Artificial Intelligence for Condition Monitoring and Fault Diagnosis of Induction Motors

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***Abstract*—**Three phase squirrel cage IMs are used most commonly for industrial process. During its operation internal faults may occur due to mechanical, electrical, magnetic, thermal and environmental strains. If these internal faults are left undetected in its early stage, it leads to unscheduled maintenance, process shutdown/repair of machines and massive financial loss in industries. This requires fault detection and non-invasive condition monitoring system so as to ensure the reliable operation of the motors. Condition monitoring involves an acquisition of signals, processing, fault signature extraction and decision making on the occurrence and type of faults. This paper highlights the prevailing trends using artificial intelligence (AI) techniques for fault diagnosis and future research options.

***Keywords*—** *Condition monitoring; induction motor (IM); on-line monitoring; fault diagnosis; Artificial intelligence;*

I. INTRODUCTION

Around 80% of the industrial motors used in an industry are IMs , the main reason behind it are lower cost, ruggedness, lower maintenance requirement, robust in structure, easiness in availability and capability to work under severe working atmosphere [1]. The fault in the motor distracts the overall production of the industry that leads to increase idle time and revenue loss. For reliable operation and to reduce the idle time, early recognition of the faults is seriously desirable which necessitates condition-based monitoring of the IM. Condition monitoring is a process of noting out the operating features of a motor in such a way that any change in the drift of target constraints could be used to forecast the necessity for maintenance before any severe deterioration occurs. This infers the continuous estimation of the health of equipment's. Formerly, time-based maintenance was mainly used maintenance approach [2]. This kind of early recognition of failures can improve performance of the motor, availability, reduce consequential harm, breakdown repairs, reduce the maintenance cost and the risk of unpredicted failures. A reliable identification scheme aids in extending machine's life. Owing to this the new tendency in the industry is in the direction of condition-based preventive and predictive maintenance as a substitute of the conventional time-based maintenance. In condition based repairs one relies on the information obtained by condition monitoring systems that evaluates the machine's condition. Thus, the fundamental to the success of condition based repairs is to have an accurate means of condition valuation and identification of fault. Condition monitoring practices measurements taken when a machine is in operation for concluding whether a fault be present or not.

The condition monitoring involves use of expensive movable device (for example, a personal computer) typically with a single sensor/device input for carrying out tests at fixed intervals, capable of performing frequency spectrum investigation on a single sensor input (such as vibration or current signal). In accumulation, this needs a proficient operator to be capable for forecasting the faults in the induction motors. This type of tests are performed at long intervals (days, months and years), which may be substantially delayed for instant action, and this service may be pricy. In broad, this practices the sinals which can be easily measured mechanical or electrical quantities (speed, current, voltage, toque and flux). The IM failures have been diagnosed using different types of signal processing technique such as Fourier transform [3-4], Hilbert transforms [5] and wavelet analysis [6] on the captured motor signals. The modern researchers have used artificial intelligence techniques in combination with signal processing methods. This technique give an automatic approach for diagnosis process and obtains signals with the data acquisition card and other linkages. Afterward, using signal processing techniques the extracted features are given to the developed intelligent method for detection and diagnosis purposes.

II. IM FAULTS

The Induction machine faults occurrence possibility is given in [7,8] and is mentioned in Table I. These faults have been categorized according to the main parts of a machine – faults associated with the stator, faults associated with a rotor, bearing related faults and other faults.

TABLE I. Types of IM faults

Studied by	Bearing fault (%)	Stator fault (%)	Rotor fault (%)	Others (%)
IEEE	42	28	8	22
EPRI	41	36	9	14

A. *Bearing Faults*

These bearings comprise of an inner and outer ring with a set of balls or rolling elements located in raceways spinning inside these rings. Failures in the inner raceway, outer raceway or rolling elements will yield unique frequency components in the measured motor vibration and other sensor signals. These bearing faults cause frequencies which are functions of the bearing geometry and the speed [9]. Rotor eccentricity can also be caused by bearing faults [10].

B. Stator Faults

Stator faults are most common in IMs. Stator winding faults are often caused by insulation failure between two neighboring turns in a coil. This is called a shorted turn or turn-to-turn fault and results in further heating and produce a disparity in the magnetic field in the motor. If unnoticed, the local heating will further damage to the stator insulation till catastrophic failure takes place [11].

C. Rotor Faults

The rotor which is the interior part of an IM rotates when the supply is given to the stator of the machine by an electromagnetic field induction theory [12]. Faults which occur in the rotor of the machine are due to cracked end rings, broken rotor bars, eccentricity and shaft bent etc. However, such faults do not initiate the failure of the IM, but frequently can be responsible for their breakdown [13-14].

D. Other Faults

Eccentricity arises due to unequal air-gap distribution between the stator and the rotor [15]. This can be produced by defective bearings or manufacturing failure. If the eccentricity is large, then the unbalanced radial forces lock-up the stator and rotor. Such a condition can damage both the stator and rotor. Eccentricity in induction machines has been categorized as static, dynamic and mixed air-gap [16]. The location of minimal radial air-gap length is fixed in the case of static air-gap eccentricity while it rotates with the rotor in case of dynamic air-gap eccentricity. Static eccentricity and dynamic eccentricity concur in mixed eccentricity. It is stated that up to 10% air-gap eccentricity is permitted [17].

III. CONDITION MONITORING TECHNIQUES

There is a challenging task for experts and researchers to analyze faulty IM performance and its diagnosis under abnormal condition. Therefore, numerous condition monitoring techniques have been recognized to identify IMs. Various condition monitoring techniques of induction machines have been discussed in subsequent sub-sections.

A. Vibration Monitoring

One of the oldest condition monitoring techniques is vibration monitoring is and is usually used to detect mechanical faults for example bearing failures or mechanical imbalance [18]. A piezo-electric transducer providing a voltage signal which is proportional to acceleration is frequently used. This acceleration signal can be integrated to provide the velocity or position. An absolute measurement is measured which is relative to free space using seismic vibration transducers [19]. Relative vibration is relative to a stationary point and usually limited to the measurements of displacement [20].

B. Motor Current Signature Analysis (MCSA)

MCSA is a non-invasive, online monitoring technique for the diagnosis of an IM. In most applications stator current is monitored for diagnosis of different faults of IM [21]. MCSA is the process of acquiring signals of motor current and voltage by carrying out signal conditioning. Such current and voltage signals are acquired through a current transformer (CT). Captured data is then examined with advanced tools such as digital signal processing (DSP) tools [22], artificial intelligence (AI) techniques [23] to get more information from the signals. Various faults including loose wedges, core damages, defective bearings, inter turn shorts, foundation looseness, static eccentricity, rotor bar damages and dynamic eccentricity are noticeable by MCSA method without upsetting the motor operation [24].

C. Torque Monitoring

Different kinds of faults in IM produce harmonics that contains special frequencies in the air-gap torque. Though, the air-gap torque measurement is not possible directly [25]. The instantaneous power at the input terminals contains the charging and discharging energy in the windings. From the output terminals, shaft, rotor and mechanical load of a rotating motor constitute a torsion spring system that has its specific natural frequency [26]. Attenuation of the air gap torque is altered for different harmonic orders of the torque components approach.

D. Temperature Monitoring

Temperature monitoring of electrical motor is accomplished by measuring local temperatures of the motors. Thermal models of electric motors such as finite element and lumped parameter models have been developed by researchers [27].

E. Noise Monitoring

Acoustic noise can be measured for the noise monitoring from IM air-gap eccentricity. It has been observed from the literature review that the noise monitoring method is not effective compared to other monitoring approaches [28]. However, in all condition monitoring techniques, various sensors and actuators are used to collect data from the models. Sensors transform a signal or other physical variable from one form to another which can be utilized more proficiently by the system. Different types of sensors are outlined in Table II.

TABLE II. SENSOR CATEGORIES

Type	Examples
Mechanical Type	Positional variables, force, velocity, acceleration, torque, stress, strain, mass, pressure, density etc.
Electrical Type	Current, voltage, charge, resistance, capacitance
Magnetic Type	Conductivity, magnetic field, permeability, flux
Radiation Type	Gamma rays, x-rays, visible light, wavelength, intensity etc.
Thermal Type	Thermal conductivity, temperature, heat etc.

IV. ADVANCED ELECTRICAL CONDITION MONITORING TOOLS

High-speed development of technology has introduced various new methodologies in the repairs management which comprises the detection and localization of faults to interpose various types of faults. Advanced MCSA diagnostic tools applied to condition monitoring of IMs are [29]:

A. Digital Signal Processing Tools

DSP based algorithms are developed based on the information of frequency errors, vibration, phase unbalance, and noise. Advanced DSP methods such as Fourier transform, S-transform, short term Fourier transform (STFT), fast Fourier transform (FFT) and Wavelet transform is employed in condition monitoring of IMs [30].

B. Stator Current Park's Vector Approach

The Park's vector approach [31, 32] is based on the locus of the instantaneous spatial vector sum of the three-phase stator currents. This locus is affected by stator faults and air-gap eccentricity. The Park's vector can be analyzed graphically or by examining its frequency spectra [33].

C. Multi-criterion Analysis

The Multi-criterion analysis assesses the health condition of the IMs based on all health effectible considerations. In this method, the IM assembly is fractioned into different attributes and sub attributes such as stator and rotor winding, insulation, core and mechanical components together with external factors.

D. Artificial Intelligence Techniques

i) Artificial Neural Networks (ANN)

Artificial neural networks are modeled on the neural connections in the human brain. Each artificial neuron (shown as a circle) receives several inputs, applies preset weights to each input and produces a non-linear output based on the result [34, 35]. The neurons are connected in layers between the inputs and outputs. The training of the neural network is made by feeding in selected sets of parameters corresponding to known healthy and faulty motors and adjusting weights of the neurons to give the prerequisite output in each case.

ii) Fuzzy Logic Controllers

The fuzzy logic controller is a problem evaluating control system structure. It gives an easy track to reach a precise conclusion on the basis of ambiguous, imprecise, vague, missing inputs information [36].

V. AI BASED CONDITION MONITORING

Mo-yuen Chow et al. [37] developed a higher order neural network-based incipient fault detector which gives an accurate and real-time sign of the existence of incipient failures in ac IMs. This network provides accuracy better than that of the detectors based on the conventional neural network. The results give a high level of accuracy, more than 95%, which is acceptable for applications in real-world. R.R. Schoen et al. [38] presented a method which requires no user interpretation of the motor current signature for on-line recognition of incipient failures in IM, even in the existence of unknown line and load conditions. A choosy frequency filter learns the typical frequencies of the induction machine while working under all normal load circumstances. The created frequency table is condensed to an adaptable number through the use of a set expert system rules which is based upon the known physical construction of the machine. The list of frequencies forms clustering algorithm inputs are compared to the learned functional characteristics of a noble motor. The impending failure in motor was simulated by introducing a rotating eccentricity to the test motor. The system was able to detect the current specula variations created by the fault condition after training the neural network. J. Penman & C.M. Yin [39] proposed an artificial network which was used as a learning and pattern recognition device, able to successfully associate patterns of the input signal with appropriate motor conditions. The Multilayered perceptron (MLP) was used in the neural network which was trained by a back-propagation algorithm. The limitation of the MLP can be resolved by an alternative methodology, using unsupervised methods, like Kohonen feature maps (KFM) technique. The results of applying KFM to condition monitoring of electrical drives expose the practical gains of unsupervised schemes, which comprise the capability to learn and give classifications without supervision. Zhang Chaohai et al. [40] were developed a novel methodology for incipient faults in single phase squirrel- cage IMs for on-line by using the artificial neural-networks (ANNs). The most common types of faults are directed: bearing wear and stator winding fault under constant load torque circumstances. Simulation results indicate that ANN application is reliable for fault diagnosis in IMs. R. R. Schoen et al. [41] presented a scheme for on-line detection of IM incipient faults that requires no user intervention of the motor current signature, even in the existence of unknown and line conditions. A selective frequency filter learns the characteristic frequencies of the induction machine while operating under all normal load conditions. The generated frequency table is reduced to a manageable number through the use of a set of expert system rules based upon the known physical construction of the machine. This list of frequencies forms the neural network clustering algorithm inputs which are compared to the operational characteristics learned from the initial motor performance. This only requires that the machine be in "good" operating condition while training the system. Since a defect continues to degrade the current signature as it progresses over time, the system looks for those changes in the original learned spectra that are indicative of a fault condition and alarms when they have deviated by a sufficient amount. The combination of a rule- based (expert system) frequency filter and a neural network maximizes the system's ability to detect the small spectral changes produced by incipient fault conditions. S. Caldara et al. [42] developed a set up for a novel fuzzy-based diagnosis system, and uses a systematic methodology for the choice of the utmost meaningful diagnostic variables, the relative linguistic variables, the membership functions and the rule-base. The work also describes the diagnostic system for a linear motor drive. This allows the on-line identification of the operational conditions of the double sided linear IM drive under diagnosis with use of a fuzzy processing employing a data base. This data base is built by using tests made on the drive itself and tested experimentally. F. Filipetti et al. [43] addresses the problem of the real time load torque disturbances in asynchronous machines. This uses the current pattern to reconstruct torque pattern, using the machine itself as a torque sensor. The problem is studied utilizing both relationships developed under simplifying assumptions and a more complicated model of the machine. The results are thus obtained are compared with the experimental ones, which validates that ANN approach is efficient method for the torque pattern recognition.

R. M. Bharadwaj et al.[44] presented sensor less adaptive speed filter for IMs based on ANN. This requires only panel information and the real motor voltages and currents for the preliminary setup speed filter. This provides acceptable speed response in steady state as well as in transient state. The paper demonstrates the effectiveness and accuracy of the adaptive state filter on a challenging real-world filtering problem. Hamid Nejjari and Mohamed El Hachemi Benbouzi [45] proposed methodology based on Park's vector approach for diagnosis of IM faults. Stator current Park's vector patterns are first learned by using ANN to discriminate between "healthy" and "faulty" IM. This process was tested on both decentralized and classical approaches. The decentralized architecture facilitates a satisfactory distributed realization of new types of faults for the initial NN monitoring scheme. The result thus obtained provides the acceptable level of accuracy, signifying that hybrid Park's vector–neural networks approach is useful for industrial application. Rangarajan M.Tallam et al. [46] developed a new and novel scheme for stator winding turn fault recognition based on ANN for IMs. For learning the model of a healthy machine, a feed-forward neural network, has been used in combination with Self-organizing Feature Map to show the motor condition. This novel scheme is able to give an early indication of a stator turn fault. Experimental results show that this method is not sensitive to unbalanced supply voltages and asymmetries in the machine. I Lasurt et al. [47] describes the fuzzy logic based application for the development of innovative method for the IM condition monitoring and fault diagnosis. In this scheme, higher order statistical (HOS) analyses are used as a pre-processing process applied to a motor vibration signal. A combination of data reduction, parameterization & fuzzy logic processes is then applied to the HOS signatures for diagnosis of the motor fault. Zhongming Ye and Bin Wu & A. R. Sadeghian et al. [48] presented online fault detection algorithm based on ANN for mechanical fault in IM. Two types of mechanical faults (air gap eccentricity and the rotor bar breakage) and different load conditions, i.e. light, medium and heavy are considered. By wavelet packet decomposition of the motor stator current, new feature coefficients achieved which are used as input of the ANN. This algorithm is able to distinguish between healthy and faulty motor conditions with high degree of accuracy. S. Premrudeepreechacharn et al. [49] presented a scheme using supervised and unsurprised ANN for IM fault detection and diagnosis. After appropriate training of the ANN, this system detects the fault on the machine using current spectral of the machine. The supervised NN is capable of detecting the faulty motor, but it cannot classify the types of fault. The unsupervised NN is capable of classifying the type of fault using the magnitude of sideband component. Simulations show good learning ability and performance of the proposed technology. Michael J. Devaney and Levent Eren [50] have developed a circuit monitor for motors that are continuous in use. Incipient bearing faults are detected by the presence of characteristic motor vibration frequencies linked with the various kinds of bearing faults. They show that circuit monitors can detect these frequencies by using wavelet packet decomposition & a radial basis ANN. M. Alexandru and D. Popescu et al. [51] proposed Neuro-Fuzzy logic for IMs condition monitoring. The training set is obtained from a faulty machine dynamical model as simulator. Two Neuro-Fuzzy structures will be considered for learning the exact input-output relation of the fault detection procedure by using measured data. Results show that Neuro-Fuzzy logic may be used for precise fault diagnosis of IMs if the input data are handled in an optimized way. Tian Han et al. [52] proposed a method which integrates artificial intelligence algorithms: principal component analysis (PCA), genetic algorithm (GA) and an artificial neural network (ANN) for IM condition monitoring and fault diagnosis. Three-directional vibration signals and three-phase stator current signals are to be measured. Data transform into feature information provides a solution for multi-sensor data that makes continuous condition monitoring and diagnosis of faults where lots of data transfer is required. The efficiency of the proposed system is validated through monitoring and diagnosis of IM conditions. Hua Su and Kil To Chong [53] developed NN modeling of IM in vibration spectra for online electrical fault detection. For processing the quasi-steady vibration signals the short-time Fourier transform (STFT) is used to continuous spectra. This processed signal can be used to train the neural network model. The electrical faults are identified from changes in the expectation of modeling error. The effectiveness of the system is demonstrated based on the experimental observations. X. Huang et al. [54] proposed method for rotor eccentricity fault detection in a closed-loop IM drive system. The eccentricity-related fault signals are present in the current as well as the voltage of motor. Since the speed and mechanical load can change widely in variable speed applications, the amplitudes of the fault signals will change therefore. An ANN is used in the detection to learn the complex relationship between the eccentricity-related harmonic amplitudes and the working conditions. Corresponding to an operating condition the NN can estimate a threshold, which can be used to forecast the motor condition. The experimental results validate that this method. S. P. Santos and J. A. F. Costa [55] presented a new case study in on-line condition monitoring of IMs on the application of multiple decision trees. The database was developed through a simplified mathematical model of the motor, considering the effects which are caused by asymmetries in the phase impedances of motors. A comparative analysis is performed (based on the neural networks, k-Nearest neighbor and Naïve Bayes) for individual running and a multi-classifier (based on the Bagging and Adaboost) approaches. The results show that the multi-classifier systems give better results than those of the separate experiments. R. Saravana Kumar et al. [56] developed tools (JavaNNS and LabViEW) used to IM faults detection. Feed Forward NN has been used where the input datas are obtained from the positive and negative sequence component obtained from hardware circuit for identifying the stator fault. The side band frequency of input motor current is acquired from Tektronics power analyzer to identify the motor rotor fault. The result obtained more accurate as compared with the conventional technique in identifying the motor internal condition. Yanbin Sun and Yi An [57] proposed a scheme using MATLAB-Simulink tools. The key machine of cold-rolling electric drives is taken. RBF neural network has been designed for diagnosis. Through validating the trained network, this system proves good ability of forecasting and diagnosing the three-phase IM faults, also it has a good application prospect. D. Matic et al. [58] developed ANN for online rotor broken bar fault detection. Fault can be detected by monitoring the spectrum amplitudes at certain frequencies in the current of the motor. These discriminative features are used for training of feed-forward back ANN. Broken rotor fault can be identified by this neural network. D. M. Yang [59] has applied three vibration analysis methods- the Hilbert-based bi spectrum, the Hilbert-based bi-spectrum diagonal slices and Hilbert based summed bi-spectrum for diagnosis of IM rolling element bearing conditions. Trained ANN has been developed which has been used to automate diagnosis of the bearing condition. Results shows that the developed approach can be successfully applied and the one method based on the Hilbert-based summed bi-spectrum provides a performance which is suitable for implementation in real time condition monitoring of IM. H. Singh et al. [60] presented the diagnosis and classification of supply voltage for lowered voltage quality conditions using Fuzzy Min-Max NN. The experimental results demonstrate that the proposed scheme gives an excellent performance for detection and classification of electrical supply voltage quality to electrical motors.. S. Sornmuang and J. Suwatthikul [61] presented an application of ANN for detecting the bearing fault in IM. A feed forward network was realized to detect a very small fault in a bearing shield. This network was trained by real vibration data which is collected from a test bench. The proposed method gives an efficient result for detecting incipient IM faults. H. Singh et al. [62] have developed the fuzzy min-max NN for detection and diagnosis for broken rotor bars and eccentricity faults in IMs. A series of experiments have been conducted, where the acquired current signals under numerous motor conditions is used to form a database. The power spectral density is then used to extract the discriminative input features for detection and classification of IM faults. R. A. Patel and B. R. Bhalja [63] have developed a mathematical model of for detection of broken rotor bar fault in three-phase IM. Using MATLAB Simulink both the models (for healthy as well as defective motor) are developed. The model simulates different conditions of fault by changing number of broken rotor bars. Three-phase voltage, three phase current and THD of all currents and voltages are acquired from the model. The data thus created is used to train ANN that diagnoses the condition of IM. Gongora et al. [64] have presented a NN based method for bearing fault detection for grid connected IMs by considering the real time conditions such as unbalanced voltage and varying torque. The performance of the proposed fault method is validated by using a personal computer for online experimental tests. Turker Ince et al. [65] have developed ANN for the detection of faults in IM at early stage. This system contains two feature extraction and classification in a single body system, which has a capability to learn the optimal features with the appropriate training. This system can be easily modified to comprise the detection and classification of both mechanical and electrical faults with signatures on mechanical or electrical quantities (i.e., current).Here they used 1-D convolutional neural networks for combining the feature extraction and classification phases of the motor fault detection into a single learning framework. Juan Jose Saucedo-Dorantes et al. [66] have proposed methodology which is based on a hybrid feature reduction that provides an adequate processing of the vibration signals which is acquired from the machine. This methodology is applied to identify multiple faults in an induction machine by performing some tasks sequentially like signal decomposition, statistical-time-based features estimation, feature optimization using genetic algorithm in combination with the principal component analysis, feature selection (by means of Fisher score analysis),feature extraction & finally different faults are identified by a classifier which is NN based. The performance and the effectiveness is validated experimentally and compared with classical feature reduction schemes, making this methodology suitable for industrial application.

VI. CONCLUSION

Online monitoring and diagnosis for real time systems is a challenging task before researchers. AI based condition monitoring of IM was discussed in this paper provides more accurate, efficient and easy diagnosis for numerous types of the fault of an IM. The modeling and analysis of induction machines using AI aid to avoid the different type of recoverable financial loss and non-recoverable time loss. This paper has provided brief survey of current research in condition monitoring using AI technique. The future research scope is to develop methodology for combined multiple faults for continuous remote monitoring of induction motors in hazardous localities (such as petroleum processing plants or remote mining sites) and in critical applications where the maximum reliability is required.

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