INDUCTION MACHINE ON-LINE CONDITION MONITORING AND FAULT DIAGNOSIS – A SURVEY

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Abstract

Induction machines play a pivotal role in industry and there is a strong demand for their reliable and safe operation. They are generally reliable but eventually do wear out. Faults and failures of induction machines can lead to excessive downtimes and generate large losses in terms of maintenance and lost revenues, and this motivates the examination of on-line condition monitoring. On-line condition monitoring involves taking measurements on a machine while it is operating in order to detect faults with the aim of reducing both unexpected failures and maintenance costs. This paper surveys the current trends in on-line fault detection and diagnosis of induction machines and identifies future research areas.

1 INTRODUCTION

Condition monitoring of electric machinery can significantly reduce the cost of maintenance and the risk of unexpected failures by allowing the early detection of potentially catastrophic faults. In condition based maintenance, one does not schedule maintenance or machine replacement based on previous records or statistical estimates of machine failure. Rather, one relies on the information provided by condition monitoring systems assessing the machine's condition. Thus the key for the success of condition based maintenance is having an accurate means of condition assessment and fault diagnosis.

On-line condition monitoring uses measurements taken while a machine is operating, to determine if a fault exists. Fig. 1 shows a block diagram of the general approach. Each of the blocks will be discussed in turn in this paper. Starting from the left, common motor faults are shown. Different types of sensors can be used to measure signals to detect these faults. Various signal processing techniques can be applied to these sensor signals to extract particular features which are sensitive to the presence of faults. Finally, in the fault detection stage, a decision needs to be made as to whether a fault exists or not.

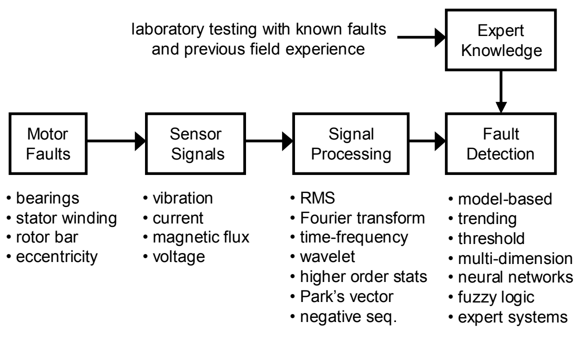

Fig. 1. The on-line condition monitoring process.

2 INDUCTION MOTOR FAULTS

Induction machine failure surveys [21,33] have found the most common failure mechanisms in induction machines (see Fig. 2). These have been categorised according to the main components of a machine – stator related faults, rotor related faults, bearing related faults and other faults.

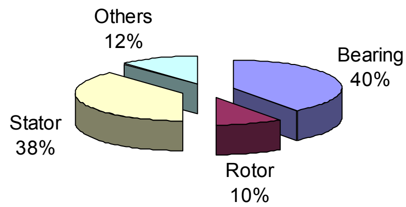

Fig. 2. Types of induction machine faults.

2.1 Bearing Faults

The majority of electrical machines use ball or rolling element bearings and these are one of the most common causes of failure. These bearings consist of an inner and outer ring with a set of balls or rolling elements placed in raceways rotating inside these rings. Faults in the inner raceway, outer raceway or rolling elements will produce unique frequency components in the measured machine vibration and other sensor signals. These bearing fault frequencies are functions of the bearing geometry and the running speed [39]. Bearing faults can also cause rotor eccentricity [24].

2.2 Stator Faults

Almost 40% of all reported induction machine failures fall into this category. The stator winding consists of coils of insulated copper wire placed in the stator slots. Stator winding faults are often caused by insulation failure between two adjacent turns in a coil. This is called a turn-to-turn fault or shorted turn. The resultant induced currents produce extra heating and cause an imbalance in the magnetic field in the machine. If undetected, the local heating will cause further damage to the stator insulation until catastrophic failure occurs. The unbalanced magnetic field can also result in excessive vibration that can cause premature bearing failures.

2.3 Rotor Faults

Rotor faults account for about 10% of total induction machine failures. The normal failure mechanism is a breakage or cracking of the rotor bars where they join the end-rings which can be due to thermal or mechanical cycling of the rotor during operation. This type of fault creates the well-known twice slip frequency sidebands in the current spectrum around the supply frequency signal.

2.4 Other Faults

Eccentricity occurs when the rotor is not centred within the stator, producing a non-uniform airgap between them. This can be caused by defective bearings or manufacturing faults. The variation in airgap disturbs the magnetic field distribution within the motor which produces a net magnetic force on the rotor in the direction of the smallest airgap. This so called "unbalanced magnetic pull" can cause mechanical vibration.

3 SENSOR SIGNALS

As the induction machine is highly symmetrical, the presence of any kind of fault in it affects its symmetry. This leads to a corresponding change in the interaction of flux between the stator and rotor, resulting in changes to the stator currents, voltages, magnetic field and machine vibration. Thus these signals can be used for on-line condition monitoring. Table 1 summarizes some of the research which has examined the use of different sensor signals to detect faults.

Table 1. References using sensor signals to detect particular fault types.

	Bearing	Stator	Rotor	Eccen-tricity
Vibration	[13,22,23, 27,39]	[1,13]	[1,13,26]	[1,9,13,22, 26]
Current	[3,11,18, 19,24,27, 28,36,41]	[3,7,11,16, 17,19,24, 30,35,36]	[2,3,9,10,11, 15,18,19,24, 25,26,29,35, 36,41]	[3,6,9,11,18, 24,25,26,34, 35,36,39]
Flux	[5]	[5,16]	[5,29,39,40]	[5,9]
Voltage &Current		[3,12,18, 20,37]	[2,3,38]	[12]

3.1 Vibration

Vibration monitoring is one of the oldest condition monitoring techniques and is widely used to detect mechanical faults such as bearing failures or mechanical imbalance [22]. A piezo-electric transducer providing a voltage signal proportional to acceleration is often used. This acceleration signal can be integrated to give the velocity or position.

3.2 Stator Current

The stator current is usually measured using a clip-on Hall-effect current probe. It contains frequency components which can be related to a variety of faults such as mechanical and magnetic asymmetries, broken rotor bars and shorted turns in the stator windings. Most of the published research work in recent years has examined the use of the stator current for condition monitoring (see Table 1), particularly using frequency analysis (see Section 4.2).

3.3 Axial Magnetic Flux

The axial magnetic leakage flux of an induction machine is readily measured using a circular search coil which is placed on the non-drive (rear) end of the machine, concentric with the shaft. The search coil produces an output voltage which is proportional to the rate of change of the axial leakage flux. This signal contains many of the same frequency components which are present in the stator current. It is particularly useful for estimating the speed as it contains a strong component at the slip frequency.

3.4 Stator Voltage

This can be safely measured using a high frequency differential voltage probe or isolation amplifier. It has been used to calculate the instantaneous power, instantaneous torque and negative sequence impedance.

3.5 Other Techniques

Temperature sensors monitoring the bearings and stator windings have been traditionally used for condition monitoring. They provide a useful indication of machine overheating but offer limited fault diagnostic capability.

Partial discharge analysis is used for detecting stator insulation faults in higher voltage motors. It consists of detecting the low amplitude, ultrafast pulses (nS) produced by electric discharges in small voids in the insulation. Partial discharges occur even in healthy machines, however an increase in the amount of partial discharge activity can be associated with insulation degradation [31].

4 SIGNAL PROCESSING TECHNIQUES

Signal processing techniques are applied to the measured sensor signals in order to generate features or parameters (e.g. amplitudes of frequency components associated with faults) which are sensitive to the presence or absence of specific faults.

4.1 RMS

Calculation of simple statistical parameters such as the overall root mean squared (RMS) value of a signal can give useful information. For instance, the RMS value of the vibration velocity is a convenient measure of the overall vibration severity [27]. In the same way, the RMS value of the stator current provides a rough indication of the motor loading.

4.2 Frequency Analysis

Frequency analysis using the Fourier transform is the most common signal processing method used for on-line condition monitoring. This is because many mechanical and electrical faults produce signals whose frequencies can be determined from knowledge of motor parameters such as the number of poles. These fault signals appear in a variety of sensor signals including vibration, current and flux [2,3,24,39]. Frequency analysis can thus provide information about a number of faults, though some faults produce similar fault frequencies and so require other information to differentiate them. It also allows the detection of low-level fault signals in the presence of large "noise" signals at other frequencies.

The use of the frequency analysis of vibration and current signals has been heavily researched to detect bearing, stator, rotor and eccentricity faults (see Table 1). Fig. 3 shows the current spectrum for a motor with one broken bar showing the characteristic 1+/-2s broken bar sidebands around the 50Hz peak [29].

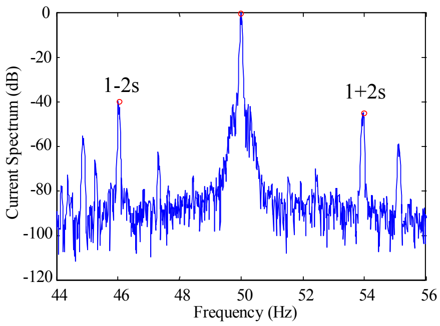

Fig. 3. Current frequency spectrum showing broken bar sidebands for a motor with one broken bar.

Frequency analysis has also been applied to quantities such as the instantaneous "partial" power and instantaneous torque [3,38] which can be computed from the measured voltage and current signals.

4.3 Other Frequency Analysis Methods

The Fourier transform used for conventional frequency analysis assumes that the frequency spectrum is not changing with respect to time over the sampling period. This assumption is not always valid, especially with mechanical loads which show considerable variation over time.

Time-frequency techniques overcome this issue by dividing the signal into short time segments over which it is relatively constant, and computing the Fourier transform of each segment. This allows the changes in the frequency content of the signal with time to be observed [3,41]. Note that the frequency resolution is limited by the size of the segments.

The wavelet transform is another frequency analysis method [3,18]. The conventional Fourier transform is based on decomposing the measured signal into sinusoids with different frequencies. The wavelet transform decomposes the signal into a set of non-sinusoidal reference waveforms. It has been generally applied to pulse type waveforms which are not conveniently represented as the sum of sinusoidal components.

4.4 Higher Order Statistics

Common statistical measures such as the mean or variance can be used to describe the probability density function of a time-varying signal. There are also higher order statistical measures such as kurtosis, which gives an indication of the proportion of samples which deviate from the mean by a small value compared with those which deviate by a large value. Some of these higher order statistical measures have the useful property that they are insensitive to Gaussian distributed measurement noise. These have been used to investigate the detection of machine faults [23,26].

It is possible to perform frequency analysis (Fourier transform) of the higher order statistical measures to obtain what is called higher order spectra. These spectra allow the identification of components in a signal which have a fixed phase relationship and hence may originate from the same source [23].

4.5 Stator Current Park's Vector

The Park's vector [6,7] is based on the locus of the instantaneous spatial vector sum of the three phase stator currents. This locus is affected by stator winding faults and air-gap eccentricity (see Fig. 4). The Park's vector can be analysed graphically as shown, or by examining its frequency spectra [7].

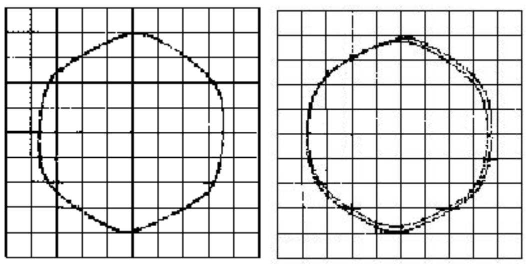

Fig. 4. Park's vector for a healthy motor (left) and a motor with airgap eccentricity (right) [6].

4.6 Negative Sequence Currents

When ideal three-phase voltages are applied to a perfectly symmetrical three-phase machine, the machine currents are equal in magnitude. A fault such as a shorted turn or eccentricity introduces an imbalance between the phases causing unbalanced phase currents. This imbalance increases with fault severity and can be described mathematically using a negative sequence current component [12].

Note however that imbalances in the supply voltages can also cause imbalances in the phase currents. It is thus necessary to measure the supply voltages so that this can be taken into account [37].

5 FAULT DETECTION METHODS

The final and most difficult step in the on-line condition monitoring process is to examine the features and fault parameters extracted in the previous section and to decide if a fault exists, and if so, what type of fault. Presently this is often done based on the knowledge and experience of an expert user. However, there has been considerable research into means for automating this process using classification techniques such as artificial intelligence and pattern recognition.

The key difficulty with this step is the sensitivity of the measured fault parameters to machine specific details such as size, power, construction type and loading. Thus for a reliable fault detection/classification algorithm to be developed, an extensive set of "healthy" and "faulty" reference data is generally required. The final accuracy of the fault detection algorithm is clearly limited by the size, breadth and quality of the reference data which was used to develop it.

5.1 Model-Based Approaches

The effect of particular faults on parameters such as the machine output current can be predicted using analytical [10] or finite-element modelling approaches [14]. These models can allow accurate fault diagnostics for a given machine if detailed electromagnetic machine design information is available. Note that it may be difficult to use the results from one motor to set general fault thresholds (see Section 5.3).

5.2 Trending

This involves observing a fault parameter over a period of time so as to be able to detect sudden changes which could be associated with the presence of faults. There still remains the difficulty of determining how much of a change in the parameter corresponds to a fault condition.

5.3 Fault Thresholds

The simplest fault detection algorithm is to use a threshold for a given parameter. For instance, there are tables which show the acceptable levels of mechanical vibration amplitude depending on the size of the machine [22]. Another example is the "rule of thumb" for the broken bar sidebands in the current spectrum. It has been reported that if these sidebands are less than -54dB with respect to the main peak then the motor is healthy, if they are greater than -45dB then the motor is faulty, else it is marginal.

5.4 Multi-Dimensional Space Techniques

Multiple fault parameters can be taken into account by representing each fault parameter as one dimension of a multi-dimensional space. A given set of parameters corresponds to a point in this space. Points for healthy operation are located in different regions in this space from points for faulty operation.

The support vector classification approach [4] tries to find a linear combination of parameters (geometrically represented by a hyperplane) that will separate the healthy data from the faulty data (see Fig. 5).

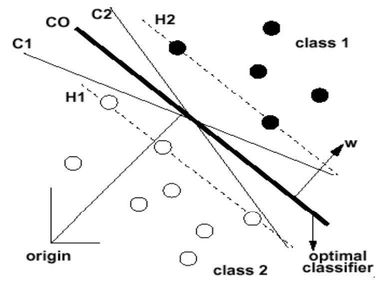

Fig. 5. A hyperplane is chosen to separate the data for healthy and faulty machines [4].

Another approach is to try to define geometric regions in the space which correspond to healthy operation and to faulty operation [41].

5.5 Neural Networks

Artificial neural networks are modelled on the neural connections in the human brain (see Fig. 6). Each artificial neuron (shown as a circle) accepts several inputs, applies preset weights to each input and generates a non-linear output based on the result [8,11]. The neurons are connected in layers between the inputs and outputs.

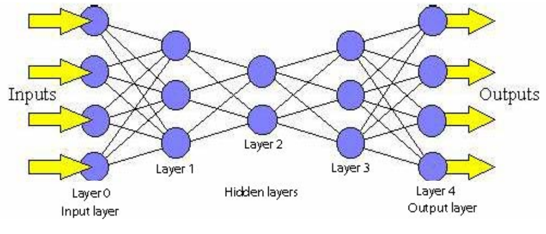

Fig. 6. Structure of a neural network.

The training of the neural network is performed by feeding in selected sets of parameters corresponding to known healthy and faulty machines and adjusting the input weights of the neurons to give the required output in each case.

5.6 Fuzzy Logic

This involves making decisions based on classifying signals into a series of bands (fuzzy values) rather than simply as healthy or faulty based on a single threshold. For instance, based on the broken bar sideband amplitude, a motor could be classified as healthy, marginal or faulty. Fuzzy logic allows combining fuzzy information from different signals together to make a more accurate judgement regarding the health of the motor [8,11].

5.7 Expert Systems

Expert systems seek to represent the knowledge of a human expert by defining a series of rules from which conclusions can be drawn. An example of a rule could be: *if* the broken bar sidebands are greater than –45dB *and* the Park's current vector is circular *then* it is likely that a broken bar fault is present [10,32].

6 FUTURE AREAS FOR RESEARCH

6.1 Use of Multiple Sensor Types

The majority of present research has used a single sensor type (e.g. motor current) combined with a particular signal processing technique (e.g. frequency spectrum) to detect a given fault. Combining information from multiple sensor types and processing techniques should improve the accuracy of fault detection (see Fig. 1).

6.2 Detection and Diagnosis of Multiple Faults

There has been little work done on the identification of multiple faults in machines. This may be complicated by the inter-dependencies of the fault signals if there is more than one fault. The use of multiple sensor types and processing techniques may also be helpful here.

6.3 Detection Based on Varying Load Conditions

Researchers have usually examined the detection of faults under full-load operation, though in practice the actual load when the machine is tested may not be controllable. Partial load operation can significantly change the fault signals. For instance, it has been shown that the broken bar sidebands of the current spectrum are sensitive to the machine loading [29].

6.4 Portability of Methods

It is difficult to generalise the results from laboratory testing on what are normally low power machines to the much higher power machines found in the field. For a fault diagnosis system to be practical, it must be applicable to machines with widely different ratings and different construction with little incremental effort [18].

6.5 Fault Detection in Inverter-Driven Motors

The existing work in condition monitoring has concentrated on the detection of faults in induction machines operated directly from the mains. Inverter-driven machines are now becoming more widely used in industry, at increasing power levels. The detection of faults in inverter-driven machines is challenging due to noise created by the high switching frequency. On the other hand, the presence of a microcontroller and sensors in an inverter mean that condition monitoring algorithms can be implemented with little incremental cost.

6.6 Remote Machine Monitoring

It is useful to have a means for continuous remote monitoring of induction machines in unmanned/ hazardous locations (such as remote mining sites or petroleum processing plants) and in critical applications where the highest reliability is required.

7 CONCLUSIONS

Accurate means for condition monitoring can improve the reliability and reduce the maintenance costs of induction motors. Condition monitoring involves sampling sensor signals, processing these signals to extract features which are sensitive to the presence of faults, deciding if a fault exists and identifying its type. This paper has provided a survey of current research in condition monitoring and has identified key areas for future research.

8 ACKNOWLEDGMENT

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