RECENT ADVANCES IN MODELING AND ONLINE DETECTION OF STATOR INTERTURN FAULTS IN ELECTRICAL MOTORS

[1]P. V. Sarode, [2]P. S. Gadhe
Assistant Professor, Department of Electrical Engineering, MSOET, Akola (M.S.), India[1], Associate Professor, Department of Electrical Engineering, MSOET, Akola (M.S.), India[2]
poojasarode05.ps@gmail.com[1], prashant.gadhe@gmail.com[2]

ABSTRACT

Online fault diagnosis plays a crucial role in providing the required fault tolerance to drive systems used in safety critical applications. Short-circuit faults are among the common faults occurring in electrical machines. This paper presents a review of existing techniques available for online stator interturn fault detection and diagnosis (FDD) in electrical machines. Special attention is given to short-circuit-fault diagnosis in permanent magnet machines, which are fast replacing traditional machines in a wide variety of applications. Recent techniques that use signals analysis, models, or knowledge-based systems for FDD are reviewed in this paper. Motor current is the most commonly analyzed signal for fault diagnosis. Hence, motor current signature analysis is a topic of elaborate discussion in this paper. Additionally, parametric and finite-element models that were designed to simulate interturn-fault conditions are reviewed.

Keywords: Analytical model, artificial intelligence (AI), condition monitoring, fault diagnosis, fault tolerance, feature extraction, induction machines, permanent-magnet (PM) machines, turn fault.

1. INTRODUCTION

In the past, fault detection in machines involved simple techniques such as overcurrent or overvoltage detection. After detection, it was required to bring the machine offline to clear the fault. In safety-critical applications, however, a shutdown of the motor may not be acceptable. This demands better fault-detection and remediation strategies. The first step in dealing with a fault in the drive is being able to detect it quickly and determine its location and severity accurately. This is particularly critical in stator short-circuit faults which can cause catastrophic damage to the machine in a very short time, making any fault compensation impossible thereafter. It has been shown in [1] that it takes less than 2 s for a single turn fault to develop into a critical fault in a typical 15-kW induction motor. Stator short-circuit faults are a problem particularly for permanent-magnet (PM) machines, since this type of fault can produce magnetic field intensity higher than the coercivity of the magnets, thereby demagnetizing the magnets permanently and, in the process, damaging the machine. However, in a fault tolerant methodology, even if the turn-to-turn fault is detected at an early stage, it is difficult to demagnetize the magnets by external means. This induces currents in the shorted turns that can damage the winding. For this reason, it is paramount that interturn faults are detected at the earliest. Short-circuit faults form 21% of the faults occurring in electrical machines [2]. It has been reported that most short circuit faults begin as interturn faults [3], which occur due to insulation failures but develop into more serious faults very quickly. Insulation failures are attributed to different reasons, with the primary reason being excessive thermal stresses. Other reasons for insulation failure include voltage stresses, aging, vibrations, or mechanical handling during assembly. Any fault is an imbalance that is reflected in the physical quantities like the torque, air-gap flux, stator currents, and others. By analyzing these signals, interturn faults can be detected. Fig. 1 shows the general steps involved in a fault-detection and-diagnosis (FDD) process in electrical motors. The signal measurement block measures physical quantities that reflect the fault. It can either be direct measurement or estimation based on observers/estimators. After the signal is obtained, fault features present in this signal are isolated in the feature extraction block. The extracted information is then fed to a fault-decision algorithm that compares it with prerecorded information on the signal to arrive at a fault decision.

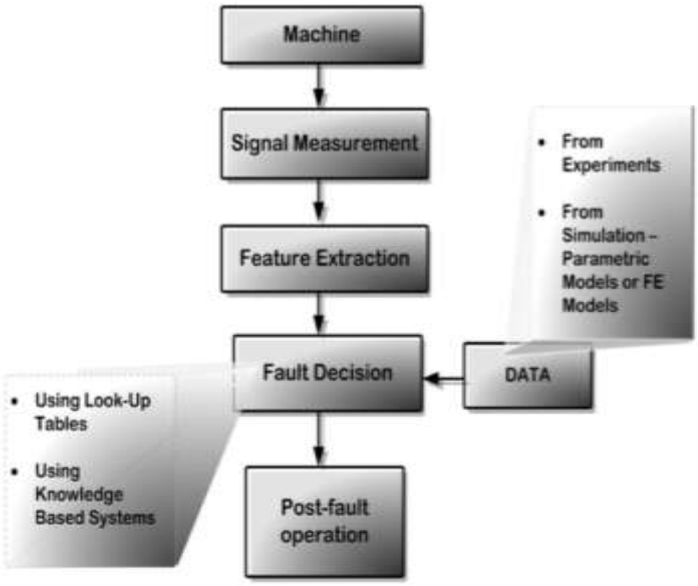

Figure 1: General overview of fault-diagnosis systems

This paper presents a review and summary of various online interturn-fault-diagnosis strategies for electrical machines with a focus on PM machines and discusses their strengths and weaknesses briefly. In this paper, the terms “fault,” “short circuit fault,” and “turn–turn fault” refer to an interturn short circuit fault unless stated otherwise.

2. MCSA

A detailed survey of different signal-processing methods that have been used to extract fault features in electric machines has been presented in [7]. MCSA has proven to be an efficient technique for fault detection and is the most sought after. In most drive systems, current sensors are already present to provide good controllability. Hence, by using stator currents for fault detection, the number of additional sensors required for fault-tolerant operation of the drive can be minimized. Also, MCSA is a completely noninvasive method for fault diagnosis. In an induction machine, the frequencies produced by interturn shorts [9] in the stator current around the base frequency are given by

$$fst1 = fs\left[\frac{m}{p}(1-s) \pm k\right] \quad (1)$$

The frequencies can be analyzed using any frequency-domain signal processing technique in order to extract the fault information. The standard method is to perform frequency analysis using Fourier transforms. Fourier series has been used to monitor the second-order harmonic component of the q-axis current (same as the third-harmonic component of phase current) in a PM synchronous machine (PMSM) under fault. FFT averages the signal in time and performs analysis in frequency domain. As the original current signal is in time domain, transforming it into frequency domain can mean loss of certain important events. These events can be speed or load variations of the machine. When such events are present, FFT is not a reliable technique for short-circuit-fault detection.

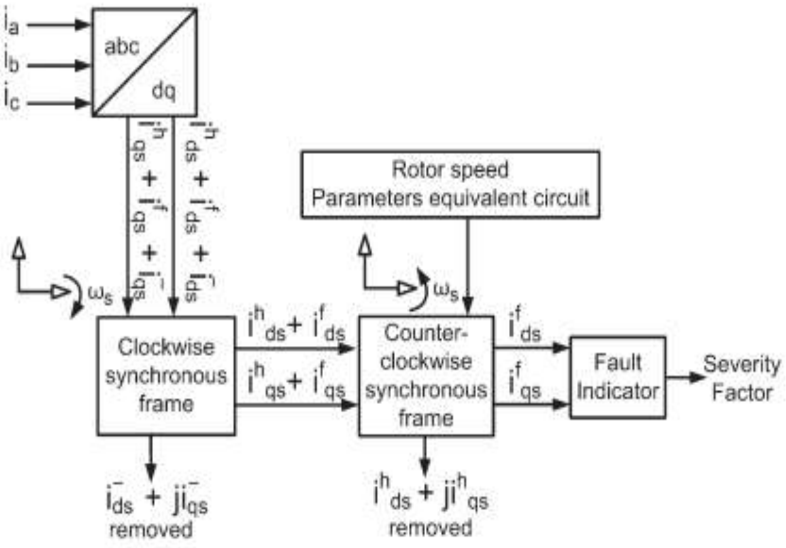

Figure 2: Multiple-reference-frame-theory-based fault diagnosis

To isolate significant fault features from the current signals when the drive is operating under dynamic conditions, it is advantageous to perform analysis in time and frequency spaces simultaneously. An extension of FFT called the short-time Fourier transform (STFT) can be used to perform time–frequency analysis. The STFT of a signal is given by

$$STFT(t,f) = \int h(t-T)s(T)e^{-2\pi fT}\,dT \tag{2}$$

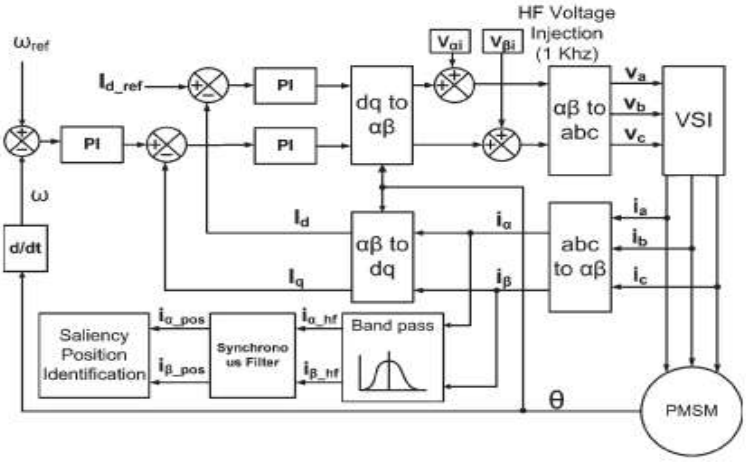

Figure 3: Fault diagnosis by HF injection technique

HF sequence components of the currents of the healthy machine were stored in a reference table. Measured HF sequence-component currents were then compared with the table values to generate residues that were used as diagnostic indices. Fig. 3 shows the blocks of the fault diagnosis method.

3. MACHINE MODELS FOR INTERTURN-FAULT ANALYSIS AND DIAGNOSIS

Computer simulation using machine models facilitates the study of short-circuit faults in electrical machines. It provides an inexpensive and convenient method for the initial development and testing of a fault-diagnosis algorithm. Machine models offer the additional flexibility of simulating different machines by changing the parameters of the model. Mathematical modeling has been the most commonly used modeling technique for studying short-circuit faults in electrical motors. A transient lumped-parameter model of a PMSM. The equivalent circuit of such a model is shown in Fig. 4.

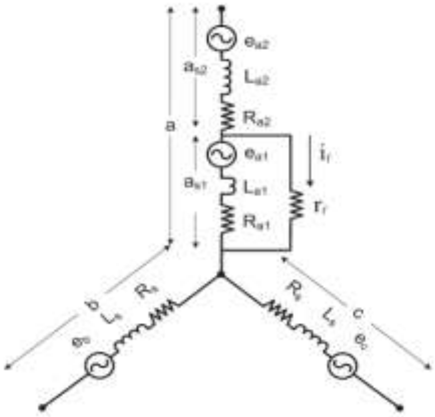

Figure 4: Equivalent circuit of a three-phase PMSM with interturn fault in phase "a"

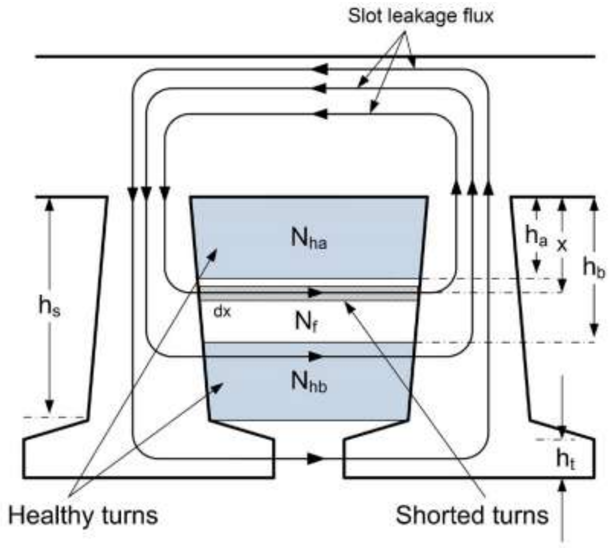

Figure5: Slot leakage-flux estimation

It is clear that machine models provide an easy way to acquire short-circuit data for fault analysis and development of fault-diagnosis algorithms, they have also been used for real time fault-diagnosis purposes. This approach to fault detection is generally referred to as model-based fault diagnosis. In this method, input to the machine is also fed to the model. Signals from both the real machine and the model are acquired simultaneously and compared against each other (residual generation) to arrive at a fault decision. This type of fault-diagnosis technique uses both the input signal and the output signal from the machine and can be completely noninvasive. During operation, the model-based fault-detection mechanism still requires the analysis of machine signals but the mathematical and computational tasks are reduced by having detailed prior knowledge of the behavior of the machine. In some cases, instead of directly using the input and output measurements for fault diagnosis, these measurements are used for state estimation. The estimated states then serve as fault diagnostic indices.

An online parameter estimation technique is used to detect faults in a PMSM with a closed-loop drive system. In this paper, the machine parameters have been estimated using a recursive least squares (RLS) algorithm. The RLS algorithm maintains the residual of the parameters at a minimum in healthy conditions.

When there is a fault, the unbalance is reflected in the estimated parameters, and the residual moves away from the minimum to indicate the fault.

In spite of the fact that FEA has become faster, it is still computationally intensive and thus considered slow for application in fault detection. The FE-based phase-variable model for fault detection. It combines the FE field model proposed and the modified winding function model to achieve considerable reduction in the computation complexity and, consequently, the time taken for fault detection.

The model is generated using field reconstruction method (FRM). FRM is used to estimate the flux linking each stator slot, which is then compared with real measured values to arrive at a fault decision (Fig. 5). This method is computationally less intensive because FEA of only one stator slot is performed and fields in the other stator slots are reconstructed using this information.

The biggest disadvantage of these model-based approaches is that any factor that was not modeled properly might lead to an erroneous detection of fault. Moreover, in the case of PM motors, which possess inherent nonlinearities, these model based approaches are to be carried out with utmost care.

4. AI APPROACHES TO FDD

Data stored can either be from a healthy machine or a faulty machine or both. In cases where less data are available, interpolation methods are used. However, this requires a higher margin of detection threshold, which slows the response to fault. Also, in case of nonlinearities, lookup-table-based fault decision systems are not very efficient.

Knowledge-based systems provide an effective alternative to lookup-table-based methods. Fault decision using NNs allows for better diagnosis of current signatures without giving false alarms. This method was used for interturn faults on an induction machine, but the method would work similarly for a PM machine.

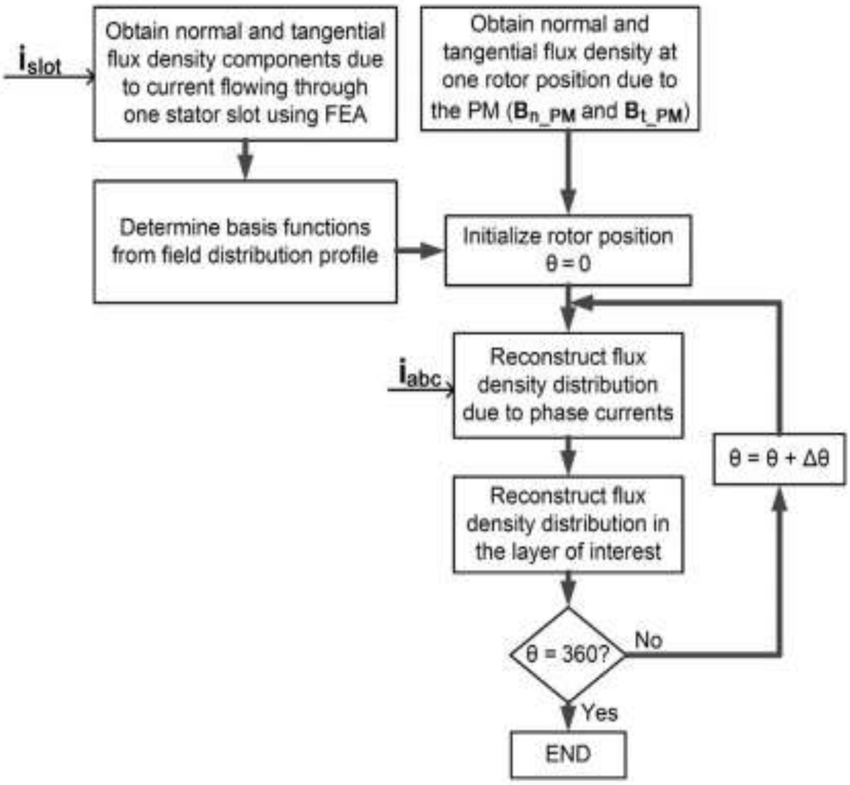

Figure6: FRM

The extracted current envelope is normalized and used as the parameter for a GMM. GMM creates a mixture for many healthy conditions as well as each type of fault considered. The detection scheme then classifies envelope signatures while running into one of these mixtures using a Bayesian maximum like lihood classifier. It classifies a new signal based on its proximity to an existing mixture. This method requires less data processing than many NN or fuzzy logic (FL) techniques, but shares other issues. For example, this method requires that the majority of the data come from fault conditions.

The problem of how many variables are needed for a best fit of an NN/FL model in the stator turn-to-turn fault detection. FFT is used to extract the fault signature from stator currents. The third harmonic of the current is identified as the best indicator. This component is then fed to an ANFIS. It should be noted that the data here on current are less granular than those of other models which would use three phase currents as inputs.

The authors use a combination of the stronger elements of NNs and FL and examine a model that uses only motor current and ωm (mechanical frequency) against one that includes three additional parameters—stator winding temperature, bearing temperature, and the noise of the motor. The five-input model also considered bearing failures, explaining the inclusion of motor noise as an input. It has been explained that a turn-to turn fault causes an imbalance in the air-gap flux, which causes a characteristic humming as the fault develops. This model improved detection by 2% over a two-input system. This illustrates the strength of AI-based fault-detection systems. It will be difficult to incorporate such noise data into mathematical-based or table-based detection methods. NNs and other AI methods are able to allow a larger range of inputs.

NNs require training using different initial values of parameters to achieve a robust model. A fuzzy NN model trained using genetic algorithms (GAs) that provides a very flexible and specific response to nonlinear situations unique to a machine construction.

In all the methods discussed, after training, the models become machine specific. Hence, for a new machine, a new set of training data will be required. Also, these methods assume that short-circuit-fault data are available to train the model. However, it is possible for unforeseen fault conditions to arise, which the model has not been trained for. As a result, the fault may not be detected or may be erroneously detected. This essentially allows the weighting of the NN on a moving basis, and the model “forgets” previous weights.

Global minimum training (GMT) is a type of training algorithm in which the NN is taught to ignore non ideal characteristics that are normal to a healthy machine. In GMT, each training vector of the database is presented to the NN several times, and the weights are updated until a sufficiently low estimation error is obtained. However, in COT, an input is presented only once. The rest of the training happens as and when data are obtained. Hence, data need not be saved to a database. The NN weights “forget” past operating conditions and only learn the present operating condition. Under COT, the monitoring regime over an interval T is divided into training and monitoring periods, where the training periods are used as the basis of the NN weights. The COT method requires no training prior to commissioning since the acceptable error is measured relative to the recently estimated states. A possible issue with this method, however, is that the model may not detect a slowly developing fault, since it will be present in all of the retained data and will be considered normal.

A method to combine the strengths of both the feed forward NN and the COT regimes is proposed using a method called Diagonal Recurrent NN. In this paper, the authors break the turn-to-turn detection solution into two—one NN detects the fault and the second one detects severity and location. This NN model is of the multilayer perceptron type and trains using back propagation algorithm. After every iteration, predicted and actual outputs are compared, and if the error is greater than a specified threshold value, the model generates an additional neuron. This method allows the model to achieve the desired accuracy using a minimum number of hidden layer neurons. This reduces computational burden.

5. CONCLUSION

This paper has reviewed different analytical, AI, and FE modeling methods developed for fault analysis and detection in induction and PM motors. Analytical modeling is by far the fastest method to analyze interturn faults but compromises accuracy. FE methods offer the most accurate simulation technique but are more time consuming. Artificial models, once trained, provide a fast and accurate simulation of the machine. However, these models are machine specific and require extensive training to provide good results under all conditions.

A purely signal-based model may be successful at detecting positives for fault behavior and will be cheap and fairly easy to implement, but incorrectly triggers for other fault situations. For this reason, a thresholding-based fault-decision process may not provide sufficient robustness. It is seen that the fault-decision process is further improved by combining feature extraction with a knowledge-based decision-making process. Motor current has been the most commonly monitored signal for faults because it is easy to monitor and no additional sensors are required. Wavelet analysis and other time–frequency analysis techniques are found to be the most efficient in extracting fault related features even under non stationary operating conditions of the drive.

Time taken to detect a fault depends heavily on the feature extraction and fault-decision processes. Algorithms used in these two steps have to be chosen and coordinated well in order to develop a quick and reliable fault-diagnosis procedure. Hence, for effective short-circuit-fault mitigation, fault diagnosis techniques must be quick in detecting not only the inception of a fault but also its location and severity. Fault diagnosis techniques developed for PM machines are few in number when compared with induction machines. There is much scope for research in this area.

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