD DAVIATION [SD]

The standard deviation is a measure of how spread out your data is. A statistic used as a measure of the dispersion or variation in a distribution, equal to the square root of the arithmetic mean of the squares of the deviations from the arithmetic mean. These Constants RMS, CREST FACTOR, SKEWNESS, and KURTOSIS AND STANDARD DEVIATION they give vital information about the nature of the signal and each characteristic frequency of the defect can be identified from the pattern of these parameters. Different vibration signals (of Induction Motor) using MATLAB. Shown in the Fig 4, Fig 5, Fig 6 and Fig 7, are different vibration signals with their rms, kurtosis, skewness, and standard deviation values.

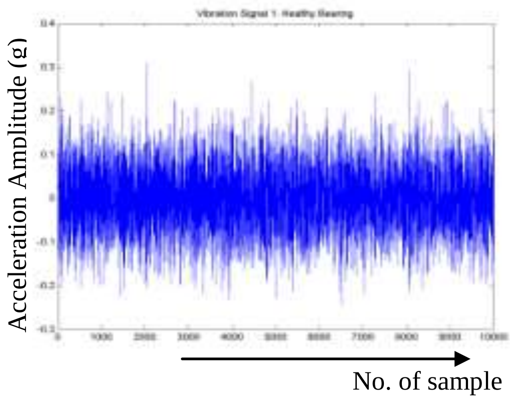

Figure 4: Vibration signal 1(Healthy bearing)

Vibration signal 1: Healthy bearing
RMS=0.016
Crest Factor = 3.14
Kurtosis=2.9178
Standard deviation= - 0.032

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Skewness=0.013

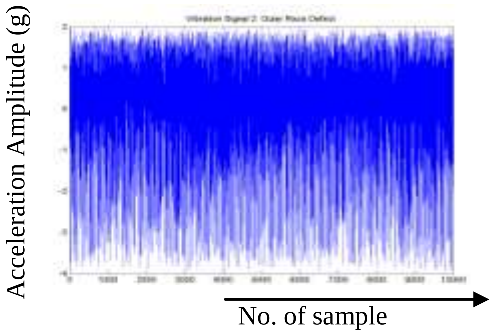

Figure 5: Vibration signal 2 (Outer race defected bearing)

Vibration signal 2: Outer race defected bearing
RMS=0.4728
Crest Factor = 4.69
Kurtosis=5.88
Skewness= - 0.448
Standard deviation=0.072

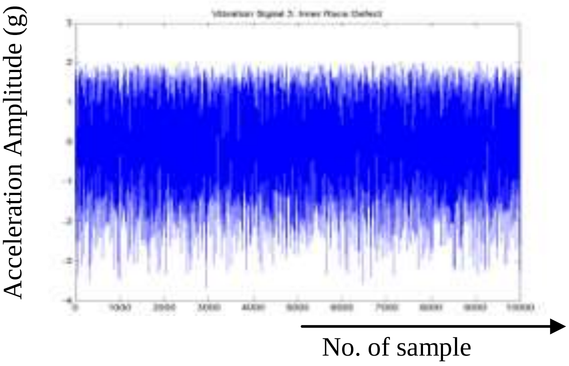

Figure 6: Vibration signal 3 (Inner race defected bearing)

Vibration signal 3: Inner race defected bearing
RMS=0.61
Crest Factor = 2.34
Kurtosis=2.51
Skewness= - 1.225
Standard deviation= 0.110

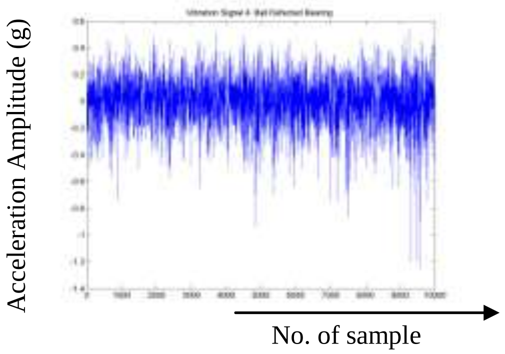

Figure 7: Vibration signal 4(Ball defected bearing)

Vibration signal 4: Ball defected bearing
RMS=0.68
Crest Factor= 5.87
Kurtosis=3.48
Skewness= - 0.091
Standard deviation=1.271

V. RESULTS OF SIGNAL ANALYSIS WHICH RECEIVED FROM DIFFERENT CONDITIONS

Signal type	0.016	3.14	2.91	-0.32	0.013
Healthy Bearing	0.472	4.69	5.88	-0.44	0.073
Outer Race defected	0.61	2.34	2.51	-1.22	0.110
Inner Race defected	0.68	5.87	3.48	-0.09	1.271
Ball Defected	0.016	3.14	2.91	-0.32	0.013

VI. IMPACT OF PROPOSED RESEARCH ON THE BODY OF KNOWLEDGE AND ITS RELEVANCE TO ACADEMIC/INDUSTRY.

- Reduce certain breakdown time for any industries.
- Extended time period of scheduled shut down.
- Increasing equipment and machine life.
- Corrective action can be implemented to prolong machine operation.
- Improve the efficiency of industrial drives.
- Significant cost-saving.

VII.CONCLUSIONS AND FUTURE SCOPE

A detailed study of various signal analysis techniques has been carried out. The Time Domain signal detections such as rms, crest factor, skewness, kurtosis and standard deviations and wavelet transform co-efficients are extracted from the vibration signal. Wavelet Transform was found to be the most suitable technique for signal analysis. The results were obtained using MATLAB toolbox.

A Condition Monitoring System could be designed to obtain other parameters like current to analyze the bearing condition. Also the efficiency of the ANN in giving results can be improved by using other models and training algorithm and by implementing Fuzzy Logic. By applying these parameters to ANN the efficiency and operating time of the process can be improved.

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