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ANALYSIS OF VIBRATIONS IN INDUCTION MOTORS USING MACHINE LEARNING

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ABSTRACT

The classical multiple signal classification method has been widely used in induction machine fault detection and diagnosis. This method can extract meaningful frequencies but cannot give accurate amplitude information of fault harmonics. Machine learning is closely related to (and often overlaps with) computational statistics, which also focuses in prediction-making through the use of computers. It has strong ties to mathematical optimization, which delivers methods, theory and application domains to the field. Machine learning is sometimes conflated with data mining, where the latter subfield focuses more on exploratory data analysis and is known as unsupervised learning. Machine learning can also be unsupervised and be used to learn and establish baseline behavioral profiles for various entities and then used to find meaningful anomalies. Within the field of data analytics, machine learning is a method used to devise complex models and algorithms that lend themselves to prediction; in commercial use, this is known as predictive analytics. These analytical models allow researchers, data scientists, engineers, and analysts to "produce reliable, repeatable decisions and results" and uncover "hidden insights" through learning from historical relationships and trends in the data. In this work, the integration of machine learning for the predictive analysis of health in induction motors is proposed so that the overall effectiveness of the system can be escalated.

Keywords – Fault Detection, Induction Motor, Machine Learning, Vibration Detection,

INTRODUCTION

An induction motor is an AC electric motor in which the electric current in the rotor needed to produce torque is obtained by electromagnetic induction from the magnetic field of the stator winding. An induction motor can therefore be made without electrical connections to the rotor. An induction motor's rotor can be either wound type or squirrel-cage type [1][2].

Three-phase squirrel-cage induction motors are widely used in industrial drives because they are rugged, reliable and economical. Single-phase induction motors are used extensively for smaller loads, such as household appliances like fans. Although traditionally used in fixed-speed service, induction motors are increasingly being used with variable-frequency drives (VFDs) in variable-speed service. VFDs offer especially important energy savings opportunities for existing and prospective induction motors in variable-torque centrifugal fan, pump and compressor load applications. Squirrel cage induction motors are very widely used in both fixed-speed and variable-frequency drive (VFD) applications [3].

Induction motors are intricate electro-mechanical devices that are widely used in industrial processes and commercial installations. Such motors have extensive usage in consequence of their sturdy edifice, unpretentious installation, undemanding control strategies, and adaptability to various industrial applications. Furthermore, induction motors may plausibly be fed from an unswerving sinusoidal power supply or by an inverter fed variable frequency drive. Most of the faults in the induction motors may be detected in the nascent stages so as to prevent untimely failures -. This paper addresses induction motor faults, their causes-effects and various detection techniques that are used for incipient fault detection in three-phase induction motors.

The power factor of induction motors varies with load, typically from around 0.85 or 0.90 at full load to as low as about 0.20 at no-load, due to stator and rotor leakage and magnetizing reactances. Power factor can be improved by connecting capacitors either on an individual motor basis or, by preference, on a common bus covering several motors. For economic and other considerations, power systems are rarely power factor corrected to unity power factor. Power capacitor application with harmonic currents requires power system analysis to avoid harmonic resonance between capacitors and transformer and circuit reactances. Common bus power factor correction is recommended to minimize resonant risk and to simplify power system analysis [4][5].

Full load motor efficiency varies from about 85% to 97%, related motor losses being broken down roughly as follows:

- Friction and windage, 5% – 15%
- Iron or core losses, 15% – 25%
- Stator losses, 25% – 40%
- Rotor losses, 15% – 25%
- Stray load losses, 10% – 20%.

Various regulatory authorities in many countries have introduced and implemented legislation to encourage the manufacture and use of higher efficiency electric motors. There is existing and forthcoming legislation regarding the future mandatory use of premium-efficiency induction-type motors in defined equipment. For more information, see: Premium efficiency [6].

Many useful motor relationships between time, current, voltage, speed, power factor and torque can be obtained from analysis of the Steinmetz equivalent circuit (also termed T-equivalent circuit or IEEE recommended equivalent circuit), a mathematical model used to describe how an induction motor's electrical input is transformed into useful mechanical energy output. The equivalent circuit is a single-phase representation of a multiphase induction motor that is valid in steady-state balanced-load conditions.

Paraphrasing from Alger in Knowlton, an induction motor is simply an electrical transformer the magnetic circuit of which is separated by an air gap between the stator winding and the moving rotor winding. The equivalent circuit can accordingly be shown either with equivalent circuit components of respective windings separated by an ideal transformer or with rotor components referred to the stator side as shown in the following circuit and associated equation and parameter definition tables [7].

MAJOR DAMAGE TYPES OF INDUCTION MOTORS

The probable reasons for induction motor impairment can be a multiplicity of factors such as filth and dirt instigated temperature intensification; unwarranted vibrations due to faulty bearings; thermal stresses due to rotor rub, rotor skewing, and end ring heating; mechanical stresses due to air gap eccentricity, frequent startups, rapid acceleration and deceleration; long persistent overload conditions; transient torques due to faulty bearings, poor supply quality, and unbalanced stator phase winding; flaws in manufacture or design; imperfect installation; deterioration due to abrasion, erosion and aging. Most of the time there are copious factors that beget motor breakdown. The most unequivocal basis for motor breakdown is damage of the bearings or winding or rotor but the paramount rationale that is often an attribute to such failures is overheating prompted through dirt, filth and grime.The literature point out that majority of the failures in the three-phase induction motors are mechanical in nature such as bearing faults, misalignment or eccentricity faults and balance related faults. The commonly occurring electrically detectable Induction motor faults are as follows

- Unbalanced Supply Condition:
- Broken Rotor Bars:
- Damaged Bearing Faults:
- Inter-Turn Short Circuits

INDUCTION MOTOR FAULT MONITORING

The features used in fault detection methods are intended to classify the motor condition as faulty and healthy and also to identify the motor fault type. The detection technique is intended to identify electrically detectable faults in the induction motors and also identify the fault severity. The classifier technique classifies the Induction motor as either healthy or faulty. The fault features are extracted from a suitable motor parameter. Good number condition-monitoring propositions have concerted explicitly with sensing related failure methodologies. All of the currently accessible techniques entail the user to acquire some competence in making a distinction amongst normal operating condition from a prospective fiasco. Ideally, it is aspired to create a diagnostic procedure that endow with a clear inference of machine health in minimum time through processing of minimal measurable inputs . Various different parameters such as temperature, current, voltage, vibration, flux and acoustics have been in force for monitoring electrical machines [8].

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The existing methods of condition monitoring of electrical machines are

1. Noise Monitoring:
2. Torque Monitoring :

The air gap torque in terms of measurable motor terminal quantities is given as:

$$\text{Torque (Nm)} = \frac{P}{\sqrt{3}}\left[(I_A - I_B)\int[V_{CA} - R(I_C - I_A)dt] - (I_C - I_A)\int[V_{AB} - R(I_A - I_B)dt]\right] \quad (14)$$

Where i_A, i_B , and i_C are three-phase line currents of an induction motor,

V_{CA} and V_{AB} are line-to-line voltages

r is half of the line-to-line resistance

p is the number of pole pairs

Frequencies of major torque harmonics associated with the certain defects in induction motors are as follows:

- Under normal operation:
  - Angular frequency of torque = 0
- With a single-phase stator:
  - Angular frequency of torque = -2ωs
- With a single-phase rotor:
  - Angular frequency of torque = 2sωs

Where ω_s is the supply frequency in rad/s, and s is the slip. Therefore, the fault condition can be identified by monitoring the special harmonics in the air gap torque.

3. Flux Monitoring:
4. Vibration Analysis:
5. Current Monitoring:

CAUSES OF FAULTS IN INDUCTION MOTORS

The reason for induction motor impairment can be a multiplicity of factors such as filth and dirt instigated temperature intensification; unwarranted vibrations due to faulty bearings; thermal stresses due to rotor rub, rotor skewing, and end ring heating; mechanical stresses due to air gap eccentricity, frequent startups, rapid acceleration and deceleration; long persistent overload conditions; transient torques due to faulty bearings, poor supply quality, and unbalanced stator phase winding; flaws in manufacture or design; imperfect installation; deterioration due to abrasion, erosion and aging. Most of the time there are copious factors that beget motor breakdown. The most unequivocal basis for motor breakdown is damage of the bearings or winding or rotor but the paramount rationale that is often an attribute to such failures is overheating prompted through dirt, filth and grime [10].

The rotor failures get trigger off by an assortment of diverse stresses and strains that appear in the rotor. Stresses can be electromagnetic, thermal, residual, dynamic, environmental and mechanical ,

. The foremost reason for the rotor failure typically resides in flaws related to imperfect casting or substandard jointing during manufacturing. Whilst the rotor bar is slighter than the bar slot, slot harmonics will surface that subsequently initiate radial advance of the bar, particularly during starting-up, accelerating and braking periods. This might beget frailty consequently ensuing in fractured and ruptured rotor bar(s). Thermal stress is another quandary, occurring when the bar cannot progress longitudinally in the rotor slot. Sustained motor overloads and frequent starts, acceleration and deceleration contribute to cultivate substantial currents that bring forth considerable mechanical and thermal stresses, consequently prompting rotor and the stator damage. Even so, the induction motor rotor faults by and large onset from a minuscule crevice or a high resistivity spot in the rotor bar. This spot shows temperature intensification which worsens the damage until the rotor bar is absolutely conked out. Subsequent to a solitary rotor bar breakage, the rotor current reassigns to the other co-existing healthy bar(s) causing the over current and ultimately a cluster of broken bars. Another frequently occurring source for the rotor failures is the over-current typically due to rotor clog up condition of the motor. It is on the whole not beneficial or feasible to mend the rotor [11].

Bearing faults are one of the prominent causes that instigate the failures in induction motors. The indications of bearing mutilation are bumpy running with jerks, abridged exactness of producing shaft movement with very less rotational tolerance and an atypical noise. The bearing faults in the electrical motors can on the whole be attributed to the material attrition and abrasion at contact points, ageing and exhaustion, misalignment, sustained load over-stresses and pressure induced welding. The erosion, attrition and abrasion of the material crop up as a result of presence of contaminants and impurities, friction induced overheating and subsequent occurrence of hot spots on the bearing balls or rolls, inner and outer races. The duration of bearing life span is also reliant on the quality of the lubricant, stresses due to mechanical load and electrical starts. The frequent start ups and rapid accelerating and decelerating periods cause repeated over stressing of the bearings. Besides unfeigned overloading, the lumber on the bearing in induction motors can be due to improper alignment or rotor unbalance, and sooner or later bring forth a state of the bearing that is not appropriate for unblemished operation of the machine.

Under ideal state of affairs, the rotor potential is believed to be zero which is not practically the case. A potential relative to the ground emerge at the rotor due to inequality in phase capacitances. The rotor voltage set off a difference of potential crosswise the bearings. This leads to a current flowing through the bearing and brings about an alteration in the chemical composition of the lubricant, consequently resulting in degradation of the quality of the lubricant. This further brings in abrasion in the bearing and may sometimes set in electrical discharges between inner and outer races, eventually leading to the inopportune bearing failures. Stator faults originate in the stator core or in the stator windings. Stator winding faults can be due to several different reasons. The insulation damage can be due to impact damage during installation, movement due to repeated starting, slack core laminations, thermal damage due to over current and due to thermal aging. Stator faults are indicated by perceiving parameters such as phase unbalance of the stator currents or the axial leakage flux or the vibration content of the motor etc.

FAULT DETECTION IN INDUCTION MOTORS

The motor under test (MUT) is made to run as line-fed induction motor or an inverter fed adjustable speed induction drive (ASID), as the case may be, by feeding an apposite 3-phase supply. The data acquisition and analysis software (the popular ones are dSPACE-Matlab or National Instrument's DAQ – Matlab etc.) along with the pertinent control card is used to develop the data acquisition setup. The input signals are processed and analysed through suitable signal processing and analysis tools so as to extract fault features and present them in a format acceptable to the successive classifier stage. The interpreter stage takes a decision on the basis of fault features presented to it as regards the motor health status. The general schematic of an experimental setup for fault detection in three-phase induction motors is as shown in fig.1 below:

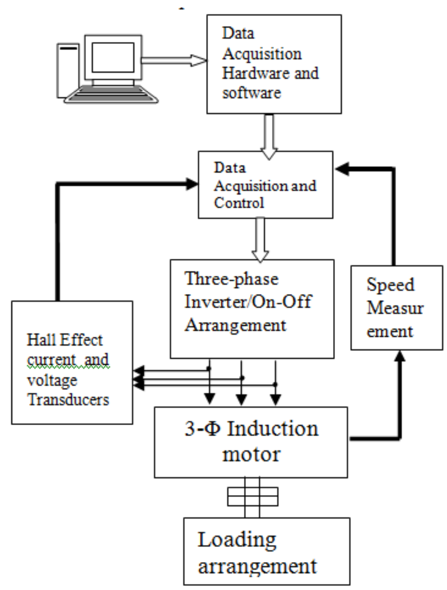

FIGURE 1 : FAULT DETECTION

APPROACHES OF MACHINE LEARNING FOR PREDICTIVE ANALYSIS

Decision tree learning - Decision tree learning uses a decision tree as a predictive model, which maps observations about an item to conclusions about the item's target value.

Association rule learning - Association rule learning is a method for discovering interesting relations between variables in large databases.

Artificial neural networks - An artificial neural network (ANN) learning algorithm, usually called "neural network" (NN), is a learning algorithm that is inspired by the structure and functional aspects of biological neural networks. Computations are structured in terms of an interconnected group of artificial neurons, processing information using a connectionist approach to computation. Modern neural networks are non-linear statistical data modeling tools. They are usually used to model complex relationships between inputs and outputs, to find patterns in data, or to capture the statistical structure in an unknown joint probability distribution between observed variables.

Deep learning - Falling hardware prices and the development of GPUs for personal use in the last few years have contributed to the development of the concept of Deep learning which consists of multiple hidden layers in an artificial neural network. This approach tries to model the way the human brain processes light and sound into vision and hearing. Some successful applications of deep learning are computer vision and speech recognition.

Inductive logic programming - Inductive logic programming (ILP) is an approach to rule learning using logic programming as a uniform representation for input examples, background knowledge, and hypotheses. Given an encoding of the known background knowledge and a set of examples represented as a logical database of facts, an ILP system will derive a hypothesized logic program that entails all positive and no negative examples. Inductive programming is a related field that considers any kind of programming languages for representing hypotheses (and not only logic programming), such as functional programs.

Support vector machines - Support vector machines (SVMs) are a set of related supervised learning methods used for classification and regression. Given a set of training examples, each marked as belonging to one of two categories, an SVM training algorithm builds a model that predicts whether a new example falls into one category or the other.

Clustering - Cluster analysis is the assignment of a set of observations into subsets (called clusters) so that observations within the same cluster are similar according to some predesignated criterion or criteria, while observations drawn from different clusters are dissimilar. Different clustering techniques make different assumptions on the structure of the data, often defined by some similarity metric and evaluated for example by internal compactness (similarity between members of the same cluster) and separation between different clusters. Other methods are based on estimated density and graph connectivity. Clustering is a method of unsupervised learning, and a common technique for statistical data analysis.

Bayesian networks - A Bayesian network, belief network or directed acyclic graphical model is a probabilistic graphical model that represents a set of random variables and their conditional independencies via a directed acyclic graph (DAG). For example, a Bayesian network could represent the probabilistic relationships between diseases and symptoms. Given symptoms, the network can be used to compute the probabilities of the presence of various diseases. Efficient algorithms exist that perform inference and learning.

Reinforcement learning - Reinforcement learning is concerned with how an agent ought to take actions in an environment so as to maximize some notion of long-term reward. Reinforcement learning algorithms attempt to find a policy that maps states of the world to the actions the agent ought to take in those states. Reinforcement learning differs from the supervised learning problem in that correct input/output pairs are never presented, nor sub-optimal actions explicitly corrected.

Representation learning - Several learning algorithms, mostly unsupervised learning algorithms, aim at discovering better representations of the inputs provided during training. Classical examples include principal components analysis and cluster analysis. Representation learning algorithms often attempt to preserve the information in their input but transform it in a way that makes it useful, often as a pre-processing step before performing classification or predictions, allowing to reconstruct the inputs coming from the unknown data generating distribution, while not being necessarily faithful for configurations that are implausible under that distribution.

Manifold learning algorithms attempt to do so under the constraint that the learned representation is low-dimensional. Sparse coding algorithms attempt to do so under the constraint that the learned representation is sparse (has many zeros). Multilinear subspace learning algorithms aim to learn low-dimensional representations directly from tensor representations for multidimensional data, without reshaping them into (high-dimensional) vectors. Deep learning algorithms discover multiple levels of representation, or a hierarchy of features, with higher-level, more abstract features defined in terms of (or generating) lower-level features. It has been argued that an intelligent machine is one that learns a representation that disentangles the underlying factors of variation that explain the observed data.

Similarity and metric learning - In this problem, the learning machine is given pairs of examples that are considered similar and pairs of less similar objects. It then needs to learn a similarity function (or a distance metric function) that can predict if new objects are similar. It is sometimes used in Recommendation systems.

Sparse dictionary learning - In this method, a datum is represented as a linear combination of basis functions, and the coefficients are assumed to be sparse. Learning a dictionary along with sparse representations is strongly NP-hard and also difficult to solve approximately. A popular heuristic method for sparse dictionary learning is K-SVD. Sparse dictionary learning has been applied in several contexts. In classification, the problem is to determine which classes a previously unseen datum belongs to. Suppose a dictionary for each class has already been built. Then a new datum is associated with the class such that it's best sparsely represented by the corresponding dictionary. Sparse dictionary learning has also been applied in image de-noising. The key idea is that a clean image patch can be sparsely represented by an image dictionary, but the noise cannot.

Genetic algorithms - A genetic algorithm (GA) is a search heuristic that mimics the process of natural selection, and uses methods such as mutation and crossover to generate new genotype in the hope of finding good solutions to a given problem. In machine learning, genetic algorithms found some uses in the 1980s and 1990s. Vice versa, machine learning techniques have been used to improve the performance of genetic and evolutionary algorithms.

Rule-based machine learning - Rule-based machine learning is a general term for any machine learning method that identifies, learns, or evolves `rules' to store, manipulate or apply, knowledge. The defining characteristic of a rule-based machine learner is the identification and utilization of a set of relational rules that collectively represent the knowledge captured by the system. This is in contrast to other machine learners that commonly identify a singular model that can be universally applied to any instance in order to make a prediction. Rule-based machine learning approaches include learning classifier systems, association rule learning, and artificial immune systems.

Learning classifier systems - Learning classifier systems (LCS) are a family of rule-based machine learning algorithms that combine a discovery component (e.g. typically a genetic algorithm) with a learning component (performing either supervised learning, reinforcement learning, or unsupervised learning). They seek to identify a set of context-dependent rules that collectively store and apply knowledge in a piecewise manner in order to make predictions.

CONCLUSION

The brief review of the commonly occurring induction motor faults has been presented. The relevant references have been mentioned for ready reference. The conventional and recent signal analysis, fault extraction and interpreter techniques have been discussed. The outcome and conclusions buoy to support the author's assumption that it is possible to employ certain new techniques so as to improve the consistency of existing, well reported, and established strategies for fault detection. Furthermore the techniques that are apt in processing non-stationary signal analysis have a definite edge over the conventionally employed techniques based upon current monitoring alone. It is worth to be mentioned that recent works in motor fault detection are anchored in analysis of stator current based on time-frequency (or time-scale) methods.

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