

FAULT DIAGNOSIS OF INDUCTION MOTOR USING MULTIPLE TECHNIQUES

Abstract

Submitted by

Arunava Kabiraj Thakur

Doctor of Philosophy (Engineering)

**Department of Electrical Engineering
Faculty Council of Engineering & Technology
Jadavpur University
Kolkata, India**

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Abstract

Induction motors are robust and reliable, yet they are liable to various faults. Unplanned process downtime caused by machine failure can result in exorbitant costs. The economic losses of the process downtime caused by an unexpected outage of the machine exceed the machine maintenance costs considerably. If there are any electrical or mechanical faults in the machine, some abnormalities in the system are discovered, so fault prediction is critical to protect the machine from an unplanned shutdown.

There are limited numbers of skilled specialists for monitoring processes in the plants. Human experts are also unable to identify the exact type of fault due to different types of measurement data. The classification of fault is intended to determine the kind of fault that occurred in the machine and to distinguish the causes of the observed abnormal conditions. Following the determination of the fault condition, the necessary actions will be taken immediately to troubleshoot the problem and reduce economic loss by avoiding an unscheduled machine shutdown. Identification of unknown fault patterns in induction motors is a challenging task in modern industries. Vibration analysis technique and motor current signature analysis technique are two popular techniques for fault identification in the rotating machine, but conventional systems are not adequate to identify unknown faults, and it is very difficult to distinguish the fault types if more than one fault occurs in the machine. Therefore, a sophisticated and intelligent fault classification system needs to be developed to reduce dependency on human beings.

In this research, a robust fault classification system has been developed to identify multiple unknown fault patterns using different fault classifiers. Unknown faults have been classified among the trained known classes of six known faulty induction motors and one healthy induction motor. The unsupervised method of fault classification using current signature analysis does not need any system modelling but does need accurate training.

Agunava Kabiloj Haker
27/02/2023

Experiments were carried out using a data acquisition system to collect data samples (amplitude vs. time) of current signals from various faulty induction motors and one healthy induction motor under various loading conditions. Data samples were also taken from unknown faulty induction motors under various loading conditions.

Intelligent fault classification needs two steps: first, the features are extracted from the input signals, and then the features are fed to the classifier. Dimension reduction of features is essential for reducing computation times and memory storage of an algorithm to make the classification process simpler. Simultaneously, it is important to retain the most important features from the data and delete the redundant ones. Principal component analysis (PCA)-based feature extraction and dimension reduction techniques have been found to be more efficient than all other dimensionality reduction techniques in terms of classification accuracy. PCA can play an important role for feature extraction and dimension reduction in the current signature analysis method, while in the post processing stage; classifiers can be used for the classification of faults in induction motors. Features are extracted using PCA individually from faulty current signals in the time domain, FFT spectrums of current signals, wavelet coefficients of decomposed current signals, and cross correlated signals to compare the classification accuracies and sensitivities of different signals processing techniques. Various classifiers have been used for fault classification, such as nearest neighborhood, SVM, DDAG, and PNN.

Among various groups of known faults, the technique of the nearest neighbourhood has been used to find the unknown faults. PCA transformations of current signals in the time domain and PCA transformations of current signals' FFT spectra were used separately to make the classifications. The graph shows the two-dimensional characteristics of each phase current signal as well as the signal spectra. The "nearest neighborhood" minimum distance rule is used to classify and authenticate the three unknown faults in both domains. To determine which classification approach is better, the sensitivities of the two have been compared.

Faults have also been classified by applying multiclass SVM, and the DDAG technique has also been applied to overcome the drawbacks of the OAO pairwise SVM classification method, where training data and test data have been kept at the same load. ANNs can handle multi-class problems by producing probabilities for each class, but ANNs can also overfit if training goes on for too long—a problem that SVMs do not have. SVM models are easier to

understand. There are different kernels in SVM that provide a different level of flexibility. Classifications have been performed using the features of the time domain and the features of the frequency domain both to select the better one and to select the best SVM kernel for fault classification. The nonlinear kernels are providing better classification accuracy than the linear kernel, and there is a limitation of the linear kernel for fault classification in the time domain, but the linear kernel is able to classify faults in the frequency domain. The reason for the inability of the linear kernel to classify faults in the time domain has been explained using the linear regression method.

The faults are classified in the time-frequency domain also, and wavelet transforms are normally used for time-frequency domain analysis. For many types of signals, a variable window size is required according to the frequency to increase flexibility. It applies a variable-sized windowing technique. A shorter time interval and a longer time interval are used for the analysis of high-frequency components and low-frequency components of a signal, respectively. Signal analysis using the wavelet transform is very effective for dealing with local aspects of a signal, like breakdown points, trends, and self-similarity. The selection of the most optimal mother wavelet is a challenge when performing a task using wavelets because the same signal produces different results when applied to different mother wavelets due to their different coefficient reconstruction, de-noising, feature extraction, and component separation from the time domain and frequency domain signals, respectively. There are several mother wavelets that are used for fault analysis of induction motors. The optimal mother wavelet has been selected among various mother wavelet families for decomposition of current signals because optimal mother wavelets need to be selected for the current signature-based fault analysis method. The optimal level of decomposition must also be selected because, after a certain level of decomposition, the quality of the de-noised signal may be reduced due to data reduction. The optimal mother wavelet, including the optimal decomposition level, has been selected depending on the results of four parameters. Following the selection of the best mother wavelet, the current signals of all faulty motors were decomposed to classify three unknown faults using multi-resolution analysis. After that, the three unknown faults were classified using the multi-resolution analysis (MRA) technique of wavelets. Statistical features are extracted from the approximate and detail coefficients of decomposed signals at each level, and the Euclidean norm of each feature parameter has also

Arunava Kabiraj Haker
27/02/2023

been calculated. The unknown faults have been authenticated by calculating the norm differences.

SVM provides nearly 100% classification accuracy for fault classification in the frequency domain using the RBF kernel, where feature data from trained and test classes are kept under the same loading condition. P. Gangsar and R. Tiwari investigated the importance of fault prediction performance using a load independent classifier because finding test and training data at the same load is not always possible. The probabilistic neural network (PNN) has been used for fault classification in different domains, where the training of the model has been carried out with faults and the number of fault current signatures recorded at no load condition only, but the testing of the model is carried out with current signatures of unknown faults at three loading conditions. PNN is a type of neural network that is faster than a multilayer perceptron network and uses Bayes' optimal classification to generate accurate predicted target probability scores. PNN networks are relatively insensitive to outliers. PNN networks generate accurate predicted target probability scores. Faults have been classified by extracting the features through PCA transformation from current signals, FFT spectrums of current signals, and approximate coefficients of decomposed current signals at different levels for comparative study. The wavelet decomposition level has been found to have the highest classification accuracy. The values of the spread parameter have been varied from 0.2 to 0.8 to tune the PNN during training because the classification performance of the PNN varies due to changes in the spread parameter. The appropriate value of each spread parameter was estimated after comparing classification accuracy for each spread parameter.

Different signal processing techniques have been applied to detect faults in induction motors through current signature analysis, but cross correlation is also a signal processing technique that has been applied for fault analysis in induction motors. The cross-correlation technique is the sequence between two input signals that measures the extent of similarity between these two signals, and the idea of a cross-correlation based feature extraction technique is new in pattern recognition problems. Cross correlation has been used in this work to detect faults in the induction motors, and the sensitivities of cross correlated signals with other signals have been compared. Cross correlated signals have been developed to find the degree of correlation between the current signals of healthy motors and the current signals of faulty motors. The cross-correlation technique has been applied earlier for fault classification of transformer winding, monitoring for gearbox fault, and stator winding fault, but this

technique has not been applied to detect multiple types of fault patterns in induction machines. Three unknown types of faults were classified and authenticated using features of signals from different domains, such as time domain signals, cross-correlated signals, FFT spectra, and time-frequency domain (DWT) signals in multiple decomposition levels, using the nearest-neighborhood classification method. The features are extracted from every type of signal using the PCA transformation. Sensitivity depends on the magnitudes of the nearest distances; the higher the distance, the lower the chance of misclassification due to the large data boundary. The sensitivities of every type of signal have been compared, and it has been shown that the sensitivity of fault classification does not depend on the level of wavelet decomposition.

Key words: PCA, FFT, Wavelet transform, cross correlation, MRA, nearest neighborhood, SVM, DDAG, and PNN.

Arunava Kabiraj Hoque
27/02/2023

Alok Mukherjee
27/02/2023
Alok Mukherjee
Assistant Professor
Govt. College of Engg. & Ceramic Technology
Kolkata-700010

Anabinda Das
27/02/2023
Professor
Electrical Engineering Department
JADAVPUR UNIVERSITY
Kolkata - 700 032

Palash Kundu
27/2/23
Professor
Electrical Engineering Department
JADAVPUR UNIVERSITY
Kolkata - 700 032