Condition Monitoring Techniques for Induction Motors

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Abstract – **Induction motors are used in various work environment and critical industrial processes, operating conditions and well-being of these machines need to be monitored to avoid potential failures. In this paper, an extensive literature review is conducted for condition monitoring techniques for induction motors. Various state-of-art techniques are presented and summarized under three categories: 1) signature extraction based approach, 2) model-based approach, and 3) knowledge-based approach. Advantages and drawbacks of several commonly used methods are demonstrated. Although research has been conducted in this area for several decades, condition monitoring and fault diagnosis of induction motors remains an active research area, especially recent emerging transition from traditional techniques to knowledge-based approach using artificial intelligent, which opens a pathway to an exciting new research direction.**

Index Terms — **Artificial intelligent, condition monitoring, induction motors, machine learning, signal processing**

I. INTRODUCTION

Induction motors are most widely used electric machines in various industrial sectors and home appliances due to their compactness, ruggedness, and reliability features. Compare to other types of motors, induction motors require the least maintenance. Although relatively robust, faults still occur in induction motors, which can interrupt critical processes and production [1][2][3].

The maintenance of an induction motor can be classified into three types: 1) scheduled maintenance; 2) breakdown maintenance; and 3) condition-based maintenance. The scheduled maintenance involves the planned scrutiny and repair of machines at a given time, which usually requires an expert to effectively overhaul and pinpoint motor defects, so that repair can be done before the machine resumes work. The breakdown maintenance employs the process of allowing the machine to run until it eventually wears out. This maintenance methodology is more costly, due to having to replace the entire machine rather than repair or replace parts. The condition-based maintenance includes observing and getting periodic update about the condition of a machine during operation and taking proactive step when a fault is at the incipient stage, to avoid severe damage and unplanned process down-time [1]. Therefore, it has become necessary to develop a condition-based maintenance culture, which will prevent untimely interruption of work process, reduce process downtime and maintenance costs [1][2][3]. The principal objective of condition monitoring techniques is to construct a reliable mechanism for fault detection at the incipient stage, so that the machine can be shut down in a controlled manner for checking and repairing, thus avoiding excess outage time imposed by sudden breakdown [2].

Industrial survey has revealed that a large percentage of faults occur at stators, rotors, and bearings [2]-[5]. The statistical percentages of fault occurrence and fault types are shown in Fig. 1 [1]-[5]. Similar survey results for medium-size induction motors conducted by IEEE industrial application society (IAS) and Electric Power Research Institute (EPRI) are provided in Table I [6].

Faults in machines usually occur in a cascade sequence, a certain fault occurrence at a point in the machine could deteriorate and cause a more severe fault occurrence at other location in the machine. For example a fault stimulated by unbalance voltage supply initially provokes an inter-turn fault through stator winding insulation degradation, which could further deteriorate to a single line fault and a line-to-line fault [1]-[3]. The cascade fault sequence phenomenon makes it imperative to detect faults at the incipient stage [3].

The fault detection can be divided into three fundamental categories: 1) signature extraction based approach; 2) model-based approach; 3) knowledge-based approach [7][8]. Condition monitoring techniques can also be classified into two broad types: invasive and non-invasive. Table II highlights advantages and disadvantages under the two types.

In this paper, an extensive literature review is conducted for state-of-the-art condition monitoring techniques for induction motors. The three fundamental categories are discussed in detail serving as the backbone of the paper. These approaches are applied to detect several critical conditions of induction motors including broken rotor bars, stator winding inter-turn fault and insulation deterioration, bearing fault. The objective of this review is to strike a balance between accuracy of methodology and implementation constraint with economic advantage in view.

The paper is organized as follows: in Sections II, III and IV, the signature extraction based approach, the model-based approach, and the knowledge-based approach are explained, respectively, several techniques related to each approach are demonstrated; conclusion are drawn in Section IV.

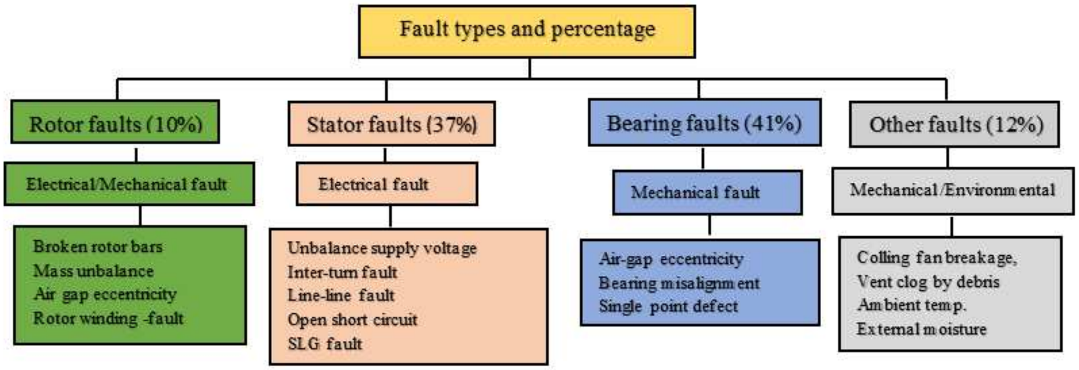

Fig. 1. Fault types and percentage of occurrence in induction motors [1]-[5]

TABLE I
FAULT SURVEY RESULTS FOR INDUCTION MOTORS FROM IEEE-IAS AND EPRI [6]

Major Components	IEEE-IAS % of failures	EPRI % of failures
Bearing related	44	41
Stator related	26	36
Rotor related	8	9
Others	22	14

TABLE II
ADVANTAGES AND DISADVANTAGES OF INVASIVE AND NONINVASIVE METHODS

Invasive Methods		Non-Invasive Methods	
Advantages	Disadvantages	Advantages	Disadvantages
Provide accurate and reliable results through the use of sensors	Installation of special sensors are required	Does not require installation of special sensors.	An indirect approach
A more direct approach	Complex installation process	Relatively easy implementation procedure.	It might require expert's opinion.
It might not require much expertise to understand result.	A more expensive technique	More economical approach	It does require a more analytical approach
	It might interference with motor normal operation during application.	No interference with normal motor operation during application.	

II. THE SIGNATURE EXTRACTION BASED APPROACH

The signature extraction based approach is utilized by surveying fault signatures in time and/or frequency domain. Signatures extracted from recorded signals are employed to diagnose faults. Significant amount of research has been done in this area [8]. Among various condition monitoring techniques, monitoring signals can be current, voltage, or power, vibration, temperature, and acoustic emission.

When considering condition monitoring, the investigation usually involves steady-state and transient-state modes. Prior to the innovation in signal processing, researchers concentrated on fault detection techniques in steady-state mode, which includes techniques such as Fast Fourier Transform (FFT). With the innovation in signal processing, techniques that study transient mode have attracted more research interests [2].

A. *Broken Rotor Bars (Steady-state Analysis)*

It has been proven that faults of induction motors introduce additional frequency components in the stator current signal, therefore, stator currents as input data are widely used in condition monitoring, and the frequency spectrum of the stator current is analyzed for condition monitoring purpose [2]-[5], [9]-[15]. The classical approach used in an industrial environment for the detection of broken rotor bars in induction motors is based on the analysis of the stator current in steady state [15].

Among various spectral analysis methods, Motor Current Signature Analysis (MSCA) is one of the most popular techniques for online monitoring induction motors in an industrial environment. It has remote monitoring capability using the stator current as monitoring signal, which can be conveniently measured at the motor control center. This remote monitoring capability is an advantage of MCSA over vibration, speed, or flux spectrum analysis. MCSA has been most successful in detecting broken rotor bars or end rings [9].

The frequency of the motor current spectrum for a faulty motor with broken rotor bars is characterize by a certain upper and lower band frequencies, otherwise known as sideband frequencies [2]-[5],[9]-[15]. Most research on broken rotor bar fault have mainly focused on steady-state condition. Nonetheless, some research investigation has shown that steady-state study cannot be relied on under certain conditions [16].

For a healthy motor, there is symmetry of cage winding, and only forward rotating field exist, thus, the rotor frequency equation is shown in Equation (1). However, with the presence of a broken rotor bar fault, asymmetry exists and a resultant backward rotating field relative to forward rotating rotor generates additional frequency in the motor current harmonic spectrum [13]-[15]. The frequency is known as a lower side band rotor frequency expressed in Equation (2). An upper sideband current constituent is prompted by the stator winding, which due to rotor oscillation as shown in Equation 3 [10]-[16].

$$f_2 = sf_1 \quad (1)$$

$$f_{b\_lower} = f_1(1-2s) \quad (2)$$

$$f_{b\_upper} = f_1(1+2s) \quad (3)$$

From Equations (1)-(3), the broken rotor bar fault generates a resultant current constituent of frequencies expressed in Equation (4) [4][5],[10]-[16].

$$f_b = f_1(1 \pm 2s) \quad (4)$$

Where f_b represent broken bars frequency, f_1 is the supply frequency, and s is the rotor slip.

References [9][10] provide a general formula for multiple frequency bands related to a broken rotor bar as follows:

$$f_b = f_1(1 \pm 2ks), k = 1,2,3... \quad (5)$$

It is reported in [10] that additional frequency components related a broken rotor bar exist, which can be observed from the stator current harmonic spectrum as follows:

$$f_b = \left[\left(\frac{k}{p}\right)(1-s) \pm s\right] f_1 \quad (6)$$

Where p is the number of pole pairs, and k/p = 1, 2, 3.

A single broken rotor bar could not instantaneously cause induction motor failure. However, a multiple broken rotor bars could cause motor start-up failure due to insufficient accelerating torque during start-up procedure [10].

MCSA provides sensitive detection of broken rotor bars, the criterion for fault threshold is well established between −50 dB and −35 dB with respect to the fundamental component [9].

Although MCSA has been successful in the field, false fault indication is a common issue using this technology. A false positive (FP) indication (false alarm) refers to the case where a fault alarm is given for a healthy rotor, which can result in unnecessary inspection of the motor and interruption of the process. A false negative (FN) indication refers to the case where MCSA fails to detect the fault condition. The consequence can be very serious. For example, protrusion of a broken bar or a bar fragment into the air gap or stator end winding can lead to a forced outage of the motor and the entire process that it drives. Fig. 2 shows a broken bar fragment causing stator end winding insulation failure of a 6.6-kV 500-kW induction motor. Typical causes of FP and FN are shown in Table III [9].

As an example, the rotor axial air duct causing FP as listed in Table III is demonstrated in [17]. Rotor axial air ducts are used in large motors for cooling and reducing weight and material. Axial air ducts cause the reluctance of the magnetizing flux path to vary depending on the relative position between rotor ducts and the rotating magnetic field. The magnetic asymmetry produced by air ducts can result in the modulation of the magnetizing current proportional to twice the slip frequency, i.e., $2sf1$. The ducts produce $2sf1$ current sidebands if the pole number of poles and the number of air ducts of the motor are equal. In this case, the modulation of stator current causes torque pulsation and motor vibration at $2sf1$, which can be misinterpreted as rotor faults, when current- or vibration-based spectrum analysis is performed. A direct example of this from the field is a 6.6-kV 2400-kW eight-pole motor at a power plant in USA that was diagnosed with rotor damage. The broken-bar frequency component measured with MCSA was between −32 dB and −37 dB, which exceeded the alarm level and indicated a broken rotor bar. The vibration spectrum analysis indicated a broken bar as well. However, when the motor was examed, it turned out to be a false positive indication due to equal number of axial kidney holes and poles in this motor [17].

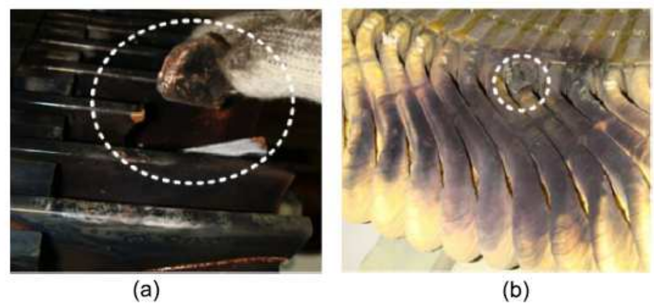

Fig. 2. Stator end winding insulation failure due to broken rotor bar fragment in a 6.6-kV 500-kW induction motor [9]

TABLE III
TYPICAL ROOT CAUSES OF FP AND FN INDICATIONS PRODUCED BY MCSA-BASED ROTOR FAULT DETECTION [9]

Actual rotor condition	Diagnosis of MCSA: Healthy	Diagnosis of MCSA: Faulty
Healthy	True Negative	False Positive • Low frequency load oscillations • Axial air duct • Magnetic anisotropy • Rotor ovality • Porosity (*Al* die cast rotor)
Faulty	False Negative • Outer cage fault in double cage rotor • Nonadjacent broken bars • Load variation • Incorrect speed estimate	True Positive

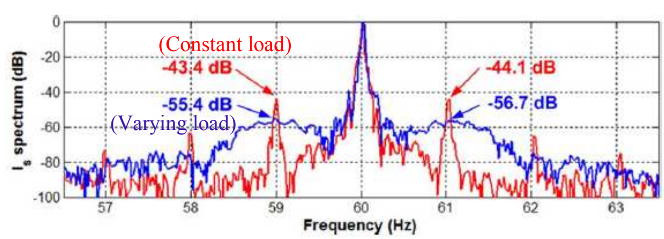

Fig. 3. MCSA results for the same motor with a broken rotor bar under a constant load and a gradual varying load condition [9].

Another issue with MCSA is that MCSA is intended for steady-state operation, so it becomes ineffective for cases where the load level varies with time. MCSA results for the same motor with a broken rotor bar under a constant load

(1785 r/min) and a gradual varying load (1775–1795 r/min) condition are shown in Fig. 3. It is found that the f_b component exceeds −45 dB for the case of a constant load, which can lead to a correct fault detection, but for the case a gradual varying load, the f_b component is measured below −55 dB although the machine does have a broken rotor bar[9].

In addition to the MCSA, a subspace spectral estimation technique, also known as high-resolution spectral analysis, is proposed in [18] to detect broken rotor bars and bearing faults. Stator current measurements serve as the signal. The advantage of this technique is that it can detect the faults and also determine their severity. Frequency components including frequencies close to the fundamental frequency are separated based on high-resolution spectral analysis. Once fault sensitive frequencies are estimated, their corresponding amplitudes are obtained by using the least squares estimator, and a fault severity criterion is derived from the amplitude estimates [18].

The fault severity is represented by Fault Severity Criterion (FSC) values, a higher FSC value means a more severe fault. Fig. 4(a) shows the FSC values for an induction motor vs. the number of broken rotor bars (BRBs), where 0 corresponds to a healthy induction motor without a broken rotor bar, and other values correspond to the number of broken rotor bars. The two methods, Root-MUSIC and TLS-ESPRIT, are used and show comparable results in Fig. 4(a). Fig. 4(a) indicates that the FSC value increases with the number of broken rotor bars. Fig. 4(b) shows the FSC values vs. sample number using the TLS ESPRIT method. This figure indicates that the FSC values also increase with sample number [18].

B. Broken Rotor Bars (Transient Analysis)

Although widely used, the spectral analysis of the stator current in steady state for broken rotor bar detection has two major issues: 1) load dependence; 2) exterior influences.

Regarding load dependence, the separation of the frequency associated with broken rotor bars and the main frequency is dependent on motor inertia, and thus, as load increases, the separation increases. With a lower load, the separation could decrease until both spectral lines cannot be distinguished, making it difficult to detect the fault. Under the aforementioned condition the steady state investigation technique cannot be termed reliable [15]. Also, continuous fluctuations of motor load gives rise to changes in frequency associated with the broken rotor bar, thus, making it difficult to automatically detect the rotor fault [15].

Regarding external influences, frequencies similar to those used for rotor bar breakage detection can be generated by other causes, such as low-frequency oscillating torque loads, voltage fluctuations, bearing faults, voltage fluctuations etc, which reduces reliable fault detection [15].

To overcome these problems, the analysis of the current and/or other magnitudes during transient processes of induction machines have been recently investigated [14][15][19].

In References [14][15], an algorithm to detect broken rotor bars based on Discrete Wavelet Transform (DWT) application on start-up current transient is proposed. A phenomenon known as single mean-square computation determines a weighing function, and from its value, motor

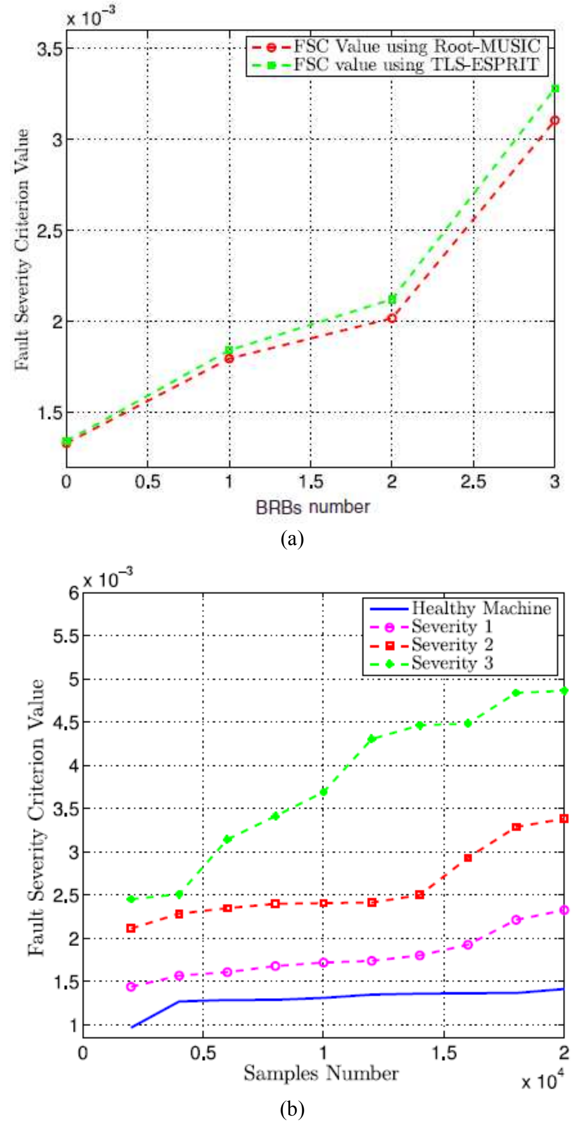

Fig. 4 FSC values: (a) FSC vs. the number of BRBs, (b) FSC vs. sample number using TLS ESPRIT [18].

condition is monitored online. The Field Gateway Programmable Array (FGPA) is used for the implementation of the algorithm. The method uses time-scale decomposition of the original signal to detect the frequency associated with broken rotor bar fault and determine its severity. The amplitude of frequency associated with broken rotor bars increases when there is increase in load and the number of broken rotor bars. When the load on motor is near a name-plate value, the speed of the motor is far below that under no load. In this state, the motor fault frequency related to broken rotor bars is more alienated from the main operating frequency, thus making it easy to detect. However, when the motor load is close to no-load, the fault frequency associated with broken rotor bars becomes difficult to identify because it's close to the motor operating frequency [14][15].

The Wavelet theory has proven to be a powerful tool for the analysis of transient processes. The DWT decomposes the motor start-up transient current into a set of low frequency signals. Each signal contains the information of the original signal within a certain frequency band. When a broken rotor bar occurs, a characteristic harmonic with a particular frequency variation appears during the motor startup process. The evolution of this harmonic is reflected clearly in the low-frequency wavelet signals, which allows the detection of broken rotor bars because the same healthy machine will not have such a particular frequency variation. The proposed approach in [15] focuses on low frequency high-order wavelet signals, the frequency bands for these signals are shown in Table IV. Fig. 5 shows the Wavelet analysis of a start-up current and the FFT analysis of a steady-state current for a loaded machine with two broken rotor bars [15].

TABLE IV
FREQUENCY BANDS FOR HIGH ORDER WAVELET SIGNALS [15]

Level	Frequency band
$d7$	19.53 – 39.06 Hz
$d8$	9.76 – 19.53 Hz
$a8$	0 – 9.76 Hz

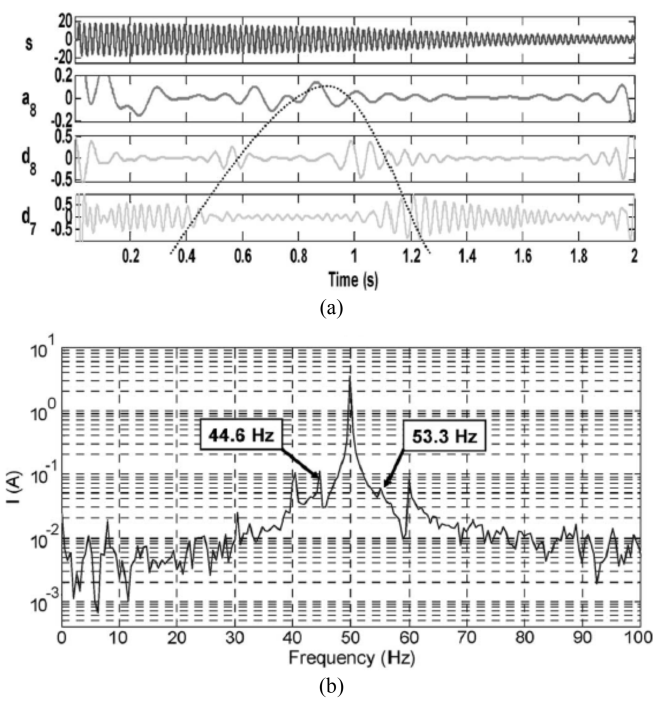

Fig. 5 Loaded machine with two broken rotor bars. (a) Wavelet analysis of start-up current, (b) FFT analysis of the current in steady state [15].

To apply the proposed method in [15], the guideline is that the start-up time of an induction motor should be longer than 0.5 s. One drawback of this method is that it is not suitable for induction motors supplied power by variable frequency drives.

Luckily, the broken rotor bar detection for variable speed drive-fed induction motors at start-up can be achieved by high-resolution spectral analysis proposed in [20], where the time–frequency spectrum is able to graphically show a different pattern for healthy and faulty conditions of the motor [18][20].

Reference [19] proposes an automated method for the detection of the number of broken rotor bars of an induction motor. It is based on transient analysis of the start-up current using wavelet approximation signal, which isolates a characteristic component that emerges once a rotor bar is broken. After the isolation of this component, a number of stages are applied that transform the continuous-valued signal into a discrete one [19].

C. Stator Winding Inter-turn Faults and Winding Insulation Monitoring

Stator faults such as a single line to ground fault are often a result of winding insulation degradation. The inter-turn defect is considered to be the source of insulation deterioration resulted from the cumulative damage from the dielectric stresses of overvoltages, high temperature, and other adverse conditions. If undetected, these defects can increase in size until a catastrophic fault occurs, thus damaging the machine. The early detection of stator winding insulation deterioration prior to a complete failure provides an opportunity for a scheduled maintenance to be performed without the loss of production time [2]-[5][10][21][22]. Several techniques are proposed: effective negative-sequence impedance [22], voltage mismatch [21][23], short term averaging of forwards and backwards rotating stator current phasors [24], air-gap flux [25], and three-phase currents [13] etc.

When the three-phase currents monitoring method is used, a harmonics analysis is required. Ideally, only a single space harmonic exists in the rotor magnetic field of an induction motor, but in actual machines, owing to rotor slotting; the rotor magnetic field does have additional harmonics [13].

It has been reported in [10] that axial leakage flux can help detect inter-turn fault. Voltage induced in a search coil place in the centre of the machine shaft is a function of the flux component [11]. Equation (7) is the voltage spectral component used for detecting this fault type known as rotor slot harmonics [5][13].

$$f_t = \left[k \pm \left(\frac{n}{p} \right) (1-s) \right] f \qquad (7)$$

Where $k = 1, 3$, $n = 1, 2, 3$ and p is number of pole pairs, and s is the slip. The rotor slot harmonics frequency depends on the number of rotor slots, supply frequency, slip and machine pole pairs. Rotor slot harmonic order can be calculated as follows [10][13]:

$$H_{RSH} = k\frac{N_r}{p} \pm 1 \quad (8)$$

Where N_r represents number of rotor slots, p is number of pole pairs, k=1, 2, 3…

D. Bearing Faults - Vibration and Acoustic Monitoring

The bearing is an indispensable component of any electrical motor. Main duty of bearings is to provide slipping of the rotor inside the stator, maintaining a uniform air gap. Generally, there are two kinds of bearings, sleeve and rolling-element bearing. More often, rolling element (ball and roller) bearings have been used in many electrical machines while sleeve bearings are a good fit for large electrical machines. In general, a bearing has three main components that can typically experience damage: inner race, outer race and rollers or balls [27]. Because bearing fault accounts for most fault in induction machines, thus it is of almost importance to monitor bearing condition [28].

Vibration signal analysis is the most industrial accepted approach. Motor vibration data contains substantial analytical information about stator and rotor winding and core condition, air gap eccentricity, voltage or current unbalance etc. Most research on detecting bearing failure is based on vibration analysis [29][30].

A motor current spectral method for bearing fault detection is proposed in [28][31]. Their findings recommend that fault frequencies property that are present in motor vibration as a result of bearing faults can also be detected in the motor current. However, bearing defect in motor current is more tedious to detect than bearing defect in motor vibration. There are two types of bearing faults. Single point defects and generalized roughness. Fig. 6 represents a flow chart of the types of fault and their characteristics effects [31].

Every bearing fault has characteristic frequencies, which are expressed as follows [32]:

$$F_{CF} = \frac{1}{2}F_R\left(1 - \frac{D_B\cos(\theta)}{D_p}\right) \quad (9)$$

$$F_{ORF} = \frac{N_B}{2}F_R\left(1 - \frac{D_B\cos(\theta)}{D_p}\right) \quad (10)$$

$$F_{IRF} = \frac{N_B}{2}F_R\left(1 + \frac{D_B\cos(\theta)}{D_p}\right) \quad (11)$$

$$F_{BF} = \frac{D_P}{2D_B}F_R\left(1 - \frac{D_B^2\cos^2(\theta)}{D_P^2}\right) \quad (12)$$

Where D_p represents ball pitch diameter, F_R represents speed of rotor, θ is ball contact angle, N_B is number of balls, and D_B is ball diameter [32].

This method uses the peak amplitude signal as the indices for bearing fault detection. Amplitude signal for healthy and faulty bearings for no load and full load were obtained. It was discovered that amplitude peak increases when the size of outer race of bearing defect increases. For a varying load there was a varying amplitude peak, large enough to detect fault condition [30] [32].

The advantage of acoustic emission (AE) monitoring over vibration monitoring is that the former can detect the growth of subsurface cracks, whereas the latter can detect defects only when they appear on the surface. It is also important to note that the energy released by neighboring components in the vibrational frequency range (up to 50 kHz), which often masks the vibrational energy released from a defective rolling element bearing, do not affect the AE signal released in the very high frequency range.

Nevertheless, the direct vibration spectrum from a defective bearing may not indicate the defect at the early stage [27][32]. Figs. 7 and 8 shows vibration velocity signal output for a healthy and a faulty motor conditions [32].

E. Signal Injection Techniques

The signal injection based temperature estimation technique is an invasive method that requires injecting either a DC or an AC signal into the system [33]-[43].

The dc current injection technique was first introduced in 1980 by Derek A. Paice [33]. The idea is to let a small dc current (3% of the rated ac current) to flow through the motor winding in one phase by means of a series asymmetric resistance. From the measurements of the dc current and dc voltage, the stator winding resistance and the temperature can be evaluated.

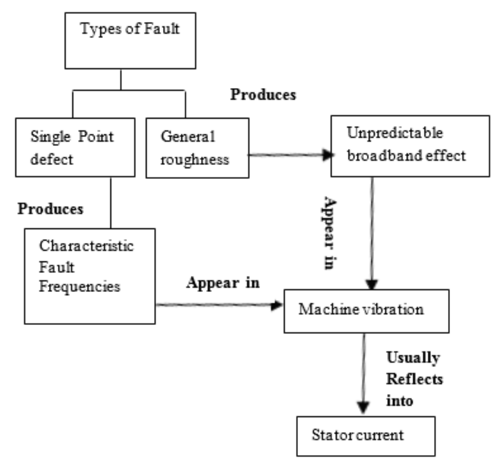

Fig. 6. Flowchart showing effects of two categories of bearing faults [32]

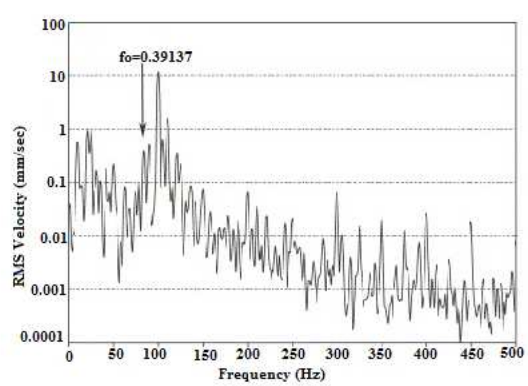

Fig. 7. Spectrum of vibration velocity of a motor with a healthy bearing [32].

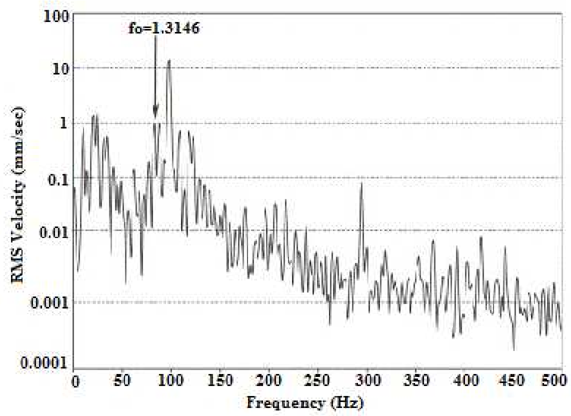

Fig. 8. Spectrum of vibration velocity for a motor with 1500μm bearing defect [32].

The disadvantages of the DC signal injection approach include: 1) additional hardware is required to realize the signal injection, 2) the estimated temperatures are average quantities so local hotspots in electrical circuits cannot be identified, and 3) the continuous injected dc current could cause torque pulsation and magnetic saturation.

Reference [41] proposes an improved DC signal injection technique for stator-resistance (R_s)–based thermal monitoring of small line-connected induction machines. A simple device is developed for injecting a small dc signal into line-connected induction machines for stator resistance estimation. The proposed scheme intermittently injects a controllable dc bias into the motor with very low power dissipation, which reduce the influence of torque pulsation caused by continuous injected dc current in [33]. Fig. 9 shows this DC signal injection approach [41]. The obtained varying dc resistance can be used to perform temperature estimation and determine thermal time constant. This procedure is independent on parameters of the machine, nor model. It's relatively simpler method than the thermal model [35]. Based on the linear relationship of resistivity with temperature of the stator winding, the stator winding temperature is estimated as follows [38][41][43]:

$$T = T_0 + \frac{R - R_0}{\alpha R_0} \quad (13)$$

$$R = R_0[1 + \alpha(T - 25)] \quad (14)$$

Where R_0 represents winding resistance at 25°C, α is a constant and a property of winding element, R_0 and R are the resistance at T_0 and T, respectively.

The AC signal injection monitoring techniques are proposed in [34]-[38]. Both high frequency and low frequency signal can be used for this technique.

Stator resistance - rotor resistance $(R_s - R_r)$ based induction machine temperature estimation is proposed in [39]-[43]. Based on the estimated stator resistance and rotor resistance, stator and rotor temperature are estimated correspondingly [40].

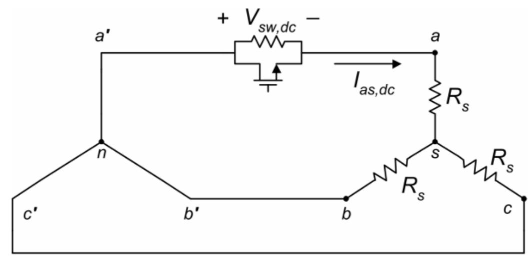

Fig. 9. DC equivalent circuit of source, motor and DC injection circuit [41].

III. The Model-Based Approach

The model based approach relies on machine's mathematical modeling. Various approaches have been proposed to model the behavior of the induction motor under fault conditions [8].

In Reference [44], an algorithm shown in Fig. 10 was developed for modeling and simulation of transient state of induction motor. The unbalanced voltage problems can be simulated using the created direct mathematical model of the induction motor.

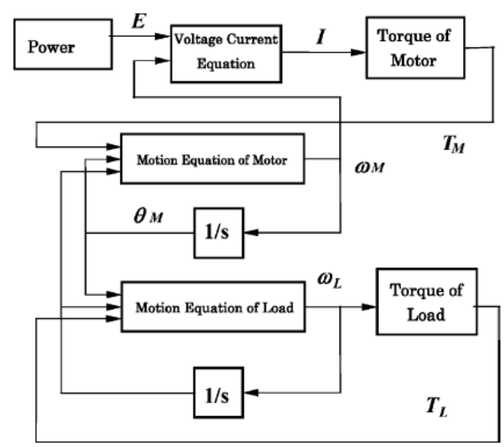

Fig. 10. Block diagram of mathematical model for induction motors [44].

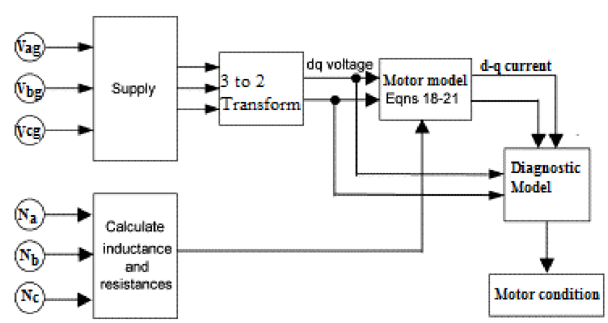

Fig. 11. Simulation of an asymmetrical induction motor model [47]

In References [45]-[47], Matlab/Simulink model of induction motor was implemented and simulated results were analyzed for different faults conditions. The d-q model transform was employed for modeling of induction motor. Both healthy condition and asymmetry condition modeling for stator inter-turn fault was carried out. Fig. 11 shows simulation model for an asymmetric induction motor [47].

IV. The Knowledge-Based Approach

Artificial intelligent techniques have been applied in fault diagnosis of very complex time-varying and non-linear systems. However, their application in condition monitoring and fault diagnosis of induction motors is new.

A comparison of various artificial intelligent methods including Naive Bayes, k-Nearest Neighbor (KNN), Support Vector Machine (Sequential Minimal Optimization) (SVM/SMO), Artificial Neural Network (Multilayer Perceptron) (ANN/MLP), Repeated Incremental Pruning to Produce Error Reduction, and C4.5 Decision Tree is provided in [48], it is found that for stator faults, the KNN, and ANN/MLP methods show better performance with 100% accuracy; for broken rotor bars faults, both ANN/MLP and KNN methods have accuracy rates over 99.7%; for bearings faults, the KNN, ANN/MLP, and C4.5 methods present promising results; for multi-classification, the ANN/MLP and KNN methods exceeds 92.5% accuracy; for robustness tests with defective bearings, the SVM/SMO method shows the best performance in terms of accuracy and processing time [48]. Based on the comparison, it shows ANN has the best performance for various fault detection. In addition to ANN, the SVM started gaining attention recently in this research area, SVM has excellent performance in generalization, so it can produce high accuracy in classification of machine condition monitoring [30].

The implementation of ANN models for Fault prediction hinges in the fact that they can be used to infer a function from observations. This technique comes handy in applications when it`s practically impossible for computation to be done manually due to complexity of the data. Back-Propagation (BP) neural network is the most common type of ANN employed for solving fault diagnosis and prognosis problems.

A unique advantage besides a few others that makes BP application stands out, is because it does not require the knowledge of the exact form of analytical function on which the model should be built. In essence, for a BP model to operate, certain precision application order such as function type, number and position of parameters are not required. Moreover, it is compatible with various conditional operation, for example it has capacity for a multi-input, multi-output, quantitative or qualitative, complex system with very good abilities of data fusion, self-adaptation and parallel processing. Thus, it is best suited for fault diagnosis selection [49].

BP is a multilayer feed-forward network usually containing the input layer, hidden layer, and output layer which employs the training methodology of error back propagation algorithm. Fig. 12 shows the BP neural network with a single hidden layer. BP network utilizes the steepest decent method by varying the weights and limits of the network to minimize the sum of squared errors [49][50].

The aim of ANN training is to attain the proper fit that meets the input and the target of training data. Following training of BP network, calculations for final output of the updated weight are carried out for each set of test data. For a given fault diagnosis type, the features collected after training can be utilized as database by BP network for prediction and classification of fault conditions of induction machines [49].

Before application of ANN technique for broken rotor bar detection, the following were considered: 1) appropriate input variables selection, 2) number of output variables, and 3) layers and neurons in each layer. Pilot test were carried out on the networks. The selected network is composed of two input variables. The first input variable represents harmonic amplitude associated with the broken rotor bar, the second input variable is the slip *s*, used for reliability improvement of the desired classification. Fig. 12 shows multilayer neural network construction for the broken rotor bar fault detection

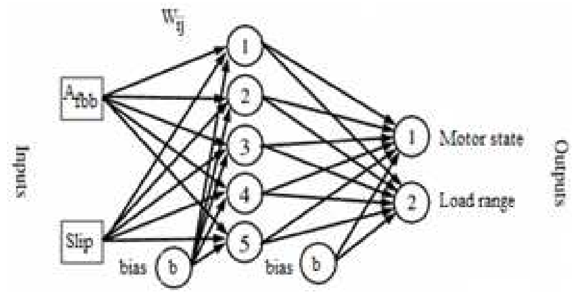

Fig. 12. Neural network architecture [50]

The network is configured such that, there are two inputs neurons, one hidden layer of five neurons and two outputs neurons. The motor state neuron output corresponds to zero for the healthy machine, 0.5 corresponds to the case of one broken bar and 1 for the case of two broken bar. For the second neuron, which characterizes the load range. In this case, 0 corresponds to the case of low loads, 0.5 corresponds to half loads and 1 corresponds to the full loads. All activations functions of neurons are sigmoid. The training algorithm used is the BP gradient. With the chosen inputs, the results are acceptable after a few tens of iterations. Fig. 13 shows the broken rotor bars detection under different loads [50].

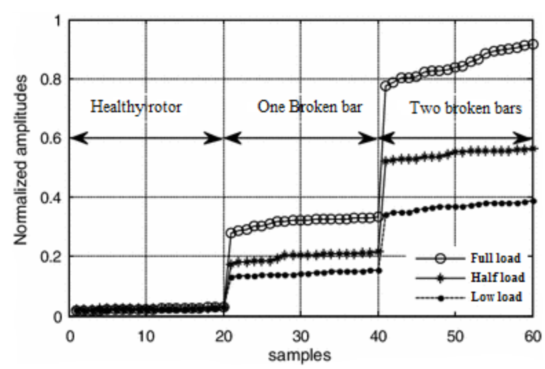

Fig. 13. Normalized amplitudes of broken rotor bar components at different loads and motor states (the motor is 1.1 kW) [50].

Reference [51] demonstrated the application of ANN for detection of four types of bearing faults. Fig. 14 shows the learning curve of neural network (NN) with eight input feature. The training stops when the Mean Square Error (MSE) reaches zero or a predefined maximum number of epochs is reached. Fig. 14 confirms that the training with average 75 epochs, (defined limit for this case) satisfy the MSE stopping condition.

ANN can also be used for insulation degradation fault detection. A specialist model procedure of ANN was employed in [52][53]. The K-means algorithm operates condition-based monitoring by separating the data in individual classes, but unable to give interpretation motor condition, thus expert knowledge is required.

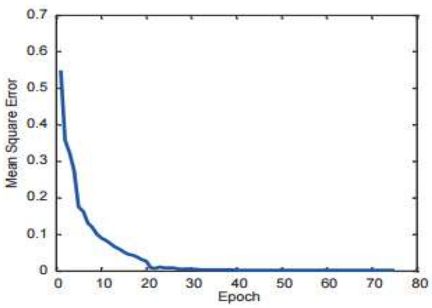

Fig. 14. The learning curve of NN with eight input feature [51].

V. CONCLUSIONS

Various condition monitoring approaches for induction motors have been discussed in this paper under the three categories: 1) signature extraction based approach, 2) model-based approach, and 3) knowledge-based approach. The strengths and drawbacks for several commonly used methods are analyzed comparatively.

Due to non-invasive nature of knowledge-based approach using artificial intelligent and machine learning and its excellent performance, it can be concluded that this method: 1) is a more reliable methodology; 2) can be employed for real-time condition monitoring; and 3) has high accuracy. The reliability and accuracy of this technique can compensate for the relative time constrain associated with data training required prior to the fault classification, which is usually perceived as a drawback. Therefore, the knowledge-based approach using artificial intelligent and machine learning opens a pathway to an exciting new research direction in condition monitoring and fault diagnosis of induction motors.

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