Open access • Journal Article • DOI:10.1109/MIE.2020.3016138

Condition Monitoring of Industrial Electric Machines: State of the Art and Future Challenges — Source link

Sang Bin Lee, Greg C. Stone, Jose A. Antonino-Daviu, Konstantinos N. Gyftakis ...+3 more authors

Institutions: Korea University, Polytechnic University of Valencia, University of Edinburgh, Michigan State University ...+2 more institutions

Published on: 18 Dec 2020 - IEEE Industrial Electronics Magazine (Institute of Electrical and Electronics Engineers Inc.)

Topics: Condition monitoring and Prognostics

Recent Challenges in Condition Monitoring of Industrial Electric Machines

Abstract

The limitations of thermal, vibration, or electrical monitoring of electric machines such as false indications, low sensitivity, and difficulty of fault interpretation have recently been exposed. This has led to a shift in the direction in research towards applying new techniques for improving the reliability of condition monitoring. With the changing environment, the purpose of this article is to provide an overview of the recent trend in the industrial demand and research activity in condition monitoring technology. The new developments in insulation testing, electrical testing, flux analysis, transient analysis, and fault prognostics are summarized. The future challenges and recommendations for future work for the new technologies are also stated to support researchers target research/development efforts according to industrial needs.

I. Introduction

Reliable operation of medium-high voltage electric motors and generators is critical for maintaining the productivity, efficiency, and safety of the industrial facility. Surveys on the reliability of electric machines have identified that failures can occur in all the motor components, where the risk of failure depends on the type and design of the machine, operating conditions, and application [1]–[2]. For a long period of time, condition monitoring of electric machines relied on off-line testing/inspection and thermal/vibration monitoring. Since the 1980s, there has been a significant amount of research effort towards developing electrical monitoring tools for preventing in-service failure of the machine and process, as it can provide remote monitoring at low cost. A number of literature surveys summarize the work on electrical detection of machine faults, as it has been the main focus of research [3]-[5]. With the technology applied in the field for 20+ years, the limitations of electrical monitoring such as false indications, low sensitivity, and difficulty of fault interpretation have been exposed. In addition, there are difficulties that arise from variable frequency drive (VFD) operation with the increase in the number of inverter-fed motors. This has led to a recent shift in the direction in research towards applying new techniques such as airgap and stray flux monitoring, transient analysis, intelligent algorithms, and fault prognostics for improving the reliability of condition monitoring and for providing a clear course of action for maintenance. With the changing environment, the purpose of this article is to provide an overview of the recent trend (last 5 years) in the industrial demand and research activity in condition monitoring technology for induction and synchronous machines [6]-[7]. The future challenges and recommendations for future work are also stated for each topic to support researchers target research and development efforts according to industrial needs.

II. Insulation testing

Industrial surveys have consistently shown that the electrical insulation used in stator and rotor windings is one of the components most likely to cause motor failure [1]-[2], [6]-[7]. This is because organic materials included in the insulation system such as polyamide-imides, polyesters, and epoxies tend to have much lower mechanical strength and thermal capability compared to the metals that form the bulk of an electrical machine. Failure in the strand insulation of stator and rotor windings or failure in the turn insulation of rotor windings, does not directly lead to machine failure. However, failure of the groundwall (GW) insulation in both rotor and stator windings, or failure in the turn insulation in stator windings, leads to an overcurrent that rapidly fails the machine. The strand, turn, phase, and GW insulation components shown in Fig. 1 degrade slowly over time due to oxidation (thermal aging), thermo-mechanical aging (load changes and on/off cycling), mechanical aging if the conductors or coils vibrate due to magnetic forces, and/or contamination by moisture or oil combined with particulates [6]-[8]. In addition, for conventional machines rated 3.3 kV and above or inverter-fed motors rated 400 V and above, small electrical sparks called partial discharges (PD) can also age and fail the insulation [7]. Therefore, insulation testing is performed to identify machines with weak insulation to prevent in-service failure.

There is a long history of performing off-line insulation tests such as insulation resistance (IR) and dissipation factor (DF) to determine if the machine windings are at a high risk of failure. The dc resistance of the insulation and the ratio between the capacitive and resistive components of the leakage current are measured with the IR and DF tests, respectively. The IR test is only capable of detecting severe problems in the GW insulation in stator and rotor windings, and is insensitive to thermal and mechanical aging. The DF test has mainly been used for detecting thermal aging and contamination, but many end-users have stopped using it, as it is costly to perform and can only measure the average condition of the GW insulation. For windings rated 3.3 kV and above, off-line measurement of PD pulses is often performed, as it can give an indication of the weakest part of the insulation that is likely to fail. However, it is not as preferred by end-users as on-line PD testing that is capable of performing testing under realistic thermal and mechanical stresses without motor shutdown [9]. The only on-line test for GW insulation condition assessment in stator windings that has achieved widespread application is the on-line PD test. This test requires the installation of capacitive PD sensors on each phase during manufacturing or shutdown, and they have been installed on over 20,000 machines rated 6 kV and above. The principle challenge with on-line PD testing has always been the separation of stator PD from other pulse-like electrical "noise" that can be produced by power line corona, inverters, power tool operation, etc., as shown in Fig. 2. If the noise is greater than the stator PD signal, the risk of false indications is increased. Most of the effective techniques for separating PD from noise such as pulse shape analysis, time-of-pulse travel between a pair of sensors, and/or time-frequency maps were developed more than a decade ago [7]. Although pattern recognition based on AI methods have been attempted by researchers to help separate stator PD from noise and identify the PD source location [10], they are yet to be accepted in the field due to reliability issues. Another challenge for on-line monitoring of PD is detecting PD on windings fed by fast rise-time voltage source VFDs. The voltage impulses have frequency content (and pulse shapes) similar that of the PD itself, which makes separation of PD from switching noise challenging [11]. The problem is becoming greater with increase in DC bus voltages levels and decrease in rise- and fall-time with wide bandgap (WBG) switching devices such as silicon carbide, and it is not yet clear whether on-line PD detection with VFDs employing WBG devices will be practical.

Stator turn insulation failure leading to GW insulation breakdown and forced outage of the machine is commonly observed in the field [12]. The surge test, which is the only off-line test available for turn insulation, is somewhat controversial, as it applies a high voltage impulse to the windings that may cause the failure of good turn insulation [7]. Although on-line methods for detecting turn insulation failure have been developed [3]-[5], there currently is no test method accepted in the field for reliable assessment of turn insulation condition [7]. Shorted turns in synchronous motor (SM) rotor windings rarely causes motor failure as in stator windings, but it is monitored as it can give an indirect warning of GW insulation aging that has a high risk of tripping the machine. The pole drop or recurrent surge oscillography tests are used to detect and locate shorted turns off-line [7]; however, they tend to yield false indications since shorted turns that occur in service may not be observable at standstill when the centrifugal force disappears (and vice versa). Researchers have developed on-line IR testers for the GW insulation, but they have not been adopted by industry, possibly since they seem to be preferentially sensitive to brush gear and inverter condition, rather than the rotor winding condition. Airgap flux monitoring is commonly used to detect shorted turns in the rotor winding [13], but there currently is no on-line test method that can detect rotor winding turn insulation aging before turn shorts occur.

With regard to advances in off-line testing, DC polarization/depolarization testing has shown the potential of obtaining more information on the insulation condition [14], but it has not been applied widely by industry or utilities to date. UV imaging has recently been widely adopted in recent years for detection of surface PD activity after rotor removal with the recent introduction of cost-effective ultraviolet imaging cameras. For insulation testing, a new test method for assessment of turn insulation condition before failure occurs would be a valuable test for improving the reliability of machines in the field. Monitoring of VFD motor insulation have also become important fields for further research with the advent of fast risetime WBG devices in electric propulsion applications. For rotor field winding insulation failure, a non-invasive on-line test that does not require installation of airgap flux sensors can find widespread application to SMs.

III. Electrical testing

Faults in the rotor or bearings can also cause failure of electric machines, and testing relies on detecting the asymmetry produced by these defects [3],[5]-[7]. Cracks, open circuits, or high resistance contacts in the rotor conductors of IMs and SMs are often observed in applications with frequent starts or load transients. The thermomechanical stress imposed due to the abrupt current variation is the main cause of failure in addition to mechanical stress and manufacturing defects. Rotor winding faults must be detected and corrected to prevent secondary damage caused by bar protrusion or arcing between the cage and core that can cause permanent irreversible damage. Rotor eccentricity refers to a condition with non-uniform airgap distribution in the machine, and can be caused by bearing wear, rotor deflection, manufacturing imperfections, etc. Eccentricity causes unbalanced magnetic pull at the minimum airgap position and leads to increase in vibration and mechanical wear. This condition must be detected to prevent accelerated aging and, in the worst case, stator rotor contact. Bearing degradation can be caused by a number of different mechanical, electrical, and thermal stresses, and leads to increased vibration and heating, and accelerates mechanical wear. The condition of the bearing needs to be monitored as it is the leading root cause of motor failure.

A fault in the electric machine creates an asymmetry in the rotating magnetic field, which induces a voltage in the stator winding at the characteristic frequency that depends on the type of fault. This results in a current flow at the fault induced frequency and distorts the current, making the fault observable in the time and/or frequency domain. Electrical monitoring has gained popularity since the 80s as a means of motor testing due to its low cost, non-intrusive, and remote nature [3]-[7]. A variety of fault detection methods based on the analysis of symmetrical components, real and reactive power, and space vector trajectory have been studied and applied in the field. The most popular method widespread in the field is motor current signature analysis (MCSA), where Fourier transform is applied to the stator current in steady state to observe the frequency components produced by the faults. Each type of fault produces a different characteristic frequency as summarized in Table I for induction (IM) and synchronous motors (SM) [3]-[5]. The fault frequency components for SMs in steady state can be found by substituting slip=0 (f_r=f_s/p).

Although it has been shown that all the frequency components in Table I increase with the severity of the fault [3], [5], [15]-[16], only the detection of IM broken bars detected through the rise in the twice slip frequency sidebands as shown in Fig. 3, has been widely accepted and applied in the field. For mechanical defects related to the bearing, eccentricity, or load, vibration analysis is considered to be more reliable. MCSA based detection may not be practical for these mechanical defects, because it is difficult to establish a universal fault severity threshold as the increase in the magnitude of the fault frequency components are dependent on the machine design and operating conditions. In addition, the relatively low sensitivity due to attenuation of the fault signature at higher frequencies is another limitation for detecting eccentricity or bearing failures, especially in noisy field environments. For detection of IM and SM faults that produce rotor rotational frequency, f_r (or 1x), sidebands, the main limitation is due to the interference from mechanical load defects. Load unbalance and misalignment, which are the most common load defects, produce f_r sideband components that are comparable to or larger than that produced by motor faults, making MCSA unreliable [17]. Detection of SM faults (slip=0) is even more challenging as all motor and load defects produce the same frequency component that interact with each other potentially producing false indications [18].

For MCSA based IM rotor fault detection widely applied in industry, improving the reliability is the main concern. Many cases of false positive (false alarm) and negative (missed fault) MCSA indications due to the influence of rotor structural or load asymmetries have been identified, as summarized in Table II [17]. Development of test methods immune to the false indications are being actively studied, since an incorrect diagnosis can compromise the reliability of the MCSA and lead to unnecessary maintenance and unscheduled interruption of production. It has been shown in a number of studies that testing under high slip (motor standstill or starting) conditions is immune to most of the false indications, as highlighted in Table II, since the flux distribution is such that rotor asymmetry does not influence fault detection, and/or the influence of load is minimal [9]. Despite these challenges, there is active on-going research on improving the diagnostics capability of MCSA due to its distinct remote, low cost, on-line monitoring advantages. Further research on developing new fault indicators for improving the reliability of fault detection, and analysis for determining fault severity for providing a course of maintenance action is needed for extending the capabilities of MCSA. Intelligent algorithms that consider simultaneous detection of faults, variation of fault thresholds, or statistical analysis are examples of research making progress for improving the reliability of fault detection and fault prediction [19]-[21].

IV. Airgap and Stray Flux Analysis

Analysis of the airgap or stray flux measurement can provide direct indication of the asymmetry in the radial or axial flux of the machine produced by fault induced anomalies. The radial component of the airgap flux can be measured with a search coil or Hall sensor installed on the stator bore. The two stray flux components used for diagnostics are the radial leakage flux component outside the yoke, and axial leakage flux component that leaks through the rotor shaft. The stray flux components can be measured with the sensor installed on the frame outside the yoke or around the shaft or on the end bell surface, as shown in Fig. 4 [22]-[25].

Airgap flux monitoring is being widely applied for detecting shorted field winding turns in synchronous generators, and also starting to be installed in SMs [7], [13], [26]. Since faults in the rotor conductors and airgap eccentricity cause distortion in the rotating MMF or airgap length distribution, they are directly reflected in the airgap flux of ac machines. [27]-[28]. Therefore, the sensitivity of airgap flux monitoring is superior compared to vibration analysis or MCSA that rely on detecting the effect of rotor faults indirectly. Another advantage of flux monitoring is that it is not influenced by load defects since they do not cause distortion in airgap flux [28], [31]. The potential of using airgap flux analysis for detecting rotor cage, damper bar, and airgap eccentricity faults have recently been shown for IMs and SMs [26]-[28]. Although airgap flux-based fault detection is capable of reliable and sensitive detection of rotor related faults, the requirement of sensor installation inside the machine is the main limitation. Some concerns on the sensitivity degradation due to inherent asymmetry between poles for small number of shorted turns have been raised, and cases of the fault being observable only under standstill and not during operation have also been reported [7], [13], [26], [35].

Most of the research on flux monitoring is based on stray flux measurement, as it is easier to install the sensor on the machine frame. The underlying principle and advantages of radial and axial stray flux monitoring are similar to that of airgap flux monitoring in that the asymmetry in the leakage flux produced due to electrical or mechanical asymmetry in the MMF or airgap is measured. The feasibility of detecting rotor cage, PM demagnetization, eccentricity, stator winding, stator core, and bearing faults have been shown in [23]-[25], [27]-[29], where the sensitivity to faults is lower than using airgap flux. The main focus of stray flux monitoring was on the detectability and sensitivity aspects [24], but the recent focus has been shifted to improving the reliability of fault detection and classifying the type of fault [28], [30]-[31].

One of the main reasons flux monitoring has not received as much attention as MCSA is because it does not provide remote monitoring. However, there recently has been increasing interest in flux monitoring since it could be a low cost option for complementing the limitations of electrical, mechanical, and thermal monitoring in terms of the reliability and diversity of fault detection. There is also a trend where motor manufacturers are providing self-diagnostics capability through integrated sensors embedded on the motor frame with intelligent algorithms for technological differentiation and improved reliability [32]-[33]. Flux monitoring can be justified if it can provide advanced warning of failure in reliability critical applications for cases where other monitoring techniques fail.

There are many research topics to be explored in the under-researched area of flux monitoring, where the first step would be to identify the detection and sensitivity capabilities of airgap and stray flux monitoring. A comparative evaluation with MCSA and vibration analysis under the different fault conditions, and identifying fault indicators with well-defined thresholds would be valuable for field application. There aren't many test results reported on motors operating in the field, and there are a number of unexplored areas such as sensor size, location, and design that would be critical for deployment of the technology in the field. Since flux monitoring is effective for identifying faults in the rotor, unexplored rotor related defects in PMSMs, wound rotor IMs, and wound field SMs could be of practical value.

V. Transient Analysis

Analysis of current, flux, or vibration under transient operation has emerged as an alternative approach to overcome deficiencies of the conventional methods that rely on analysis of steady state data [31], [34]-[37]. The main idea behind this approach is to track the change in fault frequency components over time through time-frequency transformations, which provide reliable evidence of the fault compared to monitoring the amplitude of a single component in the Fourier spectra of steady state data [34]-[35]. The different types of time-frequency transforms used are described in [5] with examples on applications to detection of motor faults [26], [31], [34]-[37]. An example of time-frequency analyses of the starting current for a motor with and without broken rotor bars is illustrated in Fig. 5, where the evolution of the fault induced component is clearly noticeable. Research on transient analysis was focused on analyzing current or flux signals during the starting transient for detecting different types of faults. Active research has led to the recent development of commercial devices with transient analysis features. The technique has proven to provide reliable results for detecting rotor cage, eccentricity, and reactor starting defects in the field [31], [34]-[35].

Transient analysis is performed when the motor is operating under extreme conditions of maximum current (starting) or zero current (shutdown) where the influence of certain faults are amplified or absent. In addition, the flux distribution and influence of load are different from that of steady state, making fault detection immune to the interference due to the structural asymmetries and characteristics of the machine and load [17]. This enables sensitive and reliable detection of rotor faults for cases where false indications are produced with steady state analysis, as highlighted in Table II. False indications can also be reduced since time-frequency patterns shown in Fig. 5 are usually more reliable indicators than single spectral harmonics (Fig. 3) which can be easily masked by other phenomena or noise. The main drawback is that motor starting (≥ 1 s) is required, which is difficult for applications that are operated continuously, and sophisticated signal processing tools with higher computational burden must be applied for analyzing the non-stationary signals.

Current research work in the transient analysis area is focused on applying the techniques to the current, flux, or vibration signals under load/speed variations and motor shutdown in addition to motor startup. The advance in this direction is required in motors operating continuously under non-stationary conditions and motors that are operated continuously without starts/stops. Another line of research is related to the application of the methodology to the diagnosis of faults in the rotor windings of wound rotor IMs and SMs [26], [36]. Investigation of optimized signal processing tools for improved visualization and quantification of the fault harmonic evolution, as well as intelligent algorithms for automatic identification of the evolutions and fault indicators are also important research topics needed in the field. One of the most important challenges for massive adoption of the technology in the field, is its adaptation to VFD operation, where detection of the transient evolution of the fault components is very difficult especially for IM rotor faults. Some work has already demonstrated the feasibility and potential of the method in soft-started and VSD-driven motors [37]. The development of such methods is of great interest for VFD manufacturers and end users, as they could be imbedded in the drive to provide automated diagnosis of the motor-drive system.

VI. Fault Prognostics

The ultimate goal of electric machine testing and diagnostics is to predict the time of failure. The purpose of failure prognosis is not simply to know when a drive component will fail, but to know this time accurately, and thus take appropriate action necessary to continue operation with minimal disturbance. Prognosis of machine faliure can increase the reliability of the system and decrease cost of operation and chances of unexpected failure. The concepts and decisions associated with failure prognosis extracted from discussions in [39]-[40], [49]-[51] are aggregated in Fig. 6. As the state of the health approaches failure, the remaining useful life (RUL) estimate approaches zero, and the estimate of the confidence in it also increases. Action is decided when the threshold for decision (mitigation, shutdown, etc.) falls within this interval, and the decision should be made well ahead of failure, so that the time to act is adequate. If the decision threshold is well-defined in relation to the confidence interval, early decision for action at A or late decision at B followed by the necessary time to act, will be effective. If instead, this threshold is set too low, points A and B will move too close to time of failure (A’, B’), leaving insufficient time for action. If the threshold is set too high, the decision will cause early interruption of service.

To predict the RUL with high precision, it is necessary to have the diagnostic tools in place first, from which the state of health of the device can be estimated. Beyond this, methods have been developed to identify trends of the features used for diagnosis based on Baysian statistics and AI. To identify trends in the degradation of a component or subsystem, it is necessary to have stored histories of similar components, and at least part of the history of the one that is being monitored. The establishment of the relationship between physical degradation and its manifestation gives validity to a prognosis technique.

Assuming precise estimation of the RUL with sufficient time, maintenance can be scheduled. This may include a complete shutdown at a convenient moment before the anticipated failure for bearings, gears, couplings and decaying insulation. A prognosis tool can give adequate warning of an impending failure, but not the ability to recover or mitigate the fault. If the estimation of RUL leaves limited time for such action, redundancies such as the 1) use of a different motor or inverter, or 2) operation with reduced phases or a neutral inverter leg, should be utilized. Such failures can be at the VFD switches, windings, etc, and the control algorithm can be changed, for instance, to inject negative d-axis current to offset the effects of a short circuit fed by the rotating PM.

To summarize, methods based on Baysian inference have been widely used and are still being developed. Hidden Markov Models [38] are based on recognizing a process of degradation, which is not directly observable, and hence trends cannot be directly developed. Kalman filter is the optimal linear estimator for linear system models. The Extended Kalman Filter [39]-[40] and the Unscented Kalman Filter linearize the model, but are not optimal. Particle Filters [41], a Monte Carlo method, is a Baysian model based estimation of internal states in dynamical systems when partial observations are made. In parallel to these, a large variety of methods and applications based on artificial neural networks [42]-[43] has been developed and utilized.

Thanks to improved computational abilities and new theories, and to the increased needs in energy conversion and transportation, research and applications of prognosis have been rapidly expanding. There is a lot of demand in applying prognostics to mechanical subsystems and components, such as bearings, gears, insulation, batteries, power electronics and capacitors. For failure prognosis to become more widely applied, the open questions such as 1) how to decrease the amount of data used to train the algorithm, and 2) how to improve the confidence, giving adequate time for reaction, have to be further addressed. Methods being investigated include the use of translational models, adapting past results from similar systems without extensive new tests, and hybrid methods combining statistical methods with neural networks [44]. Another important line of research is in applying advanced algorithms to fault clasification and prognostics of electric machines [45]-[47]. As indicated earlier, prognosis is a natural and necessary step after most diagnosis cases. Since it is based on and requires some method to identify and utilize trends, it results in a further level of complexity. Physics-based methods, offer a direct connection between operation and degradation, but they often become too complicated and require more observed variables. Advanced data-based methods are evolving, tested, and proposed, and they offer accurate predictions, albeit often based on a long history of observations [45]-[48]. Fusion of sensed data and hybrid physical/data based systems also offer a promise.[26], [49]-[51].

VII. Conclusion

An overview of the recent trend in research activity in condition monitoring technology for electric machines has been given in this article. The research being performed on insulation testing, electrical testing, flux analysis, transient analysis, and fault prognostics according to the demand from the field have been summarized. Recommendations for future work and challenges for each research topic have also been provided to guide researchers towards practical work needed in the field.

VII. References

[1] P. O'Donnell, "Report of large motor reliability survey of industrial and commercial installations, Part I- II," *IEEE Trans. Ind. Appl.*, vol. IA-21, no. 4, pp. 853-872, July/Aug. 1985.

[2] O.V. Thorsen, M. Dalva, "Failure identification and analysis for high-voltage induction motors in the petrochemical industry," *IEEE Trans. Ind. Appl.*, vol. 35, no. 4, pp. 810-818, July/Aug. 1999

[3] S. Nandi, H.A. Toliyat, X. Li, "Condition monitoring and fault diagnosis of electrical motors - a review," *IEEE Trans. Energy Convers.*, vol. 20, no. 4, pp. 719–729, Dec. 2005.

[4] R.M. Tallam et al., "A survey of methods for detection of stator-related faults in induction machines," *IEEE Trans. Ind. Appl.*, vol. 43, no. 4, pp. 920-933, July/Aug. 2007.

[5] M. Riera-Guasp, et al, "Advances in electrical machine, power electronic, and drive condition monitoring and fault detection," *IEEE Trans. Ind. Electron.*, vol. 62, no. 3, pp. 1746-1759, Mar. 2015.

[6] H. A. Toliyat, G. B. Kliman, *Handbook of Electric Motors*, 2nd ed. New York: Marcel Dekker, 2004.

[7] G.C. Stone, I. Culbert, E.A. Bolter, H. Dhirani, "Electrical insulation for rotating machines", IEEE Press/Wiley, 2014.

[8] *IEEE Guide for the Insulation Maintenance of Electric Machines*, IEEE Standard 56, 2016,.

[9] *IEEE guide for online monitoring of large synchronous generators*, IEEE Standard 1129, 2014.

[10] M. Karimi et al. "A novel application of deep belief networks in learning partial discharge patterns for classifying corona, surface, and internal discharges," *IEEE Trans. Ind. Electron.*, vol. 67, no. 4, pp. 3277-3287, April 2020.

[11] G.C. Stone, H.G. Sedding, C. Chan, "Experience with on-line PD measurement in high voltage inverter-fed motors", *IEEE Trans. Ind. Appl.*, pp 866-872, Jan. 2018.

[12] H. Kim et al, "Experience With Stator Insulation Testing and Turn/Phase Insulation Failures in the Power Generation Industry ," *IEEE Trans. Ind. Appl.*, vol. 54, no. 3, pp. 2225-2236, May/June 2018.

[13] M. Sasic, G. C. Stone, J. Stein, C. Stinson, "Detecting turn shorts in rotor windings: a new test using magnetic flux monitoring," *IEEE Ind. Appl. Mag.*, vol. 19, no. 2, pp. 63-69, March/April 2013.

[14] C. Hudon, N. Amyot, S. Bernier, E. David, M. Essalihi, "Comparison of dc ramp and polarization and

depolarisation tests on hydrogenerators", *Proc. of IEEE EIC*, pp. 114-119, 2018.

[15] W.T. Thomson, M. Fenger, "Current signature analysis to detect induction motor faults," IEEE Ind. Appl. Mag., vol. 7, no. 4, pp. 26-34, July/Aug. 2001.

[16] D. G. Dorrell, W. T. Thomson, S. Roach, "Analysis of airgap flux, current, and vibration signals as a function of the combination of static and dynamic airgap eccentricity in 3-phase induction motors," IEEE Trans. Ind. Appl., vol. 33, no. 1, pp. 24-34, Jan.-Feb. 1997.

[17] S. Lee et al., "Identification of false rotor fault indications produced by on-line MCSA for medium voltage induction machines," *IEEE Trans. Ind. Appl.*, vol. 52, no.1, pp. 729-738, Jan./Feb. 2016.

[18] W. le Roux, R.G. Harley, T.G. Habetler, "Detecting rotor faults in low power permanent magnet synchronous machines," IEEE Trans. Power Electron., vol. 22, no. 1, pp. 322-328, Jan. 2007.

[19] T. Fawcett, "Introduction to ROC analysis," *Pattern Recogn. Lett.*, vol. 27, no. 8, pp. 861–874, Oct. 2005.

[20] Q. Zhai, Z. Ye, "RUL prediction of deteriorating products using an adaptive wiener process model," *IEEE Trans. Ind. Informat.*, vol. 13, no. 6, pp. 2911-2921, Dec. 2017.

[21] E. Fournier, et al, "Current-based detection of mechanical unbalance in an induction machine using spectral Kurtosis with reference," *IEEE Trans. Ind. Electron.*, vol. 62, no. 3, pp. 1879-1887, March 2015.

[22] J. Penman, M.N. Dey, A.J. Tait, W.E. Bryan, "Condition monitoring of electrical drives," *IEE Proc. B – Elec. Pwr Appl.*, vol. 133, no. 3, pp. 142-148, May 1986.

[23] A. Ceban, R. Pusca, R. Romary, "Study of rotor faults in induction motors using external magnetic field analysis," *IEEE Trans. Ind. Electron.*, vol. 59, no. 5, pp. 2082-2093, May 2012.

[24] L. Frosini, et al, "Induction machine bearing fault detection by means of statistical processing of the stray flux measurement," *IEEE Trans. Ind. Electron.*, vol. 62, no. 3, pp. 1846-1854, Mar. 2015.

[25] M. Irhoumah et al., "Information fusion with belief functions for detection of interturn short-circuit faults in electrical machines using external flux sensors," *IEEE Trans. Ind. Electron.*, vol. 65, no. 3, pp. 2642-2652, March 2018.

[26] J. Yun et al., "Airgap Search Coil-based Detection of Damper Bar Failures in Salient Pole Synchronous Motors," *IEEE Trans. Ind. Appl.*, vol. 55, no. 4, pp. 3640-3648, July/Aug. 2019.

[27] G. Mirzaeva, et al “Comprehensive diagnostics of induction motor faults based on measurement of space & time dependencies of air gap flux,” *IEEE Trans. Ind. Appl.*, vol. 53, no. 3, pp. 2657-2666, May 2017.

[28] Y. Park, H. Choi, S. B. Lee, K. Gyftakis, “Flux-based detection of non-adjacent rotor bar damage in squirrel cage induction motors,” *Proc. of IEEE ECCE*, pp. 7019-7026, Sept. 2019.

[29] T. Goktas et al., “Comprehensive analysis of magnet defect fault monitoring through leakage flux,” *IEEE Trans. Magn.*, vol. 53, no. 4, pp. 1-10, Apr. 2017.

[29] K. N. Gyftakis, A. J. M. Cardoso, “Reliable detection of stator inter-turn faults of very low severity level in induction motors”, Early Access, *IEEE Trans. Ind. Elec.*, 2020.

[30] Y. Park et al, “Airgap flux based detection and classification of induction motor rotor and load defects during the starting transient,” Early access article, *IEEE Trans. Ind. Electron*., 2020.

[31] ABB (2018), ABB Ability Smart Sensor for motors, [Online]. Available: https://new.abb.com/motors-generators/service/advanced-services/smart-sensor/smart-sensor-for-motors.

[32] WEG Motor Group, WEG Motor Scan – whitepaper, [Online]. Available: https://www.weg.net/wegmotorscan/en.

[33] J. A. Antonino-Daviu, et al, “Validation of a new method for the diagnosis of rotor bar failures via wavelet transform in industrial induction machines,” *IEEE Trans. Ind. Appl.*, vol. 42, no. 4, pp. 990-996, July 2006.

[34] C. Yang et al., “Starting current analysis in medium voltage induction motors: detecting rotor Faults and reactor starting defects,” *IEEE Ind. Appl. Mag.*, vol. 25, no. 6, pp. 69-79, Nov./Dec. 2019.

[35] J. Antonino-Daviu et al., “Electrical monitoring of damper bar condition in salient-pole synchronous motors without motor disassembly,” *IEEE Trans. Ind. Appl.*, vol. 56, no. 2, pp. 1423-1431, March/April 2020.

[36] J. Pons-Llinares, et al, “Transient detection of close components through the Chirplet transform: rotor faults in inverter-fed induction motors,” *Proc. of IEEE IECON*, pp. 3386-3392, 2014.

[37] A. Soualhi, G. Clerc, H. Razik, “Fault prognosis based on Hidden Markov Models,” *Proc. of IEEE WEMDCD*, pp. 271-278, 2015.

[38] R. K. Singleton, E. G. Strangas, S. Aviyente, “Extended Kalman filtering for remaining-useful-life estimation of bearings,” *IEEE Trans. on Ind. Electron.*, vol. 62, no. 3, pp. 1781-1790, Mar. 2015.

[39] W. R. Jensen, E. G. Strangas, S. N. Foster, “A method for online stator insulation prognosis for inverter-driven machines,” *IEEE Trans. Ind. Appl.*, vol. 54, no. 6, pp. 5897-5906, Nov./Dec. 2018.

[40] M. S. Haque, S. Choi, J. Baek, “Auxiliary particle filtering-based estimation of remaining useful life of IGBT,” *IEEE Trans. Ind. Electron.*, vol. 65, no. 3, pp. 2693-2703, Mar. 2018.

[41] R. Liu, B. Yang, A. G. Hauptmann, “Simultaneous bearing fault recognition and remaining useful life prediction using joint-loss convolutional neural network,” *IEEE Trans. Ind. Inform.*, vol. 16, no. 1, pp. 87-96, Jan. 2020.

[42] M. Xia, et al., “A two-stage approach for the remaining useful life prediction of bearings using deep neural networks,” *IEEE Trans. Ind. Inform.*, vol. 15, no. 6, pp. 3703-3711, Jun. 2019.

[43] N. Daroogheh, et al, “Prognosis & health monitoring of nonlinear systems using a hybrid scheme through integration of PFs and NNs,” *IEEE Trans. Syst. Man Cybern.*, vol. 47, no. 8, pp. 1990-2004, Aug. 2017.

[44] H. Oh, J. H. Jung, B. C. Jeon, B. D. Youn, “Scalable and unsupervised feature engineering using vibration-imaging and deep learning for rotor system diagnosis,” *IEEE Trans. Ind. Electron.*, vol. 65, no. 4, pp. 3539-3549, April 2018.

[45] M. Xia et al., “A two-stage approach for the remaining useful life prediction of bearings using deep neural networks,” *IEEE Trans. Ind. Informat.*, vol. 15, no. 6, pp. 3703-3711, June 2019.

[46] C. Hu et al., “A prognostic model based on DBN and diffusion process for degrading bearing,” *IEEE Trans. Ind. Electron.*, early access, 2020.

[47] A. Muetze, E. G. Strangas, “The useful life of inverter-based drive bearings: methods and research directions from localized maintenance to prognosis,” *IEEE Ind. Appl. Mag.*, vol. 22, no. 4, pp. 63-73.

[48] X. Zhang et al. “An integrated approach to bearing fault diagnostics and prognostics,” *Proc. of American Control Conference*, vol. 4, pp. 2750-2755, Portland, OR, USA, 2005.

[49] R. Liu, B. Yang, A.G. Hauptmann, “Simultaneous bearing fault recognition and remaining useful life prediction using joint-loss convolutional neural network,” *IEEE Trans. Ind. Informat.*, vol. 16, no. 1, pp. 87-96, Jan. 2020.

[50] A. Chehade, Z. Shi, “Sensor fusion via statistical hypothesis testing for prognosis and degradation

analysis," *IEEE Trans. Autom. Sci. Eng.*, vol. 16, no. 4, pp. 1774-1787, Oct. 2019.

[51] C. Song, K. Liu, X. Zhang, "Integration of data-level fusion model and kernel methods for degradation modeling and prognostic analysis," IEEE Trans. Reliab., vol. 67, no. 2, pp. 640-650, June 2018.

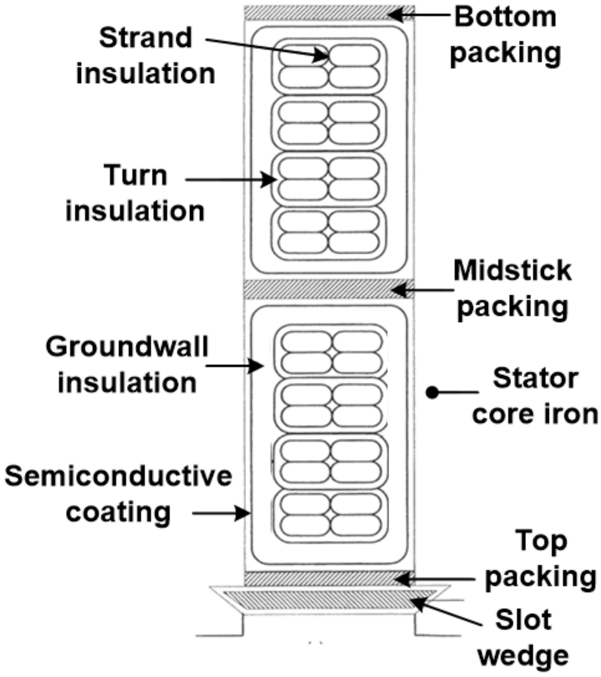
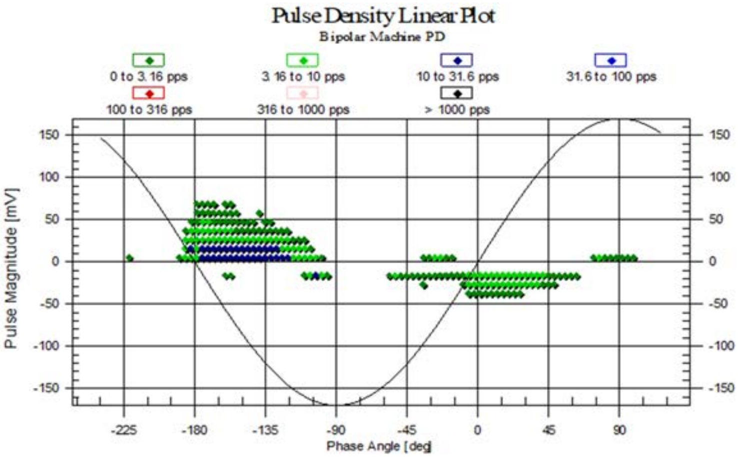
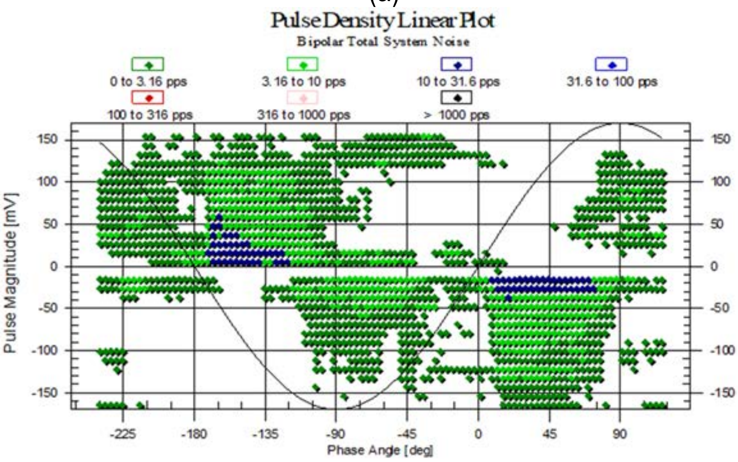


Fig. 1 Cross section of a slot containing strand, turn, phase, and groundwall (GW) insulation components in a multi-turn form wound stator coil [5]



(a)



(b)

Fig. 2 Phase resolved PD pattern of (a) typical PD activity from a stator winding and (b) similar plot of the power system noise that was separated from the stator PD using the "time of pulse arrival" noise separation method for one 50/60 Hz ac cycle.

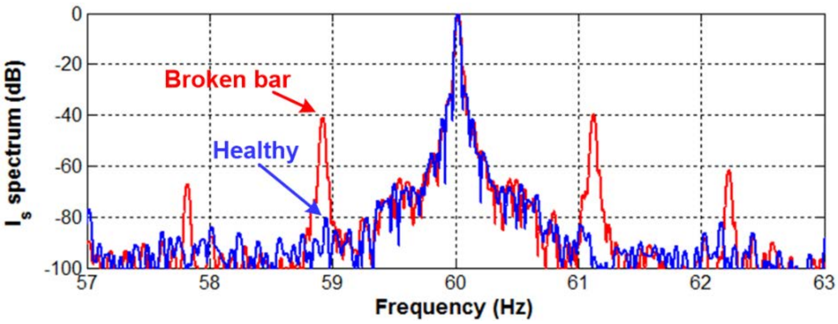
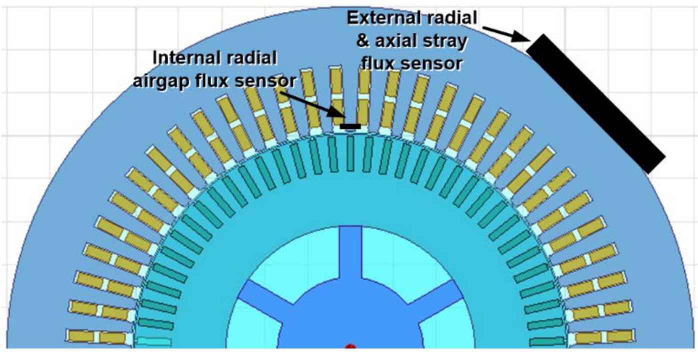
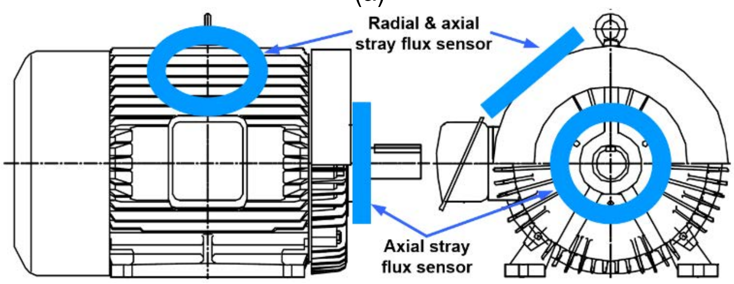


Fig. 3 Example of stator current spectra for induction motor with and without broken rotor bar



(a)



(b)

Fig. 4 Airgap and stray flux measurement for motor condition monitoring: (a) internal radial airgap flux and external radial and axial stray flux coils; (b); external radial and axial stray flux coils

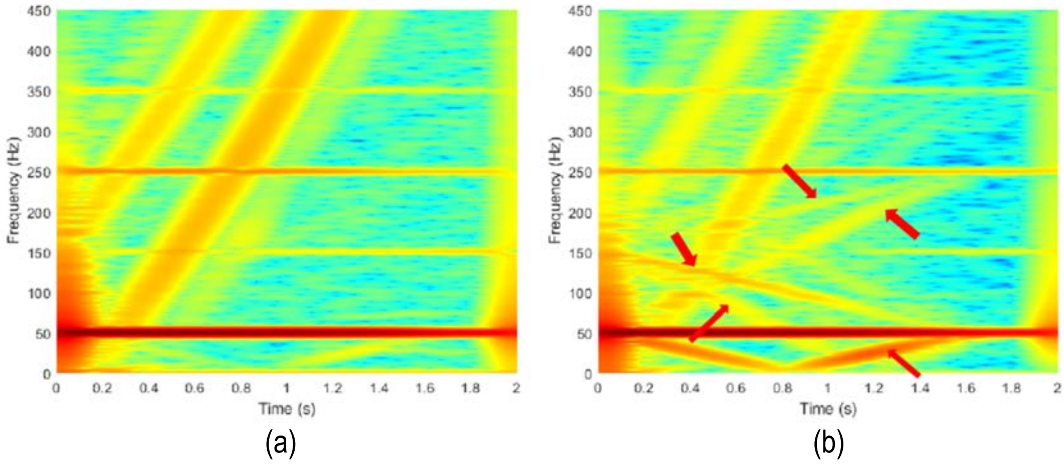


Fig. 5 Starting current time-frequency analyses for: (a) healthy induction motor, (b) Induction motor with broken rotor bars

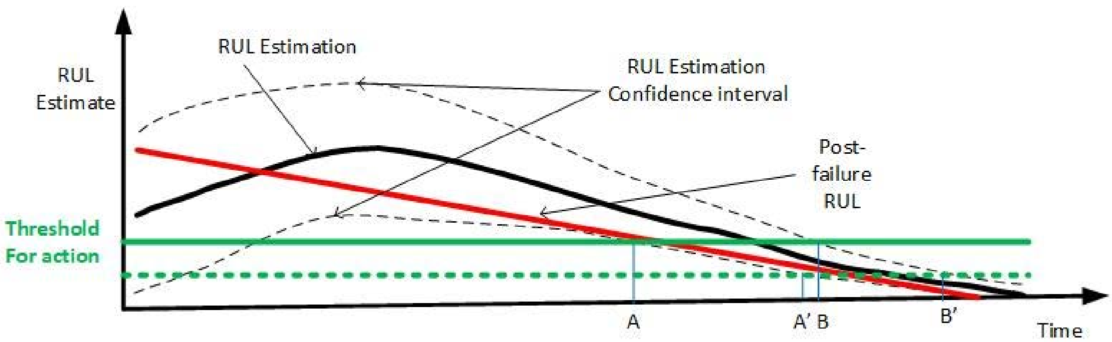


Fig. 6 Concepts and decisions associated with fault prognosis

Table I Characteristic fault frequency components produced by faults in induction and synchronous motors (f_s: fundamental frequency, f_r: rotor rotational frequency, s: rotor slip, p: number of pole pairs, R: number of rotor slots, k: integer (=1, 2, 3,…), n: harmonic order (=1, 3, 5,…), n_d: dynamic eccentricity order, N: number of balls, D_b: ball diameter, D_c: ball pitch diameter, β: ball contact angle)

Fault (component)	Characteristic fault frequency
Static eccentricity	$\left[kR\left(\frac{1-s}{p}\right) \pm n\right] f_s$
Dynamic and mixed eccentricity	$\left[(kR \pm n_d)\left(\frac{1-s}{p}\right) \pm n\right] f_s$
Mixed eccentricity, PM demagnetization, SM open damper & shorted field	$nf_s \pm kf_r = \left[n \pm k\frac{(1-s)}{p}\right] f_s$
IM broken rotor bars & end rings	$\left[\frac{k}{p}(1-s) \pm s\right] f_s$
Bearing outer race	$f_s \pm k\frac{N}{2} f_r \left(1 - \frac{D_b}{D_c}\cos\beta\right)$
Bearing inner race	$f_s \pm k\frac{N}{2} f_r \left(1 + \frac{D_b}{D_c}\cos\beta\right)$
Bearing ball element	$f_s \pm k\frac{D_c}{D_b} f_r \left[1 - \left(\frac{D_b}{D_c}\cos\beta\right)^2\right]$

Table II Typical root causes of false positive and negative indications produced by MCSA-based rotor cage fault detection (false indications that standstill and starting transient testing are immune to are highlighted)

		Diagnosis of MCSA: Healthy	Diagnosis of MCSA: Faulty
Actual rotor condition	Healthy	**True Negative**	**False Positive** • Rotor axial air ducts • Rotor magnetic anisotropy • Low frequency load oscillations • Blade pass frequency vibration • Rotor ovality • Porosity (die cast rotor)
Actual rotor condition	Faulty	**False Negative** • Outer cage fault in double cage rotor • Nonadjacent broken bars • Load variation • Light load conditions • Incorrect speed estimate	**True Positive**