EARLY FAULT DIAGNOSIS IN ELECTRICAL MOTORS USING AI TECHNIQUES*

BY

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ABSTRACT

The main focus is to exhibit a reliable mechanism for early fault detection and diagnosis so that necessary steps can be taken [5]. According to the different survey carried out, different types of fault are revealed under different conditions. Different techniques have been implemented to find out diagnosis of faulty machines which include their bearing faults, broken rotor bars, air gap eccentricity and stator winding inter turn faults [6].The purpose of the work is to obtain an effective fault diagnosis method using machine learning and advanced signal processing techniques.

KEYWORDS

Faults, Induction Motor, Diagnosis, Image Processing, Signal Processing.

1. INTRODUCTION

The most widely used motor which is having nearly 90% application in industrial processes and even in the household application is Induction motor. Thus Induction motor has varied application because of its technical and economical advantages like optimized performance under normal operating conditions and better cost position . Induction motor is also a better choice in case of Electric Vehicles.[1].While operation, Induction motor undergoes various stresses causing sudden failures due to faults. Unexpected failure in the motor may cause major issues leading to unexpected downtime, which will in turn hamper the Industrial process. statistical survey conducted by IEEE and electric power research institute (EPRI) on induction motor faults and the percentage of different faults with respect to the total number of faults is tabulated in Table 1.1 [2].

Major fault component	Studied by	
	IEEE %	EPRI %

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Rotor fault	8	9
Bearing fault	42	41
Stator fault	28	36
other	22	14

Table1. 1: Statistical survey results for induction motor faults by IEEE and EPRI.

Thus prefault detection in an induction motor is mandatory for smooth and reliable operation of any system.

2. OVERVIEW

Induction motor undergoes various stresses leading to Electrical & Mechanical faults. Mechanical stresses include bearing faults and rotor bar breakage. Whereas, electrical stresses may include stator winding short circuits and result in a complete motor failure. The fault distribution in Induction motor is as follows [3].

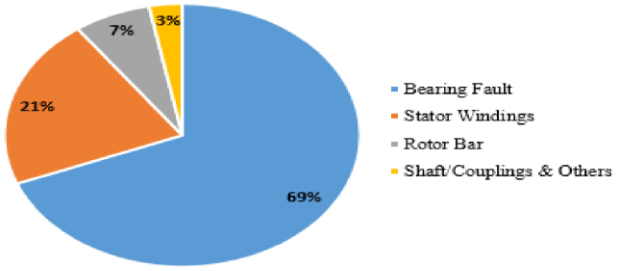

Fig.1.Different fault distribution of an induction motor [4]

Thus early fault diagnosis is mandatory to avoid fatal fault conditions. There are various techniques for fault monitoring like model based, advanced Imaging and soft computing techniques.

3. PROPOSED TECHNIQUES

MODEL BASED: Accurate models of faulty machine is mandatory during model based analysis. In most of the cases it is not possible to get the accurate model for applying the proposed technique. The Parameters to calculate phase shift between line current and phase voltage under varied loading conditions can be easily obtained and calculated by installing a experimental set-up.

ADVANCED IMAGING: Fast fourier transform uses steady-state spectral components of the stator quantities wherein the accuracy depends on load and speed of the machine. DWT technique is sustainable for signals having variable frequency spectrum.

ARTIFICIAL INTELLIGENCE: Artificial intelligence (AI) technique plays a vital role in prefault detection in induction machine as accurate models are not needed. We can also extend or modify the proposed technique for prefault detection. AI techniques like neural networks, fuzzy

logic, and fuzzy-neural networks and algorithms, acts as a powertool during maintenance decision process.

4. LITERATURE REVIEW

In this study, three methodologies are mentioned: Experimental, Advanced Imaging and AI based techniques. Induction motor has around 85-90% applications in industry. Thus it is mandatory to follow conditional monitoring of induction motor for its reliable operation. Early fault detection and analysis is playing a vital role as unexpected failure of machines will hamper the entire Industrial process and operation. Moreover, it will also affect the efficiency of the system. There has been a substantial amount of research to provide new condition monitoring techniques especially for AC Induction motors

However, an important factor for motor condition monitoring and fault diagnosis is the ability to extract the features of motor signals related to the faults. The one-line diagram of a general approach to condition monitoring for the induction motor is shown in Fig. 2[4] .

A feature extraction technique is needed for signal processing of recorded time-series signals over a long period of time to obtain suitable feature parameters for condition monitoring and fault diagnosis. By employing appropriate signal analysis algorithms, it is feasible to detect changes in signals caused by faulty components. The aim of feature extraction is to extract the signal features hidden in the original time domain. Corresponding to different signals, a signal analysis method should be properly selected such that the feature value of signals can be boosted to improve diagnostic sensitivity to a motor fault.

Most of the analysis used for fault diagnosis, was performed using fast Fourier transform (FFT) based tools on the motor current or vibration signature. However, FFT has some limitations, like the masking of characteristic frequencies by supply frequency, inappropriateness for transient signals, etc. To overcome these limitations, different new techniques are being used now [13]-[15]. Some of the present signal processing techniques is reported in the literature as critical steps for fault diagnosis. These techniques include short-time Fourier transform (STFT), Wigner- Ville distribution (WVD), power spectral density (PSD), wavelet transform (WT) [16]-[20].

The condition monitoring and fault diagnosis of induction motors have moved from traditional techniques to AI techniques.

The knowledge-based approach using AI and machine learning opens a pathway to exciting new research directions in condition monitoring and fault diagnosis of induction motors. During the past two decades, the most reported machine learning methods for fault diagnosis of

induction motors are the artificial neural network (ANN) or hybrid ANN combined with other techniques [22]-[34]. As one appealing feature of ANN that can be used for on-line applications, many of the proposed ANN methods are for on-line fault diagnosis of induction motors [22]-[25]. The hybrid ANN methods include: Park's vector–neural networks approach [25], an analytical redundancy method based neural network modeling [27], statistical and neural network approaches [28][29], and the convolutional discriminative feature learning method [30]. One of the most popular hybrid ANN methods is combining ANN with fuzzy logic, which can provide accurate fault detection with heuristic interpretation [31]-[34]. These techniques use association, reasoning and decision making processes as would the human brain in solving diagnostic problems [4]. In this chapter, the literature review for the research work is focused on condition monitoring and fault diagnosis of the induction motor. The main objective of this thesis is to develop a fault diagnosis method for induction motors using machine learning and advanced signal processing techniques.

A brief review of diagnostic techniques begins with the widespread motor current signature analysis (MCSA) based on the spectrum analysis of the stator current signal, which is effective for electrical machines operating at both constant speed and rated load. Transient conditions are the most critical, and several methods have been proposed to deal with this situation. They are mainly based on the discrete wavelet transform (DWT) or the Hilbert–Huang transform (HHT) [7]–[8]. Artificial intelligence (AI) is a powerful tool to improve the efficiency and effectiveness of fault diagnosis of electrical machines, especially during the maintenance decision process. AI techniques, such as expert systems, neural networks, fuzzy logic, and fuzzy-neural networks and algorithms, have been widely developed in recent years [9], even though they are not yet used at the industrial level. To give an insight into emerging new techniques related to condition monitoring and fault diagnosis for electrical machines, the following topics have been selected: Diagnosis of stator winding insulation failures

- Diagnosis of rotor faults
- Diagnosis of rotor eccentricity (RE)
- Diagnosis of gear and bearing faults
- Fault diagnosis by stray flux analysis
- Fault diagnosis by Park's vector approach
- Diagnosis under no stationary conditions
- Efficient digital signal processing techniques (DSPTs).

5. CONCLUSION

An attempt will be carried out for, the fault diagnosis of three-phase squirrel-cage induction motors by processing the measured stator current and vibration signals a machines in the lab through proposed techniques.

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