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A Review On Induction Motor Fault Diagnostic Techniques

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ABSTRACT

Induction motors plays a vital role in almost all the industrial drive systems because of their simple, efficient and robust nature offering high degree of reliability. These machines face various stresses during operating conditions which may lead to different types of faults. Hence condition monitoring and maintenance becomes necessary in order to avoid unexpected failures. Different fault monitoring techniques for induction motors can be broadly categorized as model based techniques, signal processing techniques, and artificial intelligence based soft computing techniques. The traditional model based diagnostic techniques provides a good detection of the fault in the machine but nowadays artificial intelligence techniques have been introduced to overcome the existing inaccuracy. Soft computing techniques enable better analysis of a faulty system even if models are inaccurate. Besides giving improved performance these techniques are easy to extend and modify. This paper provides a comprehensive study of conventional and innovative techniques.

1. Introduction

Rotating electrical machines plays a very vital role in industrial applications due to its simple construction, robustness, reliability and easy maintenance. As the induction machine is highly symmetrical in nature, the presence of any kind of fault in it affects its symmetry and results in wear and tear of machine. Hence it has been important to monitor the health of rotating electrical machines for better performance and improved efficiency. Different invasive and noninvasive methods are being used for fault detection for machines. Noninvasive methods includes establishing the motor condition by analysis of the information obtained outside the apparatus, such as terminal and environmental measurements; whereas noninvasive methods are economical and hence preferred more. Fault identification and diagnostics can improve reliability by proper repairment and replacement of machine parts.

2. Need for fault identification

Several researchers and investigators put up their significant efforts to develop different methods and procedures for detecting and diagnosing faults occurring in machines used in various industries. Fault detection and diagnosis could be used both for fault detection and quality control. The purpose of fault diagnosis in machines is to detect and remove faults and failures in order to improve the operational safety, reliability and efficiency of the production system during adverse conditions. The need of fault diagnosis has become necessary in order to avoid the replacement of the machines. Fault identification and diagnostics can not only improve reliability but also allow drive repairment and replacement to happen in a timely and orderly fashion [1]

3. Condition based maintenance

CBM is a maintenance approach carried out in return to a significant deterioration in a machine as marked by a change in an observed parameter of the machine condition. The use of CBM systems is advantageous in industry as it reduces costs by avoiding unnecessary maintenance expenditure. CBM provides the potential for the system to continue operating as long as it is performing within the predefined performance limits [2]. Also, CBM can be treated as a method which can be used to reduce the unpredictability of maintenance activities and is performed according to the requirements as indicated by the equipment condition [3]. It focuses on the prediction of degradation process of the product, which is based on the supposition that most of the flaws do not occur instantaneously and usually there are some kinds of degradation process from normal states to abnormalities [4].

4. Monitoring techniques

Condition monitoring is of great importance in industrial machinery since it not only improves the reliability and availability but also ensures safety and productivity of the systems. For electrical motors and generators, faults detection is generally performed by temperature measurements, vibration monitoring, oil monitoring, flux monitoring and current analysis [5, 6]. Among these various techniques, current analysis has several advantages since it is a non-invasive technique that avoids the use of extra sensors [7, 8]

4.1 Acoustic measurements

Acoustic monitoring method includes techniques like acoustic emission, sound pressure and sound intensity methods. Acoustic emission (AE) is the process of transient elastic wave generation due to a sudden release of strain

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energy caused by a structural deformation in a solid structure under mechanical or thermal stresses. Generation and propagation of cracks, growth of twins, etc. associated with plastic deformation are usually among the key sources of Acoustic emission [9]. Sound pressure is the effective pressure or root mean square (RMS) pressure. The effect of sound pressure generated by bearings has been researched by various scientists for fault identification. It has been observed that Sound pressure level in their frequency domain is the effective method for the fault identification in machine. Further sound intensity is defined as the time-averaged rate of flow of sound energy through unit area. Sound intensity measurement is more effective than sound pressure measurement technique for the diagnosis of bearing related faults and failures [10]. Hence Acoustic measurement proves to be important condition monitoring technique through non-destructive testing.

4.2 Vibration

Vibration monitoring is one of the oldest techniques used for the detection of mechanical faults like misalignment, unbalance, defective bearings, cracked rotor bars etc. It can be used to monitor the above faults both in their time and frequency domains. Time domain analysis emphasis mainly on statistical parameters of vibration signals like standard deviation, skewness, kurtosis etc. The simplest approach in the time domain is to measure the root-mean-square (RMS) value and crest factor. It has been observed that this method has been applied for the detection of localized defects with limited success [11]. Frequency domain analysis emphasis mainly on fourier transform (FT), specially fast fourier transform (FFT) methods to transform the time domain signals into their frequency domain signals, and is finally analyzed in their vibration and power spectra where both low and high frequency ranges of the vibration spectrum are used for determine the condition of the bearing. Vibration analysis is widely accepted technique to detect faults of a machine since it is non-destructive and reliable that allows continuous monitoring without stopping the machine [12].

4.3 Noise

Noise of electrical machinery is generated by the vibration of machine parts. The generated vibration signal is then recorded which is then allowed to data acquisition system and finally analyzed in the form of fault. The sounds produced by a machine as a result from the dynamics of its components and by regularly monitoring these sounds the occurrence of such changes can be used to diagnose the condition of the machine and the probable onset of failure and faults [13]. One of the most important parameter is the sensitivity of frequency.

5 .Different type of faults in induction motor

Whenever a machine undergoes stress conditions during the operations, it deviates from its normal behavior and leads to faults. These faults can be classified as electrical, mechanical and miscellaneous faults and are discussed below as;

5.1 Electrical Faults

According to a survey by EPRI in 1982 it has been observed that, about 41% of all induction motor failures are caused by bearing faults, 37% by stator faults, 10% by rotor faults, and 12% by miscellaneous faults [14].

5.1.1 Rotor faults

Broken rotor bars can be either partly or fully broken. This brokenness can be due to frequency, sudden start at rated voltage, due to high temperature, vibration or mechanical stress which effects motor health very severely. Rotor faults can be categorized as broken rotor bars, shorted rotor field windings and broken rotor end rings [15].

5.1.2Stator faults

It includes faults related to stator core and stator winding. Most stator faults can be attributed to various stressful operating conditions. Further stator winding faults can be classified into four types such as turn-to-turn, coil-to-coil, open circuit, phase-to-phase and coil-to-ground [16].

5.2 Mechanical faults

This type of faults occurs in the mechanical components of the machines such as bearings housings and end covers. These are discussed below;

5.2.1. Bearing faults

Bearing faults are categorized as inner faults and outer faults by their location. Contamination of lubricant, loss of lubricant, over-loading, and excess heating are the most common causes of bearing faults. Bearing defects may be classified as local or distributed [17]. The distributed defects include surface roughness, mismatched waviness and off-size rolling elements. A localized defect consists of flakes, pits and cracks on the rolling surfaces. Another problem caused by the bearing fault results in improper installation caused due to the imbalanced alignment of the bearing onto the shaft. This produces false indentation of the raceways and damages the motor physically.

5.2.2. Air gap eccentricity faults

Basically these types of faults comprise of two types namely Static eccentricity and Dynamic eccentricity. The Static eccentricity is the generation of uneven stator-rotor air gap caused due to the presence of improper adjusted air gap for plain bearings. The rotor moves from its original position at the center of the stator and rotates around its own center in static eccentricity. Dynamic eccentricity is the generation of variable stator–rotor air gap due to the wear out of bearing housings and end covers due to which rotor stars rubbing with the stator. The rotor shifts from its normal position, but rotates around the center of the stator in dynamic eccentricity.

5.3 Miscellaneous faults

It includes faults in the supporting devices which assemble the accessories of the drive system. These are classified mainly into two types:

5.3.1 Gear box fault*s*

Due to excessive load on the gearboxes, occurrence of fluctuations on the gearbox may cause vibrational defects in the motor. The main components in gear boxes vibrational spectrum are the tooth-meshing frequencies and its harmonics, along with sideband structures due to modulation effects. These sideband structures can be used as important diagnostic indications for gear fault detection. Hence, to perform a reliable and precise diagnosis of a rotor winding for motors connected to a gearbox, the effects of gearbox components in the spectrum need to be identified and scrutinized.

5.3.2 Cracked or bent shaft

These faults may be as a result of rubbing between the rotor and stator, resulting in a serious damage to the stator core and windings.

6. Diagnostic techniques for fault detection

Basically there are three types of techniques namely model based, signal processing and soft computing. In one way or the other these techniques are helpful in the detection of faults in electrical machines. These techniques are classified as;

6.1Model based techniques

Model based diagnostic techniques may be defined as an asymmetrical induction motor whose model is used to predict failure fault signatures. The difference between measured and simulated signatures is used for fault detection [18, 19].

6.2 Signal processing based techniques

Signal based diagnosis relies on advances in digital technology. It looks for known fault signatures in quantities sampled from the actual machine. The signatures are then monitored by suitable signal processors. Signal processing can be used to enhance signal to noise ratio and to normalize data to isolate the fault from other phenomenon and decrease sensitivity to operating conditions. These are then classified into following types:

6.2.1 Fourier transform

The Fourier transform of the function f(x) is the function F (ω), where:

$$F(\omega) = \int_{-\infty}^{\infty} f(t)\, e^{-i\omega t}\, dt \quad (1)$$

The FT is further sub classified into;

6.2.1.1 Fast fourier transform (FFT)

Fast fourier transform (FT) is a versatile technique using which the frequency contents of a signal can be found out.

6.2.1.2 Short time fourier transform (STFT)

STFT is the most widely being used for studying non-stationary signals. The main idea of the short time Fourier transform is to decompose up the initial signal into small piece time segments and implement the fourier transform at each level to get the frequencies that existed in that segment. The integrative result of such spectrum indicates that the spectrum is varying with respect to time. The STFT maps a signal into a two- dimensional function of time and frequency.

6.2.1.3 Discrete fourier transform (DFT)

These are discrete signals that restate themselves in a regular interval of time from negative to positive infinity. In the detection of machine faults this methodology proves to be effective as computational work requires data and information that is discrete in nature and finite in length.

6.2.2 Wavelet transform (WT)

WT is a powerful tool in the processing of non-stationary signals. It permits the use of long time intervals, where more accurate low frequency information is expected. It also permits the use of shorter time intervals where accurate high frequency information is desired .Wavelets are the functions that satisfy the requirement of both time and frequency localization [20]. Wavelets are localized in both time (through translation) and frequency (through dilation). Wavelet can produce multiple resolutions in both time and frequency domain. The signal can be reproduced accurately with the wavelet analysis using relatively small number of components [21].

6.2.2.1 Continuous wavelet transform (CWT)

CWT is one of the technique by which Wavelet Transform can be implemented. For a given wavelet mother function 'ψ' the Continuous Wavelet Transform (CWT) of the signal x (t) is defined by Eq. (2); where ψ* represents the conjugated transpose of the mother wavelet function. 's' is a scale factor, 'τ' is the translation factor and the factor $|s|^{1/2}$ is the energy normalization across different scales. Energy normalization ensures that the transformed signal has same energy at each and every scale. Scaling a wavelet means stretching or compressing it [22].

$$CWT_X^{\psi}(\tau, s) = \Psi_X^{\tau}(\tau, s) = \frac{1}{\sqrt{|s|}} \int x(t)\, \psi^*\left(\frac{t-\tau}{s}\right) dt \quad (2)$$

6.2.2.2 Discrete wavelet transform (DWT)

In discrete wavelet transform, the mother wavelet is not scaled continuously, but scaled in the power of 2. Hence, it is easy to apply it in digital computers and therefore takes less execution time.

Suppose *S* be a discrete-time signal to be decomposed into its approximate and detailed versions using the discrete wavelet analysis. The first level decomposition coefficients are cA_1 and cD_1 where, cA_1 is the approximate version of *S*, and cD_1 is the detailed representation of *S*. cA_1 and cD_1 are defined as

$$cA_1 = \sum_k^n L(K-2n)s(k)$$

$$cD_1 = \sum_k^n H(K-2n)s(k)$$

where, *H* and *L* are the decomposition filters of *S(n)* in cD_1 and cA_1, respectively[23].

6.2.2.3 Wavelet packet transform (WPT)

WPT performs multi scale decomposition on both approximation and detail coefficient which allows a good localization of fault [24]. First main contribution is to show that despite the fact that the WPT exceeds the CWT in terms of spectral and speed characterization of the vibration signal. It has been observed that CWT can perform better than the WPT, when supplemented with the maxima modulus technique, in detecting multiple faults.

6.2.3 Motor current signature analysis (MCSA)

The MCSA uses the current spectrum for locating fault frequencies of the machine. When fault occurs, the frequency based spectrum of the current becomes non identical from healthy motor. It is a system used for analyzing or trending dynamic, energized systems. With thorough analysis of MCSA, it is possible to identify the rotor and stator winding health, rotor health, static and dynamic eccentricity, coupling health including direct, geared and belted systems, load issues, system efficiency and bearing health. The motor current signature analysis method can detect these problems at an early stage and hence can avoid secondary breakdown and complete failure of the motor. In [25] an online diagnosis approach has been proposed for an induction motor that uses the MCSA with advanced signal processing algorithms.

6.3 Soft computing techniques

In addition to traditional model-based fault diagnostics, different kinds of Artificial intelligence based methods have become popular in the area of fault diagnostics of electrical machinery commonly termed as soft computing techniques and are categorized as;

6.3.1 Artificial Neural Network Technique

A neural network can substitute the faulted machine models in a more effective way in order to utilize the knowledge base of the diagnostic system with appropriate inputs and outputs. This methodology consists of training the neural network by data received through experiments performed on healthy machines and the data received through simulation done in case of faulty machines. Hence the diagnostic system can differentiate between "healthy" and "faulty" machines.

Artificial Neural Network is a computational model of the brain. ANNs assume that computation is spread out over several simple units called neurons, which are interconnected and operate in parallel and therefore known as parallel distributed processing systems or connectionist systems [26].

6.3.2 Fuzzy system

Fuzzy logic allows items to be described as having a certain membership degree in a set normally constrained to 1 and 0. When performing fault diagnosis, there are several situations in which an object is not obviously good or bad but may fall under some interior range [27]. Fuzzy logic is the reminiscent of human thinking processes and natural language which enables decisions to be made based on indistinct information [28]. The parameter amplitude is described by fuzzy subsets and the corresponding membership functions.

6.3.3 *Adaptive neuro fuzzy inference system (ANFIS)*

ANFIS is a hybrid model of artificial neural network and fuzzy system. It uses a gradient descent algorithm training paradigm and a least guaranteed to be optimal. It uses the fusion of neural network and fuzzy logic such as adaptive network based fuzzy interference system and fuzzy adaptive square algorithm to tune the parameter of the membership function [29]. ANFIS is a class of adaptive network, which are functionally equivalent to Fuzzy Inference Systems. It uses a hybrid learning algorithm to determine the membership function parameters of single output, Sugeno type fuzzy inference systems [30].

6.3.4 Support vector machine

SVM are based on structural risk minimization principle based on the statistical learning. In Support Vector Machine, the original input space is mapped into a high dimensional dot product space called as feature space, where to maximize the generalization ability of the classifier the optimal hyper plane is determined. [31]. SVM is very useful technique for fault detection of machine [32].

6.3.5 Genetic algorithm

A genetic algorithm (GA) is a stochastic and derivative free optimization technique which is based on selection, crossover, and mutation [33]. The genetic algorithm comprises of the random generation of potential design solutions and then systematically evaluates and filters the solutions until a stopping criterion is reached. Genetic algorithms generate solutions to the optimization problems using the techniques inspired by natural evolution namely mutation, selection, and crossover. Its orientation comes from ideas borrowed from the evolutionary process as well as natural selection. Genetic algorithms were applied for automatic feature selection in monitoring of the machine conditions [34]. A genetic algorithm based approach was applied for the selection of input features and number of neurons in the hidden layer [35].The Genetic algorithms optimization technique is based on trial and error approach to setup appropriate artificial neural network parameters which makes it more preferable than other evolutionary methods.

7. Conclusion

This paper has reviewed various faults of an induction motor, their classification and their diagnostic techniques. Various invasive and non-invasive methods and their utilization in the detection of faults have been studied. Various fault diagnostic techniques based on fuzzy logic, neural networks, ANFIS, and genetic algorithm are discussed in this literature. Based on our study, it has been analyzed that artificial intelligence techniques are comparatively better than traditional techniques in terms of speed, performance, efficiency and accuracy. The use of online computing techniques can greatly replace human efforts for better and reliable results, herby increasing the efficiency and decreasing the losses.

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