# Advances in Diagnostic Techniques for Induction Machines

Alberto Bellini, *Member, IEEE*, Fiorenzo Filippetti, *Member, IEEE*, Carla Tassoni, *Senior Member, IEEE*, and Gérard-André Capolino, *Fellow, IEEE*

***Abstract*—This paper investigates diagnostic techniques for electrical machines with special reference to induction machines and to papers published in the last ten years. A comprehensive list of references is reported and examined, and research activities classified into four main topics: 1) electrical faults; 2) mechanical faults; 3) signal processing for analysis and monitoring; and 4) artificial intelligence and decision-making techniques.**

***Index Terms*—Adaptive signal processing, artificial intelligence (AI), bearings, diagnostic reasoning, fault diagnosis, Fourier transforms, fuzzy neural networks, induction machines, induction motor drives, induction motor protection, industrial power system maintenance, pattern recognition, signal processing, time–frequency analysis, wavelet transforms.**

## I. Introduction

THIS PAPER analyzes the current state of the art of the diagnostic techniques for rotating electrical machines with special reference to induction machines and to the detection of actual faults. Many diagnostic techniques for induction machines can be extended easily to other types of electrical machines. Fault diagnosis of rotating electrical machinery has received intense research interest. Condition monitoring leading to fault diagnosis and prediction of electrical machines and drives has attracted researchers in the past few years because of its considerable influence on the operational continuation of many industrial processes. Correct diagnosis and early detection of incipient faults result in fast unscheduled maintenance and short downtime for the process under consideration. They also avoid harmful, sometimes devastating, consequences and reduce financial loss. An ideal diagnostic procedure should take the minimum measurements necessary from a machine and by analysis extract a diagnosis, so that its condition can be inferred to give a clear indication of incipient failure modes in a minimum time.

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A. Bellini is with the Department of Sciences and Methods of Engineering, University of Modena and Reggio Emilia, 42100 Reggio Emilia, Italy (e-mail: alberto.bellini@unimore.it).

F. Filippetti is with the Department of Electrical Engineering, University of Bologna, 40136 Bologna, Italy.

C. Tassoni is with the Department of Information Engineering, University of Parma, 43100 Parma, Italy.

G.-A. Capolino is with the Department of Electrical Engineering, University of Picardie Jules Verne, 80025 Amiens, France.

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This paper is organized in four main sections related to electrical faults, mechanical faults, signal processing techniques, and finally artificial intelligence (AI) and decision techniques. This paper has a comprehensive bibliography. The first historic book reference of seminal interest is [1], since when other books have been published [2], [3]. The journal literature on condition monitoring of electrical machines is growing rapidly, although not necessarily in the directions most useful for industry. There are a number of general survey papers on condition monitoring techniques for electrical machines of which the most relevant are [4]–[6].

Electrical machines and drive systems are subject to many different types of faults. These faults include the following: 1) stator faults which are defined by stator winding open or short circuited; 2) rotor electrical faults which include rotor winding open or short circuited for wound rotor machines and broken bar(s) or cracked end-ring for squirrel-cage machines; 3) rotor mechanical faults such as bearing damage, eccentricity, bent shaft, and misalignment; and 4) failure of one or more power electronic components of the drive system.

Induction machines are highly symmetrical electric systems because of the rotating magnetic field, so any kind of fault modifies their symmetrical properties. Characteristic fault frequencies therefore appear in the measured sensor signals, depending on the type of fault. Noninvasive monitoring is achieved by relying on easily measured electrical or mechanical quantities like current, voltage, flux, torque, and speed. The reliable identification and isolation of faults are still, however, under investigation as there are some open issues:

1) definition of a single diagnostic procedure for identification and isolation of any type of faults;
2) insensitivity to operating conditions;
3) reliable fault detection for position, speed and torque controlled drives;
4) reliable fault detection for drives in time-varying conditions;
5) quantitative fault detection in order to state an absolute fault threshold, independent of operating conditions.

The aforementioned items are also attracting considerable research and industrial interest because an efficient diagnostics system paves the way for the fault-tolerant drive that is the next target. In fact, ruggedness and intrinsic reliability were considered unique features of induction machines before the advent of power electronics. The latter have revolutionized electrical drives leading to higher performances and new potential applications although they have reduced the overall reliability.

The availability of an effective diagnostic system embedded in the drive could restore the idea of overall ruggedness of electric drives.

Currently, power converter faults are being investigated as well [7], [8], aiming at the design of a fault-tolerant drive. Specifically, several control strategies have been analyzed in order to find which of them fits better into a remedial operating mode for postfault performance [9], [10].

A recent reliability paper [11] describes the distribution of induction motor faults and shows possible scenarios for after fault, detailing the repair-replace decision process. The distribution of induction motor faults is listed in [11] as bearing (69%), rotor bar (7%), stator windings (21%), and shaft/coupling (3%). It is interesting that premium motors feature figures of reliability similar to other motors. Nevertheless, the large majority of published papers deal primarily with rotor-related faults, then with stator-related faults, and finally with bearing faults.

A motivation for this counterintuitive distribution is that stator electrical faults have been mitigated by recent improvements in the design and manufacture of stator windings. In the case of machines driven by switching power converters, however, the windings are stressed by voltages including high harmonic contents. The latter option is becoming the standard for electrical drives. One solution is the development of improved insulation material and treatment processes. On the other hand, squirrel-cage rotor design has changed slightly, and consequently, rotor faults now account for a larger percentage of total induction motor failures. Rotor bar breakages can be caused by thermal stress, electromagnetic forces, electromagnetic noise and vibration, centrifugal forces, environmental stress (abrasion), mechanical stress owing to loose laminations, fatigue parts, or bearing failures.

## II. Diagnostic Techniques for Rotor and Stator Faults

The analysis of performances of induction machines with cracked bars both from the theoretical and experimental perspective was performed as long ago as 1941 [12]. Since then, this topic has attracted great interest in both academia and industry. For academia, it is an excellent example of a rather complex nonlinear electromechanical system with a number of moving circuits mutually coupled with an asymmetrical structure. For industry, the main concern is the detection of any machine failure at an early stage in order to avoid downtime and replace damaged parts during scheduled maintenance operations, allowing remarkable cost reductions.

The analysis of performances of induction machines with stator failures has been considered only recently. Usually, procedures for the periodic assessment of machine electrical integrity are adopted. They are based on insulation evaluation by means of direct current, alternative current, or surge test methods. Since [13], methods based on negative sequence impedance have been proposed. The idea is to extend traditional inspection techniques to increase the sensitivity to a larger class of stator-winding deterioration modes, and to define an online diagnostic system, that can disconnect the machine before a complete failure.

Restriction of the analysis to deterministic systems, means that the modeling of faulty machines can be done successfully. Relying on these models, the behavior of a specific machine can be accurately analyzed but the extension of the obtained results to other machines is not straightforward. The main diagnostic aim is the identification of the cause-effect chain that is not fully achieved by reliance only on the available machine parameters.

In this paper, special reference is made to those topics only touched on by recent review papers of diagnostic techniques. The main focus is on papers trying to assess the fault severity and defining a quantitative diagnostic index for conventional machines. The latter leads to the statement of a threshold that triggers additional testing or remedial strategies. A further restriction is that only diagnostic procedures based on noninvasive and easily available quantities are considered.

### *A. Stator Faults*

Two main classes of stator winding failures can be considered: asymmetry in the stator windings such as an open-phase failure (1) and short-circuit of a few turns in a phase winding (2). The former allows the machine to operate with a reduced torque while the latter leads to a catastrophic failure in a short time. The models of the induction machine are key items and are very different for the two classes. In the case of winding asymmetry, the winding parameters are changed in the usual machine models, while in the case of shorted turns, the structure of the equations changes because of the increased number of state variables.

Traditionally, an electrical or magnetic nonrotational asymmetry of induction machine or an asymmetry in the supply voltages is detected through the stator current negative sequence. The machine behavior is not the ideal one but no drastic action must be taken in case of small asymmetries. A strong electric asymmetry, as an open phase, causes a negative sequence of similar magnitude compared with the positive one. This last event is therefore easily detected, and the protection system is activated.

A short circuit is recognized as one of the most difficult failures to detect. The usual protection might not work or the motor might keep on running while the heating in the shorted turns would soon cause critical insulation breakdown. If left undetected, turn faults will propagate, leading to phase-ground or phase-phase faults. Ground current flow results in irreversible damage to the core, and the machine must be removed from service. Incipient detection of turn faults is therefore mandatory. One of the simplest but most effective methods is the continuous monitoring of the negative sequence of the stator current.

Machine modeling under fault conditions is a key to predicting its behavior. The analysis of turn-to-turn short-circuit in a winding can be made by different models. The availability of more powerful computers and the development of new machine models able to manage geometry together with electric and magnetic features, allow us to move on from the first models of faulty machines, generally referred to as steady-state operations [14], [15], to sophisticated models where transient operation can be considered as well [16]–[18].

Four main approaches are used to model the behavior of the induction machine in the event of shorted turns.

1) Analysis of the magnetomotive forces (MMFs). The MMF of each conductor is decomposed into series components. Then, static or dynamic models with and without saturation are developed. The spatial distribution of conductors is managed by complex winding coefficients.
2) Winding function approach [16]–[18]. The linkage and the leakage inductances can be computed for arbitrary winding layout or for unbalanced operating conditions. Slotting, skewing, and saturation can be modeled and simulated by means of a suitable airgap function.
3) Dynamic mesh reluctance approach [18]. The machine is geometrically divided into flux tubes. Their reluctances are nonlinear functions of the magnetic potential. A thermal model is included as well. The shorted turns are modeled as an additional phase winding.
4) Finite element (FE) approach [19] for which the geometry of the machine (airgap, core) is discretized in an element with limited conditions. Then, the field computation can lead to torque, flux and even current evaluation.

The main issue, however, is still the lead time to a failure. For low-voltage induction machines, it is so small that an online diagnostic system may be useless. In [18], the dynamic mesh reluctance approach is used to estimate the time available to shut down the machine after a short circuit event. The worst case is a fault with a small number of shorted turns for which the lead time is around a few seconds. Counterintuitively, the lead time is only slightly increased, weakening the magnetizing field. Hence, the previous models are useful for scientific purposes and for a deep understanding of the machine behavior but not for industrial applications. In fact, these models require a thorough knowledge of machine design parameters, not usually readily available from the manufacturer, to prevent reverse engineering. An insightful comparative analysis of the four approaches is still under discussion. What is clear is that saturation must be properly modeled because of the high value of short-circuit currents [17], [18]. The modeling approaches are validated experimentally thanks to special machines where winding taps are used to realize shorted turns. Additional resistances are used, however, to protect the machine. A further unknown quantity therefore appears or reduced voltages are applied to stator terminals so that the saturation effect disappears. In summary, the available models are nice analytical tools helping engineers to predict machine behavior while the issue of detecting a short-circuit event with online measurements of a machine without interrupting its operation remains a problem.

Many proposals have been presented for the use of negative sequence current that is sensitive to different phenomena beyond stator asymmetry [13]. It is also related to the short circuit, namely, it is minimum for one shorted turn that is the worst case. An effective diagnostic procedure should distinguish between the negative sequence caused by the short circuit that must be linked to a few fundamental parameters of the machine and the negative sequence caused by unbalanced voltages, saturation, winding asymmetries, and eccentricity. Negative, positive, and zero sequences are used in order to transform a

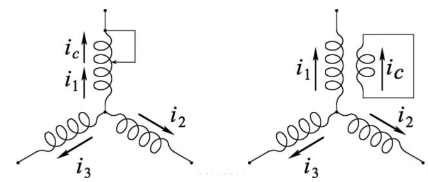


Fig. 1. Stator winding scheme with (left) a single-phase short circuit and (right) simplified scheme.

generic set of phasors into balanced vectors. Specifically, three line currents $\overline{I}_u$, $\overline{I}_v$, and $\overline{I}_w$ are transformed into three balanced vectors known as positive sequence $\overline{I}_p$, negative sequence $\overline{I}_n$, and zero sequence $\overline{I}_0$ by

$$\begin{bmatrix} \overline{I}_p \\ \overline{I}_n \\ \overline{I}_0 \end{bmatrix} = \frac{1}{3} \begin{bmatrix} 1 & \alpha & \alpha^2 \\ 1 & \alpha^2 & \alpha \\ 1 & 1 & 1 \end{bmatrix} \begin{bmatrix} \overline{I}_u \\ \overline{I}_v \\ \overline{I}_w \end{bmatrix} \tag{1}$$

where

$$\alpha = e^{\jmath a}, \qquad a = \frac{2\pi}{3}.$$

In order to take into account the effects of unbalanced voltages in [13], both current and voltage signals are acquired, and a procedure is proposed to replace the usual protection with more sophisticated systems able to disconnect the machine before a complete failure. By means of current and voltage signals, the negative sequence impedance is computed; its value is quite constant unless a failure occurs in the machine. It is suggested that a fault alarm is triggered if a deviation greater than 6% occurs. This threshold must be suitably tuned in order to consider intrinsic asymmetries. To this end, in [20] and [21], a series of tests has been presented in order to compute the cross-impedances between the voltage and current sequences and their variation with the machine load.

A detailed investigation into the behavior of cross-admittance between current negative sequence and voltage positive sequence is presented in [22], where a relationship is given between the amplitude of the cross-admittance and the number of shorted turns. This relationship is based on the assumption that the behavior of a faulty machine with $n_N$ shorted turns is similar to that of a symmetrical machine with an additional (dummy) secondary winding with $n_N$ turns, where the short-circuited current flows (Fig. 1) [23].

In [23], some assumptions were made that allow computation of the negative-sequence current caused by the short circuit with a reduced number of machine parameters, provided that the number of shorted turns is very low. In steady-state condition, the amplitude of the short-circuit current in the dummy winding $I_c$ is modeled by the ratio between the electromotive force (emf) induced by the fundamental field $\phi$ in the $n_N$ short-circuited turns and the impedance $z_n$ of the winding itself. The relationship is

$$I_c \simeq \frac{\omega n_N \phi}{z_n} \tag{2}$$

where $\phi$ is the magnetic flux per turn and $\omega$ is the pulsation of the fundamental field. In order to estimate $z_n$, the resistance is assumed as proportional to the number of shorted turns $r_n = n_N R_s/PN$, while the reactance is assumed as proportional to the square of the number of shorted turns. $N$ is the number of turns per phase and per pole, and $R_s$ is the stator resistance. Hence, the reactive part of $z_n$ can be neglected for low values of $n_N$, and (2) can be simplified by

$$I_c \simeq \frac{V}{R_s} \tag{3}$$

where $V = \omega n_N \phi$ is the supply voltage.

Relationship (3) represents the maximum value of shorted current that is achieved when $n_N \to 1$. With an increase of $n_N$, the reactance increases, and the short-circuit current decreases as confirmed by other researchers [18], [24].

Then, the current in the dummy winding can be referred to the healthy winding

$$I'_c = \frac{n_N}{3N} I_c. \tag{4}$$

These results are obtained with a simple model that neglects saturation. They are, however, in agreement with the results of [18], in which a complex model including saturation and skewing is used. The single-phase current added to the symmetrical currents of the healthy machine produces in the sequence transformation variables an increment of the positive component and a negative component of equal amplitudes. The amplitude of the negative sequence component is $I_n = I'_c/2$, whose limit value for $n_N \to 1$ is obtained from

$$I_n \simeq \frac{n_N V}{6NR_s}. \tag{5}$$

Relationship (5) is proposed to state a threshold current for the worst case, which is a single short-circuited turn once the bias introduced by the intrinsic stator asymmetry and by the voltage negative sequence component has been removed. The threshold value is, however, very low while the corresponding shorted current is very high as confirmed by an estimation made for the case $n_N = 1$, using per unit values. By restriction of the analysis from low- to medium-sized induction machines, $N$ can be assumed to be between 100 and 200 and $R_s$ between 0.05 and 0.1. In this way, approximate values of $I_n$ and $I_c$ can be obtained

$$I_n(\text{p.u.}) \simeq \frac{1}{6 \times (1 \div 2)10^2 \times (5 \div 10)10^{-2}} \simeq 0.008 \div 0.033 \tag{6}$$

$$I_c(\text{p.u.}) \simeq \frac{1}{10^{-1} \div 510^{-2}} = 10 \div 20. \tag{7}$$

The aforementioned relationships show that relying on negative sequence current makes it very difficult to detect the case of a minimum number of shorted turns. In [25], it is assumed that the reactance of the shorted turns is $(n_N/PN)x$, where $x$ is the per-phase reactance. Hence, the short circuit current becomes

$$I_c = \frac{\frac{n_N V}{PN}}{\sqrt{\left(R_f + \frac{n_N}{PN} r\right)^2 + \left(\frac{n_N}{PN} x\right)^2}} \tag{8}$$

where $R_f$ is an additional resistance used to avoid winding damage. With this assumption and in the case of a bolted fault, the fault current should be independent of the number of shorted turns, and it is about twice the locked rotor current. Both the assumptions and the results are opposite to those obtained by previous papers.

In [24], it is assumed that the reactance is proportional to the square of the number of shorted turns. The model uses multiple reference frames for easy manipulation of stator variables that in turn assume constant values. The variation of the positive sequence component with respect to healthy conditions is used as a fault indicator to avoid asymmetrical voltage effects. A quantitative relationship between $I_c$ and $n_N$ is not investigated.

In [26], a relationship linking the short-circuited turn current to the negative sequence current is presented on the basis of the transformer and symmetrical components theories

$$I_n = 0.25 \frac{n_N}{N} I_c. \tag{9}$$

This relationship is not used for the quantification of the number of shorted turns $n_N$ but to state the sensitivity required by the diagnostic procedure. Starting from the assumption that one shorted turn is the most difficult condition to detect, and that the maximum allowed short-circuited current $I_c$ is equal to the rated current, a sensitivity of 0.2%–0.3% is requested. To increase the chance of achieving this sensitivity, the authors propose a preventative “characterization” of the healthy motor to obtain a map of the effects of voltage imbalance, saturation, winding imbalance, and static eccentricity. As before, an external resistance is used to control the short-circuit current and to prevent winding damage.

In [27], the angular fluctuation of the space vector of current and voltage is investigated. The vectors are represented in a polar coordinate plot whose shape describes machine conditions. Specifically, the polar plot of ($r$, $\delta$) is analyzed to identify fault conditions, where $r$ is the magnitude of the space vector of the current, while $\delta$ is the pendulous oscillation angle representing the angular displacement between the space vectors of current and voltage. The polar plot shape is similar to an unfilled petal in the case of stator winding short circuits. The amplitude of the maximum thickness of the petal shape is proposed as the interturn fault index that should be effective regardless of the existence of any manufacturing imperfection effects. This method is attractive for visual inspection but it seems to be impractical for industrial applications.

Further proposals can be found in the literature looking at other current components influenced by stator winding short circuits. The use of signal injection was investigated in [28] in order to diagnose stator faults in drives. Although a linear relationship that links the additional signals and the fault entity cannot be stated, this procedure is proposed to detect an incipient stator winding fault. In [29], it is shown that a similar procedure is ineffective in detecting stator short circuits.

In summary, extensive research activity is focusing on stator fault detection with special reference to short circuits. The most interesting papers are those achieving a simple and effective fault detection at an early stage in order to avoid catastrophic failures. To this end, the combined use of fault detection techniques and of a periodic monitoring of stator turn-to-turn insulation is the most effective method. The most common techniques for assessing the stator turn-to-turn insulation are the surge test and the offline partial discharge (PD) test. Currently, the use of the PD test for low-voltage machines is being investigated [30].

### B. Rotor Faults

Two different types of squirrel-cage rotors exist in induction motors: cast and fabricated. Cast cage rotors are used in motors up to 3000-kW rating. Fabricated cages are used for higher ratings and special application machines where possible failure events occur on bars and end-ring segments. Cast rotors are almost impossible to repair after bar breakage or cracks although they are more durable and rugged than fabricated cages. Typically, they are used in laboratory tests to validate diagnostic procedures for practical reasons. Broken bar and cracked end-ring faults share only 5%–10% of induction machine faults but the detection of these events is a key issue. In the case of stator faults machine operation after the fault is limited to a few seconds, and in case of rotor faults, the machine operation is not restricted apart from a suitable precautionary measure during maintenance. On the other hand, the current in the rotor bars adjacent to the faulty one increases up to 50% of rated current, while in the stator, the current variation is a few percent of the original stator current. In summary, an accurate detection of rotor faults may lead to a complete diagnostic process, while the detection of stator faults can lead only to an intelligent protection system.

Motor current signature analysis (MCSA) has been extensively used to detect broken rotor bar and end-ring faults in induction machines [31]. It is well known from the rotating field theory that any rotor asymmetry generates a component at $(1-2s)f$ in the stator current spectrum with the assumption of constant speed or infinite inertia (where $f$ is the frequency of supply voltages and $s$ the machine slip). Without these assumptions, a component at $(1+2s)f$ appears in the current spectrum as confirmed by experiments. The components are equally spaced around the fundamental frequency and are usually called sideband components. Their distance from the fundamental frequency increases with the load, thus relaxing the constraint of minimum resolution for the frequency analysis. An effective diagnostic procedure must take into account both components [32].

Similarly to the case of stator faults, the behavior of the machine with rotor breakages can be analyzed with different approaches. Rotor asymmetry and construction details as slotting are modeled leading to the ability to predict accurately the behavior of a specific machine. In quasi-steady-state conditions, the speed ripple is modeled as a constant with overlapped low-amplitude components. Under these conditions, the frequency analysis of the currents shows the sideband components at $(1 \pm 2s)f$. These results cannot be extended to other machines as they depend on machine design parameters.

As in the case of stator faults, the simplifying assumptions were used to state effective diagnostic procedures that require only a few machine parameters. In [33], an insightful analysis of the link between the sideband component amplitude, and the rotor asymmetry is presented. Symmetrical stator windings supplied at frequency $f$ produce a rotating field at electric frequency $f$, which induces emfs in the rotor circuits at frequency $sf$. In the case of rotor asymmetry, the rotor currents produce a counterrotating magnetic field at frequencies $-sf$. This component produces a stator current component at $(1-2s)f$, whose amplitude is $I_{\rm l}'$ and that is referred to as the original left-side component. Consequently, a torque ripple and a speed ripple that modulate the rotating magnetic flux are generated at frequency $2sf$. This modulation produces two current components: an additional left-side component at $I_{\rm l}''$ and a right-side component at $(1+2s)f$, whose amplitudes are quite equal. The additional left sideband component overlaps the original one but they are opposite in phase, and the actual left sideband component amplitude is $I_{\rm l} = I_{\rm l}' - I_{\rm l}''$. Hence, the original left sideband component amplitude is simply obtained by summing the amplitude of the left and right sideband components $I_{\rm l}' = I_{\rm l} + I_{\rm l}'' = I_{\rm l} + I_{\rm r}$.

The speed reaction can be seen as a damping effect with a hyperbolic dependance on the inertia [32], and it decreases the original left sideband amplitude. It appears that the sum of the amplitudes of the sideband components is quite constant with the inertia and equal to the amplitude of the left component in the case of infinite combined rotor-load inertia value. Thanks to the latter assumption, a simple but effective model can be defined that leads to a quantitative analysis of the fault severity.

In case of $n_{\rm r}$ contiguous broken bars, it was proved [34] that in steady-state conditions the ratio between the amplitude of the left component and of the fundamental current component is equal to the ratio between the number of contiguous broken bars $n_{\rm r}$ and the total number of bars $N_{\rm r}$

$$\frac{I_{\rm l}'}{I} = \frac{I_{\rm l} + I_{\rm r}}{I} \simeq \frac{n_{\rm r}}{N_{\rm r}}. \tag{10}$$

Equation (10) is an approximate relationship proven with heavy assumptions (the magnetizing current, the contribution of the end-ring segment to the bar resistance, and the bar reactance are neglected). It is, however, nicely in agreement with experimental results obtained with large machines [35]. This relationship allows one to state a threshold for one broken bar that is helpful in identifying the faulty or nonfaulty conditions. Specifically, the threshold $(I_{\rm l} + I_{\rm r})/I = 1/2N_{\rm r}$ was proposed as the edge between faulty and nonfaulty conditions.

Three further phenomena are not modeled by (10) and may lead to inaccurate results:

1) saturation;
2) interbar currents;
3) magnetic asymmetry.

The diagnosis based on MCSA and on (10) is effective only if the aforementioned phenomena are not predominant. A preliminary check is suggested in order to verify these conditions.

The magnetic saturation induces harmonic components overlapping with those caused by rotor faults. In fact, saturation produces a third harmonic in the rotor current, and so a component at $(1+2s)f$ appears in the stator current. Figs. 2 and 3

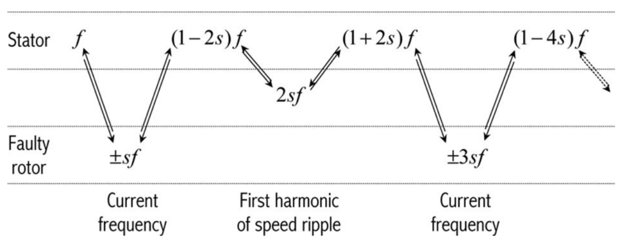


Fig. 2. Speed ripple effect owing to rotor asymmetry on stator and rotor current of induction machines.

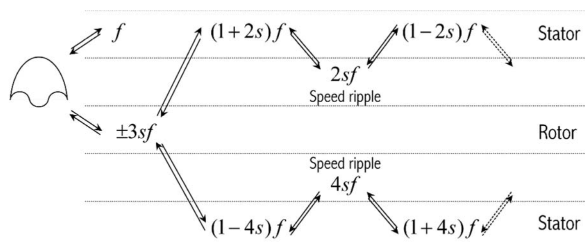


Fig. 3. Speed ripple effect owing to saturation on stator and rotor current of induction machines.

show the chain of components caused by rotor asymmetry and by saturation, respectively.

Side-band components, therefore, appear at the same frequency as a consequence of either rotor asymmetry or of saturation. Hence, an effective diagnosis of rotor faults requires that low saturation condition is verified. Some cues can be used to verify that low saturation conditions occur. As shown in [32], a component at $f_{\mathrm{sat}}$ in the current spectrum exists because of saturation, and it is independent of rotor asymmetry

$$f_{\mathrm{sat}} = \left[\frac{N_{\mathrm{r}}}{P}(1-s) \pm 3\right] f \tag{11}$$

where $P$ is the pair poles number. The component at $f_{\mathrm{sat}}$ is produced by the intermodulation between the rotor slotting frequency and the stator third harmonic caused by saturation. If the amplitude of this component is negligible, a low saturation condition can be verified.

Interbar currents [36] decrease the rotor asymmetry caused by rotor bar breakage, and consequently, diagnostic procedures based on MCSA fail. The axial vibrations that occur only in the case of rotor interbar currents can be used in combination with MCSA to handle these conditions.

Magnetic asymmetry appears for machines with particular rotor structure such as spidered rotors. In this case, unexpectedly high sideband components appear even with healthy cages. A possible adaptation of the test procedure that accounts for these conditions in presented in [35].

In the following, a review of papers that try to quantify the fault severity in order to state a suitable threshold is reported. In [37], a relationship is proposed to link the ratio between the amplitudes of the left sideband component and of the fundamental component $(I)$ to the pole pair number $P$ and the angle $\gamma = (2\pi/(N_{\mathrm{r}}/P))n_{\mathrm{r}}$ covered by contiguous broken bars

$$\frac{I_{\mathrm{l}}}{I} = \frac{\sin\gamma}{2P(2\pi-\gamma)}. \tag{12}$$

Relationship (12) is obtained heuristically as no theoretical investigation is included. It must be noted that relationships (10) and (12) in the case of one broken bar are similar and exactly equal when the two sideband components have equal amplitudes $I_{\mathrm{l}} = I_{\mathrm{l}}'/2$. In fact, replacing $\gamma$ in (12) will lead to

$$\frac{I_{\mathrm{l}}}{I} \simeq \frac{n_{\mathrm{r}}}{2N_{\mathrm{r}}}. \tag{13}$$

A similar relationship is reported in [38], together with a number of case histories that confirm it. Here, both sideband components are used to compute the average value of the amplitudes (in decibels) normalized by the amplitude of the fundamental: $I_{\mathrm{dB}} = [20\log_{10}(I_{\mathrm{l}}/I) + 20\log_{10}(I_{\mathrm{r}}/I)]/2$. From $I_{\mathrm{dB}}$, an estimated number of broken bars $n_{\mathrm{r}}$ is obtained

$$n_{\mathrm{r}} = \frac{2N_{\mathrm{r}}}{10^{-\frac{I_{\mathrm{dB}}}{20}} + P}. \tag{14}$$

The relationship (14) becomes

$$10^{\frac{I_{\mathrm{dB}}}{20}} \simeq \frac{n_{\mathrm{r}}}{2N_{\mathrm{r}}}. \tag{15}$$

By comparing (15) with (10), it can be seen that the geometric average is used instead of the arithmetical average. The difference between the two increases with the difference between the amplitudes of the left and right sideband components and increases with the inertia

$$10^{\frac{I_{\mathrm{dB}}}{20}} \neq \frac{I_{\mathrm{l}} + I_{\mathrm{r}}}{2I}. \tag{16}$$

The relationship (14) was used in [39], where experimental results are presented to validate it in the case of an induction machine with equal amplitude of the sideband components. The diagnosis of rotor asymmetry relying on the sum of the amplitudes of the sideband components of the current spectrum is also used in [40], where the synchronous reference frame is computed thanks to the voltage positive sequence in order to avoid problems caused by the fluctuation of the supply frequency.

In the case of large breakage, the chain of components at $(1 \pm 2ks)f$ is visible in the current spectrum. In [41], a diagnostic procedure is proposed that relies both on sideband components at $(1 \pm 2s)f$ and on components at $(1 \pm 4s)f$ in order to establish a multiple discriminant analysis and insulate the load effect. This procedure can be applied only in the case of heavy rotor faults.

### *C. Diagnosis of Rotor Faults by Means of Multiple Electric Signals*

The Vienna monitoring method [42] relies on voltage, current signals, and measured rotor position to check deviations in terms of instantaneous torque obtained by two different machine models. This procedure was designed for online application in variable-speed drives, and it is proposed as a quantitative diagnostic index independent of inertia and load. The computation is quite heavy, and many parameters are required: stator

TABLE I
CLASSIFICATION OF QUANTITATIVE DIAGNOSTIC TECHNIQUES FOR ROTOR FAULTS

| Current component | Estimation of $n_r$ | References |
|---|---|---|
| $(1-2\,s)\,f$ | $\frac{I_l}{I} = \frac{\sin\gamma}{2\,P\,(2\,\pi-\gamma)}$ <br> $\gamma = \frac{2\,\pi}{N_r\,/\,P}\,n_r$ | [37] |
| $(1\pm 2\,s)\,f$ | $\frac{I_l'}{I} = \frac{I_l+I_r}{I} \simeq \frac{n_r}{N_r}$ | [34], [40] |
| $(1\pm 2\,s)\,f$ | $n_r = \frac{2\,N_r}{10^{-\frac{I_{dB}}{20}}+P}$ | [38], [39] |

resistance, rotor magnetizing reactance, rotor position, and rotor time constant. A new sensorless approach based on the same method is presented in [43]. The rotor position is computed considering that torque pulsations are interacting with speed in the motion equations. It requires a heavier computation and the knowledge of inertia making it difficult to apply it in industrial application.

Another diagnostic approach is based on the frequency analysis of single-phase or three-phase instantaneous power [44], [45]. Computing the instantaneous power is similar to demodulating the sideband components, assuming that they are modulating signals of a carrier at the fundamental frequency. Then, the sideband components are reported to $2sf$. It was proved in [32] that the angular displacements of the two sideband components reported to the same frequency $2sf$ reduce the fault effect. In fact, the speed ripple introduces a double damping effect on the fault component.

In [45], a global flux index computed by the common mode, and the differential mode of the two amplitudes of the sideband components of the power signal at $(2 \pm 2s)f$ is proposed. Here, no relationship with the fault severity is defined, and this choice is not justified in the relationship with the physical root of the two sideband components.

As in the case of stator faults, the angular fluctuation of the space vectors of both current and voltage (swing angle) is investigated for rotor fault detection [27]. Here, the swing angle depicts a single shape in the polar plot, such as a filled petal rotating at frequency $2sf$. As regards stator faults, these plots are useful for a visual inspection but impractical for industrial applications. Rotor faults are also considered showing that the case of incipient faults is better analyzed by MCSA, while a quite complex procedure is proposed for bar breakages.

Diagnostic methods based on the rotor resistance variation consequent to bar breakage can also be found [46], [47]. These methods require the compensation of the thermal variation of rotor resistance, and therefore, their sensitivity is very low.

Another approach is based on the use of an additional signal injected in the stator voltage. This procedure, commonly adopted for sensorless control of induction machine drives, was successfully applied to the diagnosis of rotor asymmetries in the case of digitally controlled drives [28], [48].

Many papers investigate the use of vibration signals to detect rotor asymmetry. This approach was successfully applied even if no relationship was established between the fault severity and the vibration signal. It requires a sensor and a proper signal conditioning.

Table I reports the papers that quantify rotor fault severity and the related diagnostic indices. Extensive research activity focuses on rotor fault detection. Although this type of fault is relatively rare, it is a very interesting topic as effective remedial strategies or corrective maintenance actions may be planned as the evolution of the fault into a catastrophic failure requires quite a long time. The most interesting papers are those that seek a quantitative diagnosis of the fault so that the fault severity is assessed and an absolute threshold for incipient faults is defined. The latter can be useful for manufacturing defects where the trend of the signature is not available. Diagnostic indices were defined based on voltage, current, flux, torque, or speed measurements. There are no significant differences between them, provided that there are no specific constraints given by the available sensors, and a suitable signal conditioning is applied.

## III. MECHANICAL FAULTS

About 40% to 50% of induction motor faults are related to mechanical defects. Among them, a rough classification includes the following: damage in rolling element bearings, static, and dynamic eccentricities. These phenomena will be detailed with a review of the related bibliography.

### A. Bearing Faults

Most electrical machines use either ball or rolling-element bearings which consist of outer and inner rings. Balls or rolling elements rotate in raceways inside the rings. Bearing faults may be reflected in defects of outer race, inner race, ball, or train. Even in normal balanced operations with good shaft alignment, fatigue faults can occur. Vibrations, internal stresses, inherent eccentricity, and bearing currents owing to power electronics have effective influence on the development of such faults.

Generally, a fault in the load part of the drive gives rise to a periodic variation of the induction machine load torque. Examples of such faults causing torque oscillations include the following: general fault in the load part of the drive system, load imbalance, shaft misalignment, gearbox faults, or bearing faults. Torque oscillations already exist in a healthy motor owing to space and time harmonics of the airgap field but the considered fault-related torque oscillations are present at particular frequencies often related to the shaft speed.

Shaft vibration frequencies associated with different ball-bearing faults were given in [3]. In the following, the symbol $F_{\mathrm{C}}$ will be used for the cage fault frequency, $F_{\mathrm{I}}$ for the inner raceway fault frequency, $F_{\mathrm{O}}$ for the outer raceway fault frequency, $F_{\mathrm{B}}$ for the ball fault frequency, $D_{\mathrm{b}}$ for the ball diameter, $D_{\mathrm{c}}$ for the pitch diameter, $N_{\mathrm{B}}$ for the number of rolling elements, and $\beta$ for the ball contact angle:

$$F_{\mathrm{C}} = \frac{1}{2} F_{\mathrm{R}} \left(1 - \frac{D_{\mathrm{b}} \cos\beta}{D_{\mathrm{c}}}\right) \tag{17}$$

$$F_{\mathrm{O}} = \frac{N_{\mathrm{B}}}{2} F_{\mathrm{R}} \left(1 - \frac{D_{\mathrm{b}} \cos\beta}{D_{\mathrm{c}}}\right) \tag{18}$$

$$F_{\mathrm{I}} = \frac{N_{\mathrm{B}}}{2} F_{\mathrm{R}} \left(1 + \frac{D_{\mathrm{b}} \cos\beta}{D_{\mathrm{c}}}\right) \tag{19}$$

$$F_{\mathrm{B}} = \frac{D_{\mathrm{c}}}{D_{\mathrm{b}}} F_{\mathrm{R}} \left[1 - \left(\frac{D_{\mathrm{b}} \cos\beta}{D_{\mathrm{c}}}\right)^2\right]. \tag{20}$$

Typically, bearing faults are detected through vibration signals. The use of electrical signals is, however, preferable in many applications. There are a number of papers dealing with the detection and diagnosis of faults in rolling element bearings based on the analysis of the current of the induction machine [49]–[51]. It was shown that mechanically induced speed oscillations give rise to sidebands components of the fundamental stator current frequency. It was also demonstrated that shaft misalignment causes modulation of the current by the shaft rotational frequency. In [52], the effect of an oscillating load torque on the stator current spectrum and instantaneous power was investigated. In [53], the instantaneous motor input power was analyzed to detect mass imbalance and eccentricity. Nevertheless, the power measurement requires three voltage and three current transducers. All the aforementioned papers consider steady-state machine operation at constant supply frequency.

The physical mechanism that links vibrations to machine current spectral components is still unclear. Internal vibrations are caused by intrinsic asymmetries and construction details. Other troubles linked to the coupling of the machine with the load cause external vibrations and, consequently, new harmonic components in the stator current.

FE or winding function approaches can be used to compute machine currents, speed and torque, relying on mechanical parameters such as machine-load inertia and friction. Then, the vibration spectrum can be estimated from the torque, since they share the same harmonic contents. The correlation between the amplitudes is not straightforward for a few reasons [33].

Vibration and current have different natures. Vibration is an acceleration, and it is bound to the square of the frequency, while the current is a displacement. Hence, the current is mainly sensitive to low-frequency phenomena. Moreover, the generation of vibration requires a structural model with mass, damping, and stiffness parameters that can be solved only through FE computations. The link between vibration and current components is presented in the literature according to two approaches.

In the first approach, the vibration component at one of the mechanical characteristics frequency of the defect $f_{\mathrm{car}}$ acts on the induction machine as a torque ripple $\Delta T_i(t)$ that produces a speed ripple $\Delta\omega_t(t)$. The consequent mechanical angular variation produces an angular fluctuation in the magnetic flux. Hence, the vibration is seen as a torque component that generates two components at frequencies at $F_{\mathrm{be}}$ in the stator current [54]

$$F_{\mathrm{be}} = |f \pm k f_{\mathrm{car}}|. \tag{21}$$

In the second approach, the effect of the vibration component on the current is modeled as a static eccentricity that is represented as the sum of a forward and backward rotating eccentricity. Bearing faults therefore generate stator currents at predictable frequencies $F_{\mathrm{be}}$ related to the mechanical characteristics frequency and electrical supply frequency [55].

The correlation between the vibration level and the magnitude of the sideband currents is tested at various levels of vibration and frequency. The modulating components feature a very small amplitude that is buried in noise. The use of dedicated signal processing techniques is essential to extract the fault signature from the current efficiently.

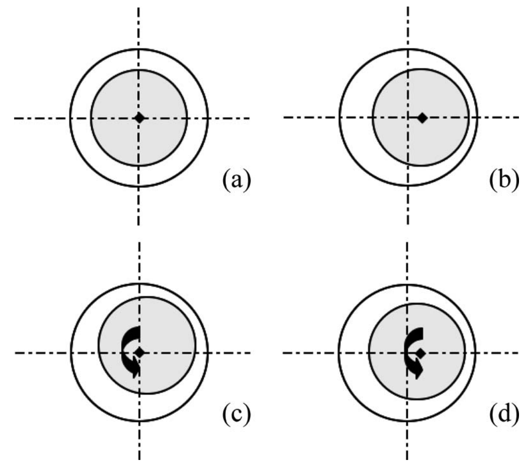


Fig. 4. Different types of eccentricity (border line is the stator inner ring, round rotor is in gray, dotted lines are centering the stator frame and center of rotation is the symbol ♦). (a) Without eccentricity. (b) Static eccentricity. (c) Dynamic eccentricity. (d) Mixed eccentricity.

Recently, the detection of torque oscillations caused by mechanical faults in induction machines under time-varying conditions was investigated by means of a stator current time–frequency analysis [56].

In summary, extensive research activity focuses on bearing fault detection based on current signals. Industrial systems, however, are still based on vibration signals as they are the only reliable media. Current signals can be used for bearing fault detection only in the case of large failures where it is desirable to detect incipient faults that quickly degenerate into other defects. Moreover, typically only single defects are investigated, while generalized roughness is of great potential interest. In fact, generalized roughness appears in lubrication defects or from the wear of bearings or a degeneration of single defects. For generalized roughness, only statistical analysis can be used, and it is an issue to which little attention has been paid.

### B. Eccentricity Faults

In the last 15 years, eccentricity faults in induction machines have been investigated extensively. It is well known by mechanical engineers that the eccentricity of a cylinder rotating around an airgap can be classified as static, dynamic, or mixed eccentricity (Fig. 4). For static eccentricity, the center of rotation is simply displaced from the original center of a certain quantity. Then, for a dynamic eccentricity, the center of rotation is still at its origin while the cylinder is displaced. Finally, for mixed eccentricity, both the cylinder and the center of rotation are displaced from their respective origin.

Airgap eccentricity is one of the commonest failure conditions in an induction machine. It may be static or dynamic in nature or a mixture of both [57]. Usually, there are interactions between the faults. An eccentricity may be caused by many problems such as bad bearing positioning during the motor assembly, worn bearings, bent rotor shaft or operation under a critical speed creating rotor whirl [58]. The eccentricity

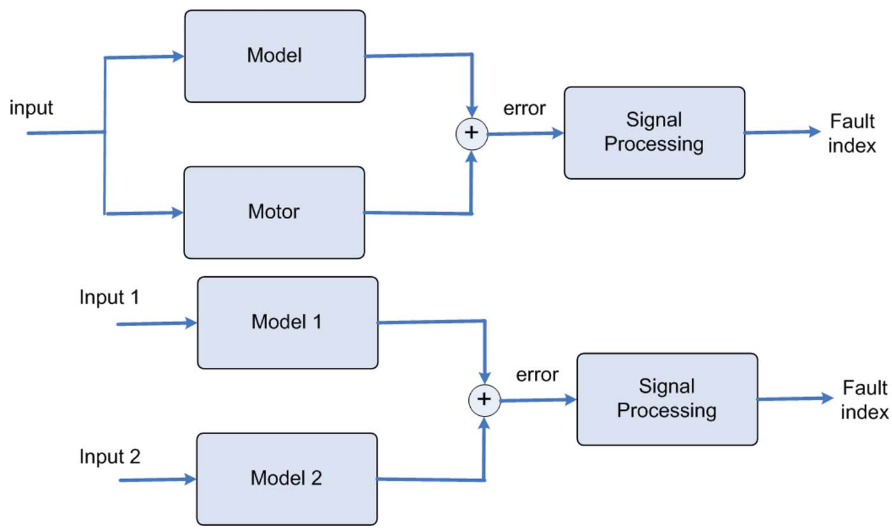


Fig. 5. Block diagram of model-based diagnostic procedure. Two methods are possible according to the same basic structure.

generates a force on the rotor that attempts to pull the rotor from the stator bore. It also causes excessive stressing of the machine and greatly increases the bearing wear. Furthermore, the radial magnetic force owing to the eccentricity can also act on the stator core and exposes the stator windings to unnecessary and potentially harmful vibration.

The first investigations were fully dedicated to modeling the eccentricity as a nonuniform airgap induction machine with both FE analysis and space vector analysis [59], [60]. It was concluded that all types of eccentricity were related to both torque and speed oscillations. The frequencies detected in stator current spectrum analysis were therefore all functions of the rotor speed. More recently, the rotor eccentricity has been evaluated through different signal analysis such as vibration, flux and current [61].

It was proved [62] that, under mixed eccentricity conditions, the stator currents contain the following frequencies:

$$f_{\mathrm{ecc}} = \left| f \pm k\frac{1 - s_{\mathrm{m}}}{P} f \right| \tag{22}$$

where $s_{\mathrm{m}}$ is the machine slip in per unit. The authors also proved that there is always mixed eccentricity on the motor. If the load torque presents an oscillation for other mechanical reasons, because the frequencies related to the eccentricity and to the load torque overlap on the current sidebands, the frequencies provided by (22) are no longer enough for the diagnosis [52], [54], [59].

The model of eccentricity using both analytical and FE methods is still under investigation so that it may be improved [57], [61].

## IV. Signal Processing Techniques for the Diagnosis of Electrical Drives

Fault detection is effective only when fault evolution is characterized by a time constant of the order of days or greater, so that suitable action can take place. In any case, a key item for the detection of any fault is proper signal conditioning and processing.

In fact, the most common diagnostic procedure can be classified in three classes: model based, signal based, and data based. Signal processing is an enabling technology for all three but with different impact and role. Moreover, with advances in digital technology over the last few years, adequate data processing capability is now available on cost-effective hardware platforms. They can be used to enhance the features of diagnostic systems on a real-time basis in addition to the normal machine protection functions. Model-based diagnosis relies on a theoretical analysis of the asymmetrical machine whose model is used to predict fault signatures. The difference between measured and simulated signatures is used as a fault detector (Fig. 5). Residual analysis and suitable signal processing are used to define a fault index.

Signal-based diagnosis looks for the known fault signatures in quantities sampled from the actual machine. Then, the signatures are monitored by suitable signal processing (Fig. 6). Typically, frequency analysis is used, although advanced methods and/or decision-making techniques can be of interest. Here, signal processing plays a crucial role as it can be used to enhance signal-to-noise ratio and to normalize data in order to isolate the fault from other phenomena and to decrease the sensitivity to operating conditions.

Data-based diagnosis does not require any knowledge of machine parameters and model. It only relies on signal processing and on clustering techniques. Data sampled from the actual machine are processed to extract a set of features that are clustered in order to classify them. Eventually, decision process techniques are used to define a fault index (Fig. 7). AI and pattern recognition techniques are widely used to achieve the above purposes.

Fault detection takes place mainly in five different ways: temperature measurements, chemical measurements, mechanical vibration measurements, electrical measurements, and PD detection. The most interesting technique is based on electrical measurements, mainly because they are readily available in the power converter and for signal processing. Among electric

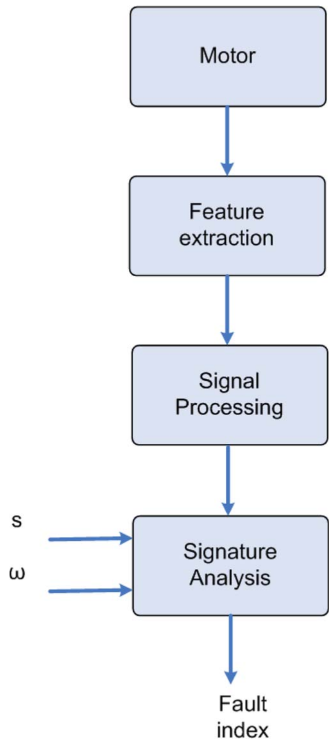


Fig. 6. Block diagram of signal-based diagnostic procedure.

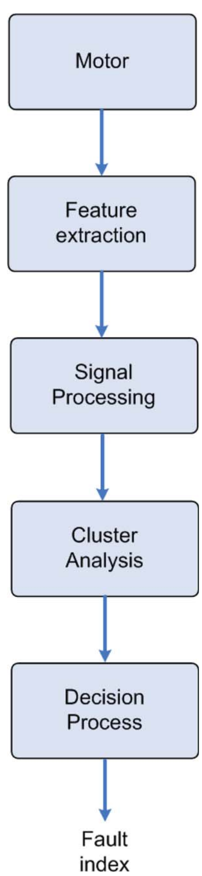


Fig. 7. Block diagram of data-based diagnostic procedure.

quantities, the contactless signals are even more attractive as they are intrinsically noninvasive. Leakage flux was successfully applied to monitor machine conditions [63], [64] provided that a suitable shield was available to prevent the influence of external sources. Typical electric quantities are machine line current, flux, and electromagnetic torque.

For conventional machines, the available quantities are three line currents ($i_u$, $i_v$, $i_w$) and three line-to-line voltages ($v_{uv}$, $v_{vw}$, $v_{wu}$). Actual quantities are usually transformed in order to obtain equations with time-invariant coefficients. Moreover, the transformation reduces the number of dimensions of the state variables, and a suitable reference frame may be retrieved in order to simplify the machine model according to the desired operations. For example, in field-oriented control, the right choice of the reference frame results in decoupling of flux and torque.

Here, the features of the instantaneous symmetrical components (ISC) transformation are briefly recalled, as this is a useful tool for diagnostic purposes. When referring to three-wire systems, ISC returns only two variables for the currents and three variables for the voltages if the star connection is accessible. The ISC transformation for stator currents is

$$\bar{i}_{\mathrm{s}} = \frac{1}{\sqrt{3}} e^{\jmath\theta_{\mathrm{rf}}(t)} \left[i_u(t) + i_v(t)\alpha + i_w(t)\alpha^2\right] \tag{23}$$

where $\bar{i}_{\mathrm{s}}$ is usually referred to as the current space vector and $\theta_{\mathrm{rf}} = \omega_{\mathrm{rf}} t$ is the angle of the chosen reference frame. The current space vector can also be computed as

$$\bar{i}_{\mathrm{s}} = \frac{1}{\sqrt{2}}(i_d + \jmath i_q) \tag{24}$$

where $dq$ variables can be obtained from three-phase instantaneous quantities by means of the following transformation matrix:

$$P_{\mathrm{s}} = \sqrt{\frac{2}{3}} \begin{bmatrix} \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \\ \cos(\theta_{\mathrm{rf}}) & \cos(\theta_{\mathrm{rf}} + a) & \cos(\theta_{\mathrm{rf}} + 2a) \\ \sin(\theta_{\mathrm{rf}}) & \sin(\theta_{\mathrm{rf}} + a) & \sin(\theta_{\mathrm{rf}} + 2a) \end{bmatrix}. \tag{25}$$

Hence, the above electrical quantities or their transformation are processed in order to retrieve diagnostic indices related to the faults. The signal processing can be classified into three main classes: spectral estimation techniques, time-domain techniques, and time–frequency techniques. Another major difference is the nature of the signal that may be stationary or nonstationary. The monitoring is usually done in a steady-state operation using classical spectral analysis tools but many drives are adjustable speed drives where mechanical speed transients may be present during a long time period. The resulting time-varying supply frequency prevents the use of classical spectral analysis. Variable speed drive applications are common in the aerospace, appliances, railways, and automotive industries and also in electric generators for wind turbines. Other signal processing methods such as time–frequency analysis or time-domain analysis allow condition monitoring in speed transients.

### *A. Spectral Estimation Techniques*

Spectral estimation techniques are widely adopted in machine diagnosis. Typically, three main subclasses can be defined: nonparametric methods, parametric methods, and high-resolution methods. Nonparametric methods include conventional Fourier analysis, optimal bandpass filtering analysis, periodogram, and Welch. Parametric methods are based on the estimation of a linear time invariant system from noise by autoregressive-moving-average model, such as Yule–Walker, Burg, or covariance. High-resolution methods include techniques such as multiple signal classification (MUSIC) and eigenvector. In [65], the authors review all these methods with regard to nonstationary signals. It appears that nonparametric methods do not solve the limits of the frequency resolution of the classical Fourier analysis. On the other hand, parametric methods have improved performances although they are affected by the signal-to-noise ratio (SNR) level. Frequency interpolation can be used to improve fast Fourier transform (FFT) performances. This improvement helps to make the existing estimation more accurate but it does not help to find more frequencies.

The other types of frequency estimation that are also based on FFT with resolution improvement are introduced with the idea that they are needed to focus on some special frequency bins and that it is not necessary to take care of the full-length FFT in the total frequency range. For example, the zoom-FFT (ZFFT) and the chirp Z-transform methods have been developed with the above concept. In the ZFFT technique, the following features have been obtained: reduction of computation time, saving of memory space, and accuracy in a specified frequency range.

High-resolution methods or subspace methods can detect frequencies with low SNR. These methods compute the autocorrelation matrix, and its eigenvalues can be separated into signal and noise spaces. These methods define a pseudospectrum function with large peaks that are subspace frequency estimates, and they are commonly used in the communication area. They have been recently introduced into the area of induction machine diagnosis by the application of the MUSIC method [65]. The latter associates the noise with the minimum eigenvalues, which allows low SNR frequency components estimation. In [66], the MUSIC and zooming methods are conjugated to improve the diagnosis by detecting a large number of frequencies in a given bandwidth.

State-of-the-art diagnostic techniques for three-phase machines rely on the frequency analysis of the stator currents [4], [5]. The spectra include data signatures directly related to either electrical or mechanical faults [31] and allow to perform a quantitative analysis of the fault severity [32].

Frequency analysis is usually computed by sampling the signal and adopting FFT algorithm. A direct consequence is that the frequency resolution at a fixed sampling frequency $F_\mathrm{s}$ is inversely proportional to the time acquisition period $T_w$ that is the available duration of signal. It appears that either high time resolution or high-frequency resolution can be achieved through FFT. Hence, Fourier analysis is bound to steady-state operation.

The most commonly adopted industrial solution relies on the aforementioned procedure and is referred to as MCSA. MCSA fails in current regulation and/or adjustable speed drives. In drives with current regulation, the current is kept sinusoidal by control loops masking the fault signatures. This limitation may be overcome by means of different quantities and by the type of control architecture used [67]. In adjustable speed drives, MCSA would require a very accurate frequency analysis leading to a huge time acquisition period which is not available under these conditions.

For example, rotor asymmetries produce sideband components in the stator current spectrum around the supply fundamental frequency and major higher harmonics. The frequency analysis has to be accurate as the load-dependent frequency shift of the sidebands is small and the fault-indicating components are usually far below the fundamental frequency.

In summary, many diagnostic techniques are based on spectral analysis, most of them operating with one machine line current, others with flux, torque or vibration signals.

The frequency analysis of the current space vector is more insightful than the frequency analysis of a phase current only. In fact, for the space vector negative and positive frequencies are meaningful in different ways so that it is possible to distinguish between clockwise and counterclockwise rotating vectors. Moreover, the choice of the reference frame $(\theta_\mathrm{ref})$ allows one to choose the base frequency of the signal. For example, the choice of a synchronous reference frame with $\theta_\mathrm{ref} = \omega t$ moves the sideband components related to rotor faults from $(1 \pm 2s)f$ to $\pm 2sf$. On the other hand, in a fixed reference frame $(\theta_\mathrm{ref} = 0)$, the components of current space vector at frequencies $\pm f$ are referred to as positive and negative sequence components and are commonly used for the detection of stator faults as detailed in the previous sections. If both voltage and current signals are considered, the corresponding space vectors can be used to define sequence impedances.

Hilbert transform is commonly used to process vibration signals and extract signature related to mechanical faults.

Short-time Fourier transform and statistical methods were used to detect both broken bars and bearing defects from the induction motor stator current in applications where the motor speed and load are time-dependent. This algorithm is based on the assumption that the changes in speed and load occur slowly, and there are sufficient intervals of time where the motor can be assumed to operate in a stationary condition.

### B. Time-Domain Analysis

Time-domain analysis is a powerful tool for three-phase squirrel-cage induction machines in faulty condition. Even in the case of nonstationary signals, these methods may be helpful as they feature a lower computational cost and, thus, require a reduced time acquisition period.

Some researchers detect faults in induction machines by analyzing the starting current transient. This enables the detection of faults under a no-load condition where the only measurable and useful information exists in the large starting transient current of the motor. In [53], the oscillation of the electric power in the time domain becomes mapped in a discrete waveform in an angular domain. Data-clustering techniques are used to extract an averaged pattern that serves as the mechanical imbalance indicator. The maximum covariance method is another technique that is based on the computation of the covariance between the signal and the reference tones in the time domain.

TABLE II
CLASSIFICATION OF DIAGNOSTIC TECHNIQUES IN TERMS OF ADOPTED SIGNAL PROCESSING TECHNIQUES AND INPUT SIGNALS

| Type of fault | Input signal | Signal processing | References |
|---|---|---|---|
| Rotor | Stator current | Frequency analysis | [31], [75], [32], [76], [69] |
| Rotor | Stator current | High-resolution methods | [65], [66] |
| Rotor | Stator current | Time-frequency analysis | [77], [71], [72], [70], [73], [74] |
| Rotor | Torque | Frequency analysis | [78], [42] |
| Rotor | Stator current | Signal injection | [79], [28], [48] |
| Stator | Flux | Frequency analysis | [63], [64] |
| Stator | Stator current | Frequency analysis | [13], [16], [67], [26], [20], [22], [24] |
| Various | Stator current | Time-domain analysis | [12], [53], [27], [68] |
| Bearings | Stator current | Frequency analysis | [49], [55], [54], [50], [51] |

It performs well in tracking frequencies in the signal. When a large frequency bandwidth and a good frequency resolution are requested, it takes a long computation time [68]. The latter is a time-domain technique that can track the fundamental frequency and the slip of the machine and then compute a diagnostic index without any spectrum analysis.

### C. Time-Frequency Analysis

Recently, the application of signal processing techniques different from frequency analysis has been proposed to diagnose machine faults [69]. Time-frequency analysis consists of the 3-D time, frequency, and amplitude representation of a signal, which is inherently suited to indicate transient events in the signal.

The Wigner distribution and its various permutations is an analysis technique that has been widely used in the detection of faults in mechanical systems [70] together with wavelet transform [71]–[74] and Hilbert–Huang transform. A reasonable success was reported using wavelets to extract fault information from the stator current prior to classification. The problems of translation variance and the inability to closely approximate sinusoidal signals make their use difficult in rotor fault detection.

In [70], the detection of rotor faults was investigated in electrical machines operating under continuously changing operating conditions. This allows an efficient diagnosis in every condition and not only during the motor start-up.

In summary, the accurate signal processing of the electrical quantities acquired for monitoring purposes in the diagnostic process is a key issue. Proper signal conditioning must be designed to take into account the availability and repeatability of the signals. Moreover, signal processing plays a crucial role in computing an index directly related to the fault severity or to stating its occurrence. Several methods have exploited almost all advanced signal processing tools. A tradeoff exists so that increasing the complexity the fault detection capability is increased together with computational cost. Table II reports selected papers dealing with advanced signal processing techniques for machine diagnosis. The cheap availability of powerful digital processors has spread the use of dedicated processing or postprocessing techniques for signal-based or model-based diagnostic techniques, respectively. Advanced signal processing techniques are not a panacea and each specialized method is best suited either to a type of machine or to a type of fault. They are not useful unless an insightful analysis of machine behavior under asymmetrical conditions is made.

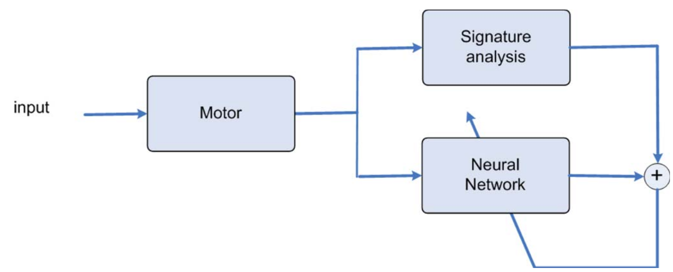


Fig. 8. Block diagram of the training of a neural network for diagnostic purposes.

## V. AI AND DECISION TECHNIQUES

A further step toward a reliable and efficient diagnostic system is the use of AI. The latter is a useful tool to improve the effectiveness and reliability of the diagnosis, mainly during the decision process [33], [80]–[82]. In the supervision of electrical equipment, diagnostic systems based on conventional computing techniques have been recently replaced by new systems based on AI techniques which increase the system efficiency. In fact, traditional systems have been developed on the basis of deterministic models (model-based systems) which are able to consider different fault conditions and to schedule a wide series of operating conditions. Their implementation in a single application leads to complex programs difficult to maintain and to manage. The term AI includes various techniques such as expert systems, neural networks, fuzzy logic, and fuzzy-neural networks that can be used autonomously or into each other to improve their efficiency and effectiveness. The above methods are attractive although they require an initial training phase that is critical for optimal operation. The training phase requires a large set of examples and may be misleading or it can produce results limited to a set of systems. Provided that the training phase is possible, these techniques are efficient and simple, and they can be adopted successfully for the diagnosis of electrical machine failures. For example, the training phase can be made reliant on motor data and on a suitable signature analysis (see Fig. 8).

Nevertheless, AI techniques can help only during the decision process and cluster analysis while the diagnostic index must be assessed independently. The AI techniques may help to speed-up the decision process with reduced human intervention. AI cannot be a panacea capable of solving any problem of diagnostics.

Artificial neural networks (ANNs) mimic the human brain structure and consist of simple arithmetical units connected in a complex architecture. They are able to represent highly nonlinear functions and to perform multi-input multi-output mapping. They learn these functions through examples. ANNs have been applied extensively in the area of condition monitoring and fault diagnosis [33], [52], [82]–[89]. Several research activities used ANNs for the condition monitoring and fault diagnosis of electrical machines [33] performing different approaches and tasks:

1) pattern recognition, parameter estimation, and nonlinear mapping applied to condition monitoring;
2) training based on both time- and frequency-domain signals obtained via simulation and/or experimental results;
3) real-time and online unsupervised diagnosis;
4) dynamic updating of the structure with no need to retrain the whole network;
5) filtering out transients, disturbances and noise;
6) fault prediction in incipient stages owing to operation anomalies;
7) operating conditions clustering based on fault types.

In [85], the different AI techniques are summarized. In [82], an multilayer perceptron (MLP) approach is developed by training the NN in order to estimate the nonlinear relationship between stator current and rotor speed versus main winding equivalent turns and dumping factor in steady-state conditions. In [52], an MLP approach is developed based on MCSA in the frequency domain for detecting anomalies in the load torque. In [90], the authors propose pattern recognition techniques applied to voltage and current measurements. In [86], a supervised MLP structure is used for the fault diagnosis of rolling bearing relying on time–frequency vibration analysis. In [84], a supervised MLP NN structure is used for the detection of broken bars based on the use of MCSA in the frequency domain. A hybrid training set is used that is obtained by simulation and experiments. Reference [83] is the pioneer paper that investigates the feasibility of an unsupervised NN approach (Khonen Feature Map: KFM) for motor fault diagnosis relying on motor current spectra. In this way, anomalies in the load torque signal can be detected with accuracy by means of electrical signals. In [88], an MLP predictor is used for the diagnosis of several types of motor faults. The MLP is trained with the motor in healthy conditions. In [89], stator faults are analyzed through an unsupervised Hebbian-based neural approach starting from the stator currents in a stationary reference frame.

Fuzzy logic is a more powerful variation of traditional logic where not only crisp values (true, false) are allowed but also a larger set of values. In this way, the knowledge representation is closer to the way humans think. Fuzzy systems are able to process natural (linguistic) variables via fuzzy if–then rules. Adaptive fuzzy systems use the learning capabilities of ANNs or the optimization strength of genetic algorithms to adjust the system parameter set in order to enhance intelligent systems performance based on *a priori* knowledge. Fuzzy and adaptive fuzzy systems were applied to motor fault diagnosis for the following tasks [81], [85], [87], [91], [92]:

1) evaluating performance indices using linguistic variables;
2) predicting abnormal operation and locating faulty elements;
3) utilizing human expertise reflected by fuzzy if–then rules;
4) system modeling, nonlinear mapping, and optimizing diagnostic system parameters through adaptive fuzzy systems;
5) fault classification and prognosis.

In [81] and [85], the issue of detecting machine faults is tackled with different neuro-fuzzy techniques. An adaptive NN builds autonomously the related fuzzy systems starting from examples without the effort of tuning the parameters of the rule set. A main advantage of this approach is that it requires a minimum of *a priori* knowledge. In [87], a fuzzy system is used to diagnose voltage unbalances and open phase in an induction motor starting from the stator current Concordia patterns. In [92], the same approach is used for a voltage-fed pulse width modulation induction motor drive. In [91], the interturn insulation and the bearing wear in induction motors are monitored by the neuro-fuzzy ANFIS technique.

Expert systems represent an attempt to emulate the human brain by knowledge representation and inference mechanisms. Within a certain domain of knowledge, expert systems are able to perform a decision making on a quality level similar to human experts, although they are expensive and time-consuming during evolution. Some research works dedicated to applying expert systems to machine fault diagnosis have been reported in the literature. The main tasks of expert systems are:

1) emulating and implementing human expertise;
2) building and online updating of system knowledge bases;
3) signal filtering, information search, and feature extraction;
4) data management and information coding in knowledge bases;
5) employment of users' interactive sessions;
6) fault classification, diagnosis, and location;
7) knowledge base building through simulation and/or experiments.

Various applications in academia prove that such techniques are well suited to coping with induction machine diagnosis [82]–[84]. Until recently, they have not been considered as serious alternatives to the classical methods. Recent developments have been oriented to satisfy the important principle of minimum configuration AI (MCAI) [81], [85], [93]. In this perspective, a diagnostic system must comply with two simple requirements:

1) it must have a minimum number of diagnostic indicators, a minimum number of neurons, or a minimum number of rules, and it must be as simple as possible;
2) it must require a minimum of *a priori* knowledge.

A diagnostic system that fails to satisfy the aforementioned leading guidelines cannot be used in any industrial environment even if is correct from a theoretical point of view. An attractive idea for the use of MCAI principles is the integration of various AI techniques in order to optimize the diagnostic procedures for the detection of both electrical and mechanical faults starting from several electrical and mechanical quantities such as currents, voltages, fluxes, control signals, acoustic noise, and vibrations [85]. A typical diagnostic session is detailed

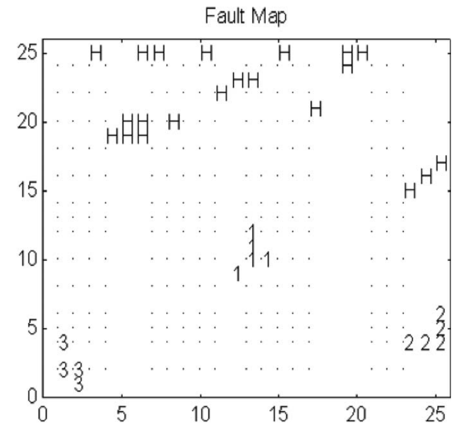


Fig. 9. Fault map obtained using a UNN. H—Healthy machine. 1—Rotor asymmetries. 2—Stator asymmetries. 3—Bearing damage [85].

in order to clarify the above concepts. Stator winding short circuits, rotor bar breakage, static and dynamic eccentricities, and bearing failures were considered. Each of them is characterized by a peculiar signature on electrical quantities. The signature analysis leads to a reliable diagnostic index whose sensitivity to the faults states its effectiveness. A typical and well-known example is the signature of broken bars that are embodied by the amplitude of the sideband components in the stator current, as reviewed earlier. The implementation of a typical diagnostic session can be divided into three main steps: the choice of suitable diagnostic indicators, the fault classification and, finally, the evaluation of the fault extent. The performances of previous procedures can be enhanced by the use of expert systems. Let us assume that an expert system based on production rules is the manager of a whole diagnostic system. The expert system embeds in the knowledge base information about the subassemblies, sensors, software, and hardware resources, including data acquisition environment and diagnostic algorithms. The expert system is in charge of the decision process on the diagnostics procedures. For example, a diagnostic session could be activated by a request by the user according to scheduled maintenance or after an anomalous behavior detected by the expert system itself. Following the activation of a diagnostic session, a three-step procedure is used in order to state the presence of the fault and its type: data acquisition, fault classification, and fault diagnosis. At first, all the data acquired from available electrical quantities are retrieved through a virtual instrument that samples and processes data for suitable signal conditioning operations [34]. Then, data are classified according to an unsupervised neural network (UNN). The UNN is chosen as the best option [83] as it clusters the available input vectors related to different faults into different regions of the output node lattice. The effectiveness of the clustering increases with the number of different input vectors. In fact, with a large number of data sets, the different areas related to different faults are clearly separated in a fault topographic map that can be used for fast visual inspection. In summary, the UNN is a diagnostic preprocessor for classification purposes. Fig. 9 shows an example of a fault classification obtained thanks to UNN. This classification is consistent with the cluster analysis block of Fig. 7.

The input vector corresponds to four conditions: H for the healthy machine, 1 for rotor asymmetries, 2 for stator asymmetries, and 3 for bearing damages. The dots represent a $25 \times 25$ neurons grid while activated neurons are marked with an alphanumeric symbol corresponding to the four conditions defined above. The 2-D map regroups these cases in distinct areas. The four conditions are clearly separated and the unsupervised approach easily clusters the input vectors into regions corresponding to the different cases. It is assumed that the expert system knowledge base has been developed in an advanced way. The input node lattice can be organized as an object of the knowledge base and the expert system is able to analyze the output node lattice deciding if the machine is healthy or not. In the last case, the kind of fault which affects the machine is determined. After the fault classification, specific diagnostic methods must be activated. Conventional methods include the use of mathematical models which can simulate the various faults. Different applications have been depicted in the literature [19], [94], and although this approach is effective, it does not satisfy the MCAI principle and requires a high *a priori* knowledge. For this reason, as already mentioned, researcher attention is often directed to simplified fault models or relationships and to other AI techniques.

In compliance with the MCAI principle, the third step can be accomplished by a supervised neural network (SNN) that is chosen as the best option, since it can synthesize the relationships between the diagnostic indices and the input vectors, starting from examples used to train the learning phase even if physical relationships are completely unknown. The most widely used SNN relies on the MLP as a mapping tool. The input vectors are selected from the sensors and the output vector is obtained according to machine health status. During the learning process, the weights are adapted in order to produce the desired output vectors. For rotor bar breakage, the input vector components are the following: number of rotor bars, the amplitude of the stator current components at frequencies $(1 - 2s)f$, machine load torque, and machine inertia [84]. The output of the MLP is the percentage of broken bar. The expert system is in charge of acquiring signals, to feed them to the SNN, and to assess results. Usually, each fault requires a specific method based on conventional techniques, AI techniques or a method based on a combination of both [84]. Different faults may require the same methodology but different *a priori* knowledge since they are the result of very different phenomena (mechanical and electrical faults). Different solutions could be adopted for the steps two and the three of the expert system. For example, in the classification step, the UNN could be replaced by a fuzzy system where fuzzy sets representing the different faults could be tuned by an adaptive neural network [81], [85]. The previous procedure is the best tradeoff between performances and compliance with MCAI principles and minimum *a priori* knowledge of the plant.

In summary, the application of AI tools in condition monitoring and fault diagnosis of electrical machines is an aid in the automation of the diagnostic process. It also helps by using the human expertise, resulting in early and accurate fault detection. It is expected that a mature use of AI techniques will be beneficial for embedded diagnostic systems for electrical machines.

## VI. Conclusion

The diagnosis of electrical machines has been an important research topic for more than a century, as reported in the vast bibliography included here. The advent of condition monitoring has revolutionized the maintenance of systems based on electrical machines. In fact, this term refers to a monitoring system that can diagnose the condition of an induction motor in order to determine the types of faults and their severity while the motor is under normal operating conditions. This requires accurate and effective fault detection that must be noninvasive and able to detect any type of faults in the early stages. Condition monitoring is the root element of condition maintenance that overcomes the shortcomings of traditional corrective maintenance and of time-based maintenance. Corrective maintenance suffers from downtime in case of failure, while time-based maintenance is typically more expensive as the pace of monitoring is higher.

From the perspective of long-term research on the diagnosis of electrical machines, it appears that recent focus has been on the use of signal processing and of AI in order to improve the performances of traditional model-based methods. The latter was fostered by the availability of low-cost high-power processor. Significant improvements were accomplished and recently the focus has moved from protection and maintenance system for large machines to a generalized condition monitoring. The cheap availability of processing power and the extended use of adjustable speed drives has extended the range of applications where diagnostics is required. MCSA is still the reference method for industrial applications and some key issues remains. Specifically, a single reliable procedure for any type of fault based on noninvasive signals is not established yet. Moreover, while fault detection has been widely investigated very little activity was focused on prognosis and remedial strategies after the fault occurrence.

Novel techniques must be investigated according to the following main guidelines:

1) accurate machine models best suited to diagnostic aims;
2) novel diagnostic indexes more sensitive to faults and robust to load and inertia;
3) sensors and measurements techniques best suited to fault detection;
4) integration between traditional and AI-based diagnostic procedures.

In case of electrical drives, the use of switching power converters often reduce the lifetime of the machine. Many research activities have been and will be oriented to diagnose machine faults under these conditions. On the other hand, the availability of digital processor and sensors used for the drive control paves the way for an integrated diagnostic procedure that should work at the system level as an intelligent protection and preventive maintenance.

As reported by the included references, a large majority of research was oriented to induction machines, often with constant speed. It is foreseen that the research in the near future will be oriented to adjustable speed drives based on induction and permanent magnet machines. An accurate diagnostic system for drives in time-varying conditions is not available yet although many proposal were presented.

Eventually, it is expected that the request of reliability and efficiency will be increased. Hence, fault diagnosis and condition monitoring should move toward the design of fault-tolerant drives. In this framework, integrated diagnostic systems and the use of machine intrinsically robust toward failures, like multiphase machines, are among the most attractive solutions. In fact, multiphase machines feature an increased number of degrees of freedom that may be used to enhance the reliability of the drive provided that electrical and mechanical fault diagnosis techniques are available.

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**Alberto Bellini** (S'96–M'99) was born in Italy in 1969. He received the Laurea degree (M.S.) in electronic engineering and the Ph.D. degree in computer science and electronic engineering from the University of Bologna, Bologna, Italy, in 1994 and 1998, respectively.

From 1999 to 2004, he was with the University of Parma, Parma, Italy. He was an honorary scholar with the University of Wisconsin, Madison, during 2000. Since 2004, he has been with the University of Modena and Reggio Emilia, Reggio Emilia, Italy, where he is currently an Assistant Professor of electric machines and drives. He is the author or coauthor of more than 80 papers and one textbook, and is the holder of three industrial patents. His research interests include power electronics, signal processing for audio and industrial applications, and electric drive design and diagnosis.

Dr. Bellini was the recipient of the First Prize Paper Award from the Electric Machines Committee of the IEEE Industry Applications Society in 2001. He serves as an Associate Editor of the IEEE TRANSACTIONS ON INDUSTRIAL ELECTRONICS.

**Fiorenzo Filippetti** (M'00) was born in Fano, Italy, in 1945. He received the Master's degree in electrical engineering from the University of Bologna, Bologna, Italy, in 1970.

Since 1976, he has been with the Department of Electrical Engineering, University of Bologna, where he was first an Assistant Professor and where he is currently a Full Professor of electrical drives. From 1993 to 2002, he was Adjoint Professor of electrotechnics and electrical drives with the University of Parma, Parma, Italy. He spent several visiting periods with the University Claude Bernard, Centre de Génie Electrique de Lyon (CEGELY), Lyon, France, and with the University of Picardie Jules Verne, Amiens, France. During 1998, he held a position at the University Claude Bernard, Lyon, as a Member of the Scientific Council of CEGELY. He is a Lecturer for the European Master in Advanced Power Electrical Engineering recognized by the European Commission in 2004. He has been the advisor of various Ph.D. and M.S. students. He is involved in national and European research projects. He has authored or coauthored more than 160 scientific papers published in scientific journals and conference proceedings since 1976, and one textbook. He is the holder of an industrial patent. His main research interests include the simulation and modeling of electric circuits and systems, and the study and application of condition monitoring and fault detection techniques for ac electrical machinery.

**Carla Tassoni** (SM'97) was born in Bologna, Italy, in 1942. She received the Master's degree in electrical engineering from the University of Bologna, Bologna, in 1966.

She was with the Department of Electric Engineering, University of Bologna, first as an Assistant Professor and then as an Associate Professor of electrical machines. She is currently a Full Professor of electrical engineering with the University of Parma, Parma, Italy. She is the author or coauthor of more than 150 scientific papers. Her main research interests include simulation and modeling of electrical systems and applications of diagnostic techniques.

**Gérard-André Capolino** (A'77–M'82–SM'89–F'02) was born in Marseille, France. He received the B.Sc. degree in electrical engineering from the Ecole Centrale de Marseille, Marseille, in 1974, the M.Sc. degree from the Ecole Supérieure d'Electricité, Paris, France, in 1975, the Ph.D. degree from the University Aix-Marseille I, Marseille, in 1978, and the D.Sc. degree from the Institut National Polytechnique de Grenoble, Grenoble, France, in 1987.

Since 1994, he has been with the University of Picardie Jules Verne, Amiens, France, where he was first a Full Professor and where he is currently the Director of the European Master in Advanced Power Electrical Engineering recognized by the European Commission in 2004. He has published more than 380 papers in scientific journals and conference proceedings since 1975. His research interests are mainly in modeling and control of induction machines and in condition monitoring and fault detection of ac electrical machinery.

Dr. Capolino has been involved in many IEEE activities in the France Section (Past Chair), the Region 8 (Chapter Sub-Committee Chair), IEEE Power Electronics Society (Associate Editor, SDEMPED founder), and IEEE Industrial Electronics Society (Associate Editor, Vice-President for Membership, Distinguished Lecturer). He is the Acting Chair for the Steering Committee of the International Conferences on Electrical Machines. He is the recipient of the IEEE-IES Dr. Ing. Eugene Mittlemann Achievement Award for 2008.