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Fault Diagnosis and Fault-Tolerant Control of PMSM Drives–State of the Art and Future Challenges

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ABSTRACT The issues of monitoring and fault diagnosis of drives with permanent magnet synchronous motors (PMSMs) are currently very relevant because of the increasing use of these drives in safety-critical devices. Every year, more and more articles are published on this subject. Therefore, the objective of this article is to update the overview of diagnostic methods and techniques for PMSM drives. Each of the main chapters of the article focuses on a specific element of the drive system (motor, power converter, measuring sensors), with particular emphasis on the components of the motor (stator windings, magnets, bearings, and rotor). The main sections on PMSM fault diagnosis are divided according to the type of methods used to obtain the symptoms of the damage. In addition, a review of methods that use the analysis of signals of the control structure for the diagnosis of damage to a vector-controlled motor is presented, as well as the latest achievements of researchers in the field of shallow and deep neural networks for the detection and classification of failures of PMSM drives. Based on the analyses presented in the literature, some development trends and challenges related to the development of diagnostics and fault-tolerant control of PMSM drives are discussed in the conclusion part.

INDEX TERMS Diagnostics, permanent magnet synchronous motors, fault detection, inter-turn short-circuits, magnetic faults, mechanical faults, signal analysis, neural networks, fault-tolerant control.

ABBREVIATION LIST

1D-LBP	One dimensional local binary patterns.
AC	Alternating current.
AD-OT	Angular domain-order tracking.
AE	Autoencoder.
AFTC/PFTC	Active/passive fault-tolerant control.
AI	Artificial intelligence.
ASD	Adjustable speed drive.
BEMF	Back electromotive force.
BLDCM	Brushless direct current motor.
BNN	Bayesian neural network.
BS	Bispectrum.
CNN	Convolutional neural network.
CS	Current sensor.
CWD	Choi–Williams distribution.
CWT	Continuous wavelet transform.
DBNN	Deep-belief neural network.
DC	Direct current.
DF	Demagnetization fault.
DL	Deep learning.
DNN	Deep neural network.
DTC	Direct torque control.
DWT	Discrete wavelet transform.
EKF/UKF	Extended/unscented Kalman filter.
EMD	Empirical-mode-decomposition.
ENN	Elman neural network.
ENV	Envelope analysis.
EPVA	Extended Park vector analysis.
ESPRIT	Estimation of signal parameter by rotational invariance technique.
ESR	Equivalent series resistor.
EWD	Equal width discretization.
FC	Frequency converter.
FDD	Fault detection and diagnosis.

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FEA/FEM	Finite element analysis/method.
FFT/DFT	Fast/discrete Fourier transform.
FI	Fault indicator.
FOC	Field-oriented control.
FS	Full spectrum.
FT	Fourier transform.
FTC	Fault-tolerant control.
GAN	Generative adversarial network.
GST	Grey system theory.
HF	High frequency.
HOS	High order spectra.
HOT	High order transform.
HT/HHT	Hilbert/Hilbert-Huang transform.
IGBT	Insulated gate bipolar transistor.
IM	Induction motor.
IMF	Intrinsic mode functions.
IoT	Internet of Things.
IPMSM	Interior PM synchronous motor.
ITSC	Inter-turn short-circuit.
KF	Kalman filter.
LO	Luenberger observer.
LSPMSM	Line-start PMSM.
LSTM	Long short-term memory.
MCSA/MVSA	Motor current/voltage signature analysis.
MLP	Multi-layer perceptron.
MPC	Model predictive control.
MRAS	Model reference adaptive system.
MUSIC	Multiple signal classification.
NN/SNN	Neural network/shallow neural network.
OA	Order analysis.
PCA	Principal component analysis.
PCB	Printed circuit board.
PDF/UDF	Partial/uniform demagnetization fault.
PM	Permanent magnet.
PMSG	Permanent magnet synchronous generator.
PMSM	Permanent magnet synchronous motor.
PNN	Probabilistic neural network.
PSD	Power frequency spectrum density.
PWVD/SPWVD	Pseudo-Wigner Ville/smoothed PWVD.
RBF	Radial basis function neural network.
RMS	Root mean square.
RUL	Remaining useful life.
SCA	Symmetrical component analysis.
SMO/HO-SMO	Sliding mode observer/higher-order SMO.
SMPMSM	Surface-mounted PM synchronous motor.
SOM	Self-organizing Kohonen map.
STAT	Statistical analysis.
STFT	Short-time Fourier transform.
SWT	Synchrosqueezing wavelet transform.
SVM	Space vector modulation.
TDE	Time delay embedding.
T-FM	Time-frequency domain method.
UMP	Unbalanced magnetic pull.
VKF-OT	Vold-Kalman filtering order tracking.
VSI	Voltage source inverter.
WNN	Wavelet neural network.
WT/WPT	Wavelet/wavelet packet transform.
WVD/WVT	Wigner–Ville distribution/transform.
ZCP	Zero-crossing point.
ZFFT	Zoom FFT.
ZSCC	Zero sequence current component.
ZSVC	Zero sequence voltage component.

I. INTRODUCTION

A. PROBLEM DESCRIPTION

Recently, rapid enhancement of 'more electrical' drive system applications is observed, not only in areas such as industrial automation and robotics but also in transport applications (so-called 'more electric' airplanes, ships, trains, vehicles, etc.) and wind power generation. This is due, among other things, to the worldwide demand to minimize carbon emissions. Systems that consume hydraulic, pneumatic, and mechanical power, so far used in conventional automation systems or transport devices, are now being replaced by electrical systems, which reduce fuel consumption, operating costs, noise, and pollution of the atmosphere. Therefore, it is now so important to design electric drive systems that meet the following requirements: small dimensions, low weight, low cost, high efficiency, and less effort in maintenance and repair.

Therefore, among other electrical machines, PMSMs have attracted much attention in the last twenty years in robotics and in traction vehicles, due to their high-power density and efficiency, high torque to volume ratio, excellent dynamic performance, simple and compact structure compared to induction or reluctance motors [1]. However, PMSMs, like other electrical machines, are not resistant to various damages of an electrical (stator windings), magnetic (PM) and mechanical (bearings, unbalance, eccentricity) nature caused by various stresses that occur during long operation in severe conditions, which are influenced by changing parameters of the power source and load. Due to the increasing use of PMSM in devices of critical nature, such as transport applications and wind power generation, detection, identification, and isolation or tolerance of these damages in their initial stage is a remarkably essential and current issue [2], [3].

Due to the growing requirements of users regarding the reliability and safety of installed drives, manufacturers of control systems for AC drives are more and more interested in embedding diagnostic functions in their converter control algorithms. The current development of sensor technology, measuring equipment, and software for digital signal processing, as well as computational intelligence, enable ongoing monitoring of the drive condition and the observation of trends. This allows the detection of failures occurring at their initial stage and the prognosis of the drive system RUL [4]–[6].

B. CONTRIBUTION OF THIS PAPER

In recent years, many review articles have been published on the FDD of electrical machines; however, most of them are related to induction motors (IM) [7]–[13], because until recently they accounted for more than 90% of all electric motors installed in industry [1]–[3]. Due to the growing interest in the usage of PMSM in various electric drives, especially high-performance drives, the methods of diagnosing failures of these drives have begun to develop intensively in recent years, and after 2010 some interesting reviews for PMSM diagnostic methods have appeared in the scientific literature [14]–[23]. Few conference papers were also published [24], [25], presenting a very preliminary review of condition monitoring and fault diagnosis techniques for PM motors.

The most interesting surveys are summarized in Table 1, taking into account whether or not the different issues are reviewed: description of the impact of the fault on the performance and state variables of the PMSM, more or less detailed analysis of different fault types, applied diagnostic methods, FTC concepts, and future challenges. The period of the analyzed literature is given for each review, taking into account references concerning PM drives only, as some of the articles also focus on IMs.

To the best knowledge of the authors, the first review on PM machine diagnostics (BLDC and PMSM) was published in 2011 [14]. It presents comprehensive information on the influence of faults on machine parameters and signals, some signature extraction methods, and preliminary work on AI algorithms applied to PMSM fault detection. In this paper, the greatest emphasis is placed on the description of modeling methods for PM motors and on the analysis of phenomena and their impact on machine parameters.

With regard to diagnostic methods, by nature, only a limited number of examples have been provided, since relatively few papers on PMSM diagnostic methods had been published by 2011. Similarly, the examples of NN applications for fault diagnosis quoted in the paper concern IM and rotating machines in general (selected mechanical damages). It is worth mentioning that the article shows the issues related to the prognosis of damage, although in relation to IM, but with an indication of the possible applications in PM drives.

The next paper [15] presents a very wide and interesting review of PMSM faults, starting from fault types, focusing mainly on electrical faults (resistive unbalance, interturn, and open phase faults), mechanical faults (static, dynamic, and mixed eccentricity, bearing fault) and magnetic faults (uniform and partial demagnetization). Next, the state-of-the-art (as of 2015) of FDD for PM machines is examined, including model-based, signal-based, and chosen knowledge-based methods, which are compared in terms of invasiveness, complexity, capability, and cost. Finally, the development trends of the fault diagnosis for the PM machine are presented.

The two 2017 review articles [16], [17] are less comprehensive, also in terms of the cited work, but nevertheless focus on the diagnostic methods used to detect different fault symptoms. However, mechanical failures are not addressed in [17]. The fault analysis methods are divided into model-based diagnosis and data-driven diagnosis in [16], without going into details of what specific symptoms are extracted using a given method. In [17] the FDD methods are classified based on the source signal. The type of fault and the most interesting application examples are also described. It should be mentioned that the open circuit fault of the inverter switches is discussed in [16].

In [18], as well as in [16], the detection of mechanical damages and AI-based methods are not taken into account at all, while different categories of FIs for ITSC and irreversible demagnetization fault are discussed. Additionally, selected literature items concerning the use of mathematical models and observers for the diagnosis of PMSM drive failures are presented, as well as certain research trends on the development of the FDD issue are formulated.

It seems that the most comprehensive overview of the literature on FDD methods applied to the PMSM drive was presented in [19] in 2018. However, the authors did not take into account methods based on the analysis of internal signals from the PMSM drive control structures. Furthermore, AI-based methods were only mentioned and not discussed in detail. The state-of-the-art diagnostic tools are presented for PM damage and DF, rotor eccentricity, UMP, open and short-circuit faults of the stator winding. It is worth noting that a unique feature of this review is the inclusion of a special section on the failure mechanism and failure detection techniques for Si metal oxide semiconductor field effect transistor (MOSFET) and IGBT switches as well as silicon carbide (SiC) MOSFET and gallium nitride (GaN) FETs. Moreover, the effect of switch faults such as open-circuit and short-circuit faults on the drive system is presented with their detection and protection mechanism (with over 33 references analyzed). Finally, an integrated methodology for monitoring the condition of PM machines is proposed; however, FTC issues are not addressed.

In the subsequent review article from 2019 [20], the analysis of the literature is limited to model-based fault diagnosis and different signal processing methods, and data-driven diagnostic algorithms are enumerated for electrical, mechanical and magnetic faults of the PMSM. The possibility of detecting damage to other elements of the drive system is not discussed, as is the FTC issue for PMSM drives. Compared to existing reviews of PMSM fault diagnostics, several new research methods have been added; in particular, selected algorithms using AI methods have been discussed.

The paper [21] is focused on PMSM servo-drive systems. The selected FDD methods for basic PMSM faults, such as demagnetization, ITSC, and rotor eccentricity faults,

TABLE 1. Comparison of this paper with existing surveys and review papers on diagnostics of PMSM drives.

Legend	√ covered; × not covered; ≈ partially covered; SF/SE – selected faults/examples; NN-neural network, DL -deep learning, (xx) – references on PMSM																
Survey paper	Year of publication	Number of references all(only PMSM)	Period of references concerning PMSM drives only	Description of fault effects	Fault type diagnostics					Methods						FTC	Future challenges
					PMSM			Freq. Conv.	Sensors	Model-based		Signal-based		AI -based			
					Electrical	PMs	Mechanical			Sympt. gener.	Observers	Ext.	Int.	NN	DL		
[14]	2011	56 (23)	2000-2010	√	≈	≈	≈	×	×	√	≈	≈	×	≈	×	×	√
[15]	2015	125 (120)	1997-2016	√	√	√	√	×	×	×	≈	√	×	√	×	×	√
[16]	2017	59 (36)	1995-2016	√	√	√	×	≈	×	√	√	√	×	≈	×	×	≈
[17]	2017	77 (68)	2005-2017	×	≈	≈	≈	×	×	×	×	√	×	≈	×	×	×
[18]	2018	143 (129)	2001-2018	√ (SF)	√	√	×	×	×	√ (SF)	√ (SF)	√ (SF)	×	≈	×	×	≈
[19]	2018	194 (135)	1995-2017	√	√	√	√	√	×	√	×	√	×	≈	≈	×	√
[20]	2019	110 (80)	2000-2019	×	√	≈	√	×	×	×	×	√		√	≈	×	×
[21]	2020	62 (59)	2003-2017	×	√ (SE)	√ (SE)	√ (SE)	≈	≈	×	≈	√ (SE)	×	≈	×	≈	√
[22]	2020	138 (89)	2002-2019	×	√ (SE)	√ (SE)	√ (SE)	√	√	×	√	√ (SE)	×	√ (SE)	×	√	√
[23]	2021	99 (77)	2012-2020	≈	≈	≈	×	√	√	≈	√	√	×	×	×	√	√
This paper	2022	338 (323)	1996-2022	≈	√	√	√	√	√	√	√	√	√	√	√	√	√

as well as sensor fault and inverter fault of the servo drive, are analyzed. The fault diagnosis methods based on signal processing and AI, proposed in recent years are summarized, and their advantages and disadvantages are discussed. However, in terms of NN applications, especially DL methods, only possibilities are shown, not examples of applications in PMSM drives. Finally, future development trends for PMSM servo system fault diagnosis technology are given.

Similarly, in [22] only selected FDD methods are analyzed for electrical faults that occur in the PMSM drive, such as open or short-circuit faults of power devices, windings and inverter legs, unstable voltages and sensor faults. However, the references concerning the FDD methods for electrical, magnetic, and mechanical faults of PMSM are only listed; not all are evaluated. Only a few works on the NN application for PMSM fault detection are presented. It should be mentioned that model-based and observer-based methods are discussed for sensor faults, and FTC solutions for PMSM drive are analyzed, including passive and active approaches.

The most recent survey on FDD for PMSM drives was published in 2021 [23]. This article focuses on four main types of PMSM drive faults: stator winding, demagnetization, inverter, and sensor faults. The selected research results of the FDD technology under these faults are shown. Also, the issue of active FTC of the PMSM drive system under different fault conditions is summarized and future development of the PMSM drive system fault diagnosis and FTC technology is addressed based on the research status. The authors of this review focus on analyzing how the existing fault-tolerant technology improves the fault-tolerant performance of the PMSM drive system from both the hardware design and the software algorithm. Current problems are highlighted, and future development directions are defined.

In analysing the survey-type articles, it should be mentioned that excellent reviews of single faults in PMSM are presented in [26]–[31], concerning ITSCs, demagnetization, and eccentricity faults, including a description of the physical phenomena connected with particular defects and fault indices used for their detection. These papers will be analysed in the next parts of this review.

One should also mention a very interesting review of existing FDD methods [32], which concerns the damage that occurs in various types of AC machines, including those with a wound rotor. Although PMSMs are also included in this review, not all recent works are taken into account, so this article is not included in Table 1.

Given that research on the fault detection and diagnosis of PMSM drive is still ongoing and has many opportunities for expansion, this paper provides a review of the state-of-the-art and recent trends in the advanced signal processing methods, NNs in fault detection and classification, including the DL approach and FTC concepts. This article also identifies gaps that can be filled in future studies.

As the reviews [14]–[16], [19], [23] discuss in detail the impact of individual failures on the properties of the PMSM, the authors of this article omitted these issues, emphasizing only their most important aspects. Contrary to the authors of some surveys, we have also made a decision not to present individual signal processing methods, as they are precisely described in the articles we cite. On the other hand, because in most of the analyzed articles, the issue of using NNs in the diagnostics of PMSM drives is not fully discussed, in particular, they lack of detailed references to the dynamically developing applications of DNNs, this review article analyzes the latest work in this topic, not only in the field of diagnostics of rolling bearings (which is very common in the literature) in PMSM motors, but also in the damage to the stator winding and permanent magnets. It should be emphasized that the authors also referred to the possibility of diagnosing PMSM failures on the basis of signals from the drive control structure as well as to the increasingly developing problem of damage compensation, i.e. FTC systems.

Thus, the objective of this article is to present an overview of recent methods and techniques for detection and diagnostics of electrical, magnetic, and mechanical faults in PMSM drives, including supplying inverter and sensors in the control structure, using advanced signal processing algorithms and NNs, with particular emphasis on the issues of FTC of PMSM drives. FDD methods are analyzed in terms of where damage occurs in the motor and drive system, according to the signal processing methods used and the type of diagnostic signals analyzed. To make it easier for the reader to follow these analyses, tabular summaries of individual methods and their evaluations are presented. The contribution of this review is, inter alia, to draw attention to the emerging trends and challenges in the field.

The organization of this paper is as follows. Section II briefly describes the fault classification in PMSM drives, focusing on motor failures and the main analysis methods presented in the literature. In the next three sections III-V the detailed literature overview is presented concerning the application of different signal analysis methods for PMSM stator and rotor faults. Section VI deals with the possibility of fault detection based on internal signals of the vector control structures of the PMSM drive. Model-based fault diagnosis methods are discussed in Section VII. Particular attention is paid to fault detection and classification using shallow- and deep-learning NNs in Section VIII. Section IX is dedicated to the frequency converter and sensor faults of the PMSM drive, and the FTC issues are discussed there as well. This review paper ends with an address to some future trends and challenges in PMSM drive diagnostics and FTC techniques.

II. FAULT CLASSIFICATION AND FAULT DETECTION METHODS IN PMSM DRIVE

A. DRIVE SYSTEM FAULTS – GENERAL REMARKS

Modern PMSM drives operate in closed-loop torque, speed, or position control systems using vector control methods: FOC or DTC. Motors are mainly supplied from two- or three-level VSIs with SVM. These inverters mostly use IGBT-based power switches because of their well-known advantages, such as high efficiency, high switching frequency, and relatively high short-circuit current handling ability. In many drives, due to safety requirements and the concept of sensor FTC, state estimators or observers are used, creating software redundancy in the case of chosen sensor faults [32]. The general structure of this drive is presented in Fig. 1.

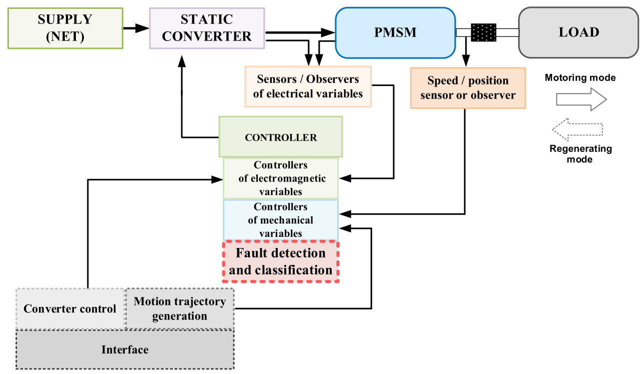

FIGURE 1. Schematic diagram of modern PMSM drive with diagnostic option.

PMSM drives are sensitive to different faults that occur not only in sensors, but also in the static converter and the motor itself. These issues will be briefly discussed, with particular emphasis on PMSM failures and detection methods in the following sections. It is clear that all these faults can lead to interruption of drive system operation and unprogrammed maintenance breaks if not compensated for component redundancy (hardware or software type) or special FTC strategies, which will also be addressed in the next part of this review.

B. PMSM FAULT CLASSIFICATION

Failures in PMSMs can be classified in different ways. In most of the papers [15], [17], [20], [21], [29] they are divided according to their type, into electrical, magnetic, and mechanical damages. However, in [19], [22], magnetic damage is attributed to mechanical damage. In turn, in [31] PMSM failures are classified by location, as stator-related failures (related to the winding and core) and rotor faults (demagnetization, eccentricity, and imbalance). In the aforementioned work [31], bearing failures were omitted, although their statistics according to [14], [15], [20] cover approximately 40-50% of all failures occurring in electric motors. Based on the available literature, the classification of PMSM faults is shown in Fig. 2, according to which they will be analyzed in this study.

According to IEEE and EPRI statistics [34], [35], stator winding failures are one of the most common reasons for AC motor failures and represent between 36% and 66% of all failures, while bearing faults represent between 13% and 41%, respectively, depending on the type and size of the machine, as shown in Fig. 3.

Due to the fact that the motor torque is generated by the interaction of the magnetic field of the stator winding and the PM magnetic field, any failure of these two elements causes disturbance of the motor operation due to deviations of the stator and rotor fields from the designed rated values. It must be said that PMs are vulnerable to losing their magnetization at high temperatures and strong opposing magnetic fields, which leads to a reduction of the motor torque. For instance, electrical faults of the stator windings, such as sudden

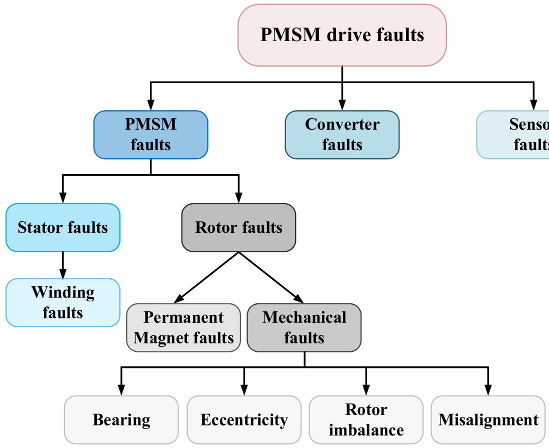

FIGURE 2. Faults classification in PMSM drive.

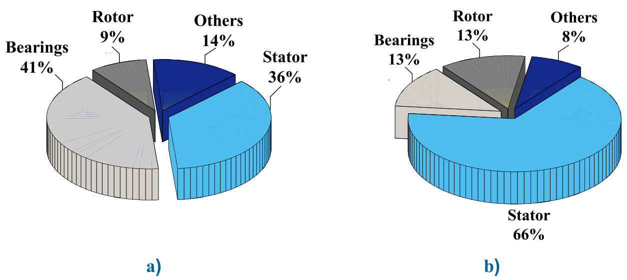

FIGURE 3. Faults percentages by various components in (a) low-voltage, (b) high-voltage electric machines.

short-circuits, cause high magnetic counter fields, which increase the risk of demagnetization. In addition, during the sudden short-circuit, the machine produces a large transient alternating electromagnetic torque, which might damage the coupling or the machine shaft.

Electrical failures of the PMSM stator winding, which start with single ITSCs, are usually caused by insulation damage. Insulation damage results from abrasion caused by mechanical stress or overheating of the winding as a result of excessive loads on the motor [14]–[20], [23], [26], [27]. ITSCs have a very destructive character, as they spread out very quickly. Stator winding failure usually starts as an imperceptible single-turn short circuit and then spreads to the entire winding, resulting in a ground fault. As a consequence, the drive and the entire technological process are stopped in an emergency, and it is necessary to repair or even replace the damaged machine, which is associated with high costs. ITSCs are considered to be one of the most difficult to detect failures in electrical machines, because this detection makes sense only in the initial stage of failure, when it is still possible to prevent damage to the entire phase or even the winding. Safety systems used nowadays in industrial drives do not react to short-circuit of several turns in a phase, because it causes too small quantitative changes of phase currents. Therefore, other solutions are sought, based on the measurement and processing of diagnostic signals, allowing online monitoring of machine condition and alerting the user in the initial stage of failure. This prevents serious failures such as phase-to-phase or ground faults and irreparable damage to the stator windings.

Magnetic damage is a unique feature of PMSMs and concerns permanent magnets. Damages may be mechanical in nature or related to the phenomenon of demagnetization [15], [18]–[20], [28]–[30], [32]. Demagnetization of PM over a longer period of time is due to thermal processes, corrosion, and the aging process. Additional exposures are also associated with the normal operation of the drive, when the magnetic field associated with the stator winding interacts with the field from the PM. Particularly during fast, repetitive drive transients, when the stator winding currents dynamically reach quite high values and the stator flux counteracts the field from PM, the magnets may gradually demagnetize. PMs are sensitive to too high working temperature [29], [30], [32]. They are made in powder technology, which is related to the problem of oxidation of elements with increasing temperature [36]. The source of the increase in PM temperature is the operation of the motor with a high load torque in difficult environmental conditions, but also damage to the stator winding in the form of ITSCs [15], [19], [20], [28]–[30], [32]. The ITSCs in the PMSM stator windings are the source of local temperature increases resulting from the large amplitude of short-circuit currents, which may cause the Curie temperature to be exceeded and the damage to the PM [18], [19], [30]. Therefore, the detection of ITSC at an early stage is very important in PMSM drives.

PM demagnetization can be uniform over all poles or partial over certain regions or poles [15], [18], [29], [32]. It causes a significant reduction of the PMSM motor torque, and thus an increase in the stator current above the value necessary to generate the same torque value in an undamaged motor. As a result, there is an increase in copper losses and an increase in the temperature of the PM machine, which contributes to further demagnetization, reincreasing the stator current, and reducing the efficiency of the motor. Demagnetization may also lead to unevenness of the rotor flux, which, together with overload, creates UMP, causing undesirable noise and damaging vibrations, and thus affects bearing wear and rotor damage [19], [37].

Mechanical failures of the PMSM are frequently occurring and involve bearing failures, eccentricity, misalignment, or imbalance. In the group of mechanical failures, bearing failures (rolling and sliding) are the most common and, according to the sources mentioned above, constitute close to 41% of all low-voltage motor faults. They are mainly due to improper assembly, poor lubrication, motor overloading, and ageing. They can lead to eccentricity failure of the motor, which in the extreme case can lead to friction of the rotor by the stator and ultimately to electrical or magnetic damage of the motor. An imbalance of the rotor and misalignment leads to changes in the motor magnetic field, which deteriorates the dynamic properties of the machine, generates additional components in the spectrum of mechanical vibrations, increases noise, and causes torque pulsation [15], [16].

Generally, PMSM overload can affect faster machine damage, and this unexpected damage or failure of the drive can lead to very high motor repair or replacement costs. Therefore, diagnostics seems to be necessary, e.g. it can help in planning preventive maintenance or even failure prognostics. Symptoms of damages can be sought in electrical signals (current, voltage), magnetic quantities such as stray flux, acoustic noise, mechanical vibrations, and local temperature changes. Damage must be detected and diagnosed in its initial state to prevent further spread. Early fault detection allows planning for the motor overhaul, which reduces the cost of repairing the device or delays and losses in production.

C. FAULTS DETECTION METHODS IN PMSM DRIVE

Observing the actual trends in the development of diagnostics of IM and PMSM drives, it can be noticed that three approaches are being developed over the years [7]–[32]:

- diagnostics using signal analysis methods,
- diagnostics using mathematical modeling,
- diagnostics using methods and techniques of AI.

Methods based on signal analysis use various methods of signal processing which allow one to isolate the symptoms of damage to the damage to the drive system. These symptoms can be used for "manual" diagnostics based on available expert knowledge or for much more advanced diagnostics using knowledge-based methods, which leads to FDD systems using the last group of methods, AI methods.

The approach based on signal analysis is currently of fundamental importance in the diagnosis of electric motors [7]–[32]. On the other hand, the third approach, based on AI methods (in particular NNs), is widely developed nowadays, especially for IM drives [15], [20], [22], [24], while NNs are not yet so often used for PMSM drives, as will be shown in Section VIII of this survey.

Diagnostic methods based on mathematical modeling use circuit models, FEM-based models, FEM-circuit models, or observers of different types. Currently, they are used only for simple diagnostics based on residuum calculation and to test signal analysis and isolate damage symptoms [14], [16], [18], [19], [25]. Much less frequently, mathematical models of AC machines with different failures are used to generate fault symptoms for the training of NN–based fault detectors or classifiers. However, it is now a rapidly growing area of research.

Diagnostics based on mathematical models (in particular, using different estimators of motor state variables and parameters) is presently applied, especially in FTC systems, where observers are used in failure detection and compensation [21]–[23]. It is especially applied in sensors fault mitigation and will be discussed later in Section IX.

Most of the diagnostic methods currently used are based on processed electrical signals, especially current, voltage, and

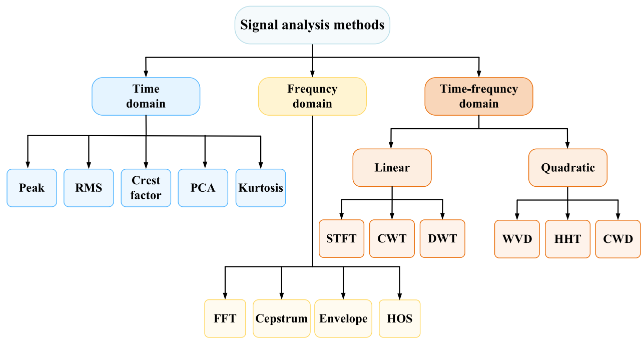

FIGURE 4. Signal analysis methods for AC motor drives.

leakage flux, as well as mechanical signals, such as vibration velocity and acceleration. Changes caused by electrical damage to the motor and converter are well reflected in the current and voltage signals of the motor. The stray flux signal [26] is also very sensitive to these damages. On the other hand, mechanical damages are very well revealed in the vibration signal. Partial demagnetization causes asymmetric and unbalanced radial forces, resulting in high vibration and noise [28]. However, unlike the measurement of currents and voltages, which are noninvasive and easy to implement in any drive, the measurement of leakage fluxes requires the installation of measuring coils, just as vibration measurements require the additional installation of vibration sensors. In the case of heavy noise caused by motor damage, an acoustic analysis based on noise can be used as an additional approach [18]. However, in this case, the ambient noise should be minimal.

The methods of digital signal processing make it possible to extract characteristic symptoms (features) for a given type of damage. These methods can be classified into three groups: time domain methods, frequency domain methods, and time-frequency methods (Fig. 4).

Time-domain methods rely mainly on statistical analysis. They use selected signal parameters such as peak values, RMS or mean values, Crest factor, PCA, and kurtosis.

Currently, in the diagnosis of electric motors, including PMSMs, the most widely used methods are in the frequency domain and the time-frequency domain [7]–[32]. The most common method that belongs to the class of frequency domain analysis is the FFT of the stator phase current or mechanical vibration. The analysis of component amplitudes in the current spectrum is known in the literature as the MCSA method, as well as its improvement, the EPVA method of the stator phase current [12], [20]. However, due to the disadvantages of FFT, such as the requirements for signal stationarity and the associated long measurement time, as well as the growing computing power of microcontroller-based embedded systems, more advanced HOS-based signal processing methods have gained popularity in recent years. In machine diagnostics, ENV and cepstrum analysis are also used, especially for vibration processing in the event of mechanical damage.

Due to the limitations of frequency methods, related to the inability to obtain information about the moment of failure, more and more attempts were made to apply T-FMs, e.g. STFT, WT, HHT and others in the diagnostics of electrical machines [6], [11], [12], [32]. However, the proper application of these methods requires an understanding of their limitations.

In STFT, the signal is divided into several time intervals with windows of a certain type and length, and each part is analyzed using FT. Therefore, the correct selection of the window size is of fundamental importance because it should be matched to the signal frequencies characteristic for a given fault, which are not always known *a priori*. Therefore, depending on the application, a compromise must be made between time and frequency resolution, as the longer window has a better frequency resolution and the smaller window has a better time resolution [6]. Thus, the STFT method is better suited for nonstationary signals with low dynamics because by using a longer window one can treat the signal in this window as approximately stationary and obtain better results when using FFT.

Therefore, in the case of systems with higher dynamics, such as PMSM drives, better results are provided by multiresolution signal processing methods, including WT. The CWT provides uniform resolution for time and frequency. However, the application of this method requires prior determination of the appropriate parameters and, in particular, the type of basic wavelet function. The selection of this function determines a uniform resolution over the entire frequency range. Therefore, an important limitation of wavelet analysis is its nonadaptive nature. In the diagnosis of electrical machines, including PMSM, both CWT and DWT are used. By continuous variation of the resolution, CWT can provide an almost total evolution of the time-frequency signal. On the other hand, DWT extracts the proper frequency ranges as a result of consecutive high-pass and low-pass filtering, which should be determined based on the damage components. For this reason, the CWT computation time is significantly longer than the DWT. However, the CWT is used for slowly developing failures, such as, for example, demagnetization or bearing failures [15], [29], [32].

Other time-frequency signal analysis methods applied in diagnostics use a quadratic time-frequency distribution [19], [27], [29], [32]. Contrary to linear methods, which decompose the analyzed signal into initial components, T-FMs use energy distributions to decompose the signal into frequency and time domains. The general form of these distributions creates the so-called Cohen class, in which distributions with different characteristics are obtained on the basis of the determined kernel function. The most representative method of this class is WVD or CWD. These distributions are characterized by high resolution since the entire signal is used to obtain energy in each frequency range. Some difficulties in these methods result from the interaction between the pairs of time-frequency components (the serious cross terms), manifested by the appearance of negative values of the power signal in some frequency ranges. This is due to the quadratic order of the analysis method and depends on the type and parameters of the kernel used. Moreover, when WVD is implemented for discrete signals, an aliasing problem may arise.

Another transformation that analyzes the time-frequency energy of a signal is HT. Since this transformation was developed for fully sinusoidal signals with a zero reference level, its modification is used for nonstationary signals, the HHT. This transformation uses the EMD method to decompose a given time-domain signal into a limited number of pure oscillating functions called IMF, to which the HT can be next applied. This distribution is similar to the FT, but, unlike the FT, it provides information in both the time and frequency domains. At each stage of the process, the analyzed signal is successively distributed into component signals from high to low frequencies. The HT is then applied to the derived IMF functions. The HHT enables the elimination of unwanted frequencies and the focus on those that are characteristic of a given damage. Thus, in the case of HHT, there is no need for prior knowledge of failure frequencies due to the adaptability of the EMD and its locality. Moreover, in the obtained time-frequency spectrum, there are no interactions of the frequency components that distort the spectrum, as, e.g. in WVD. Therefore, in recent years, HHT has found application in the analysis of transient signals [30].

The results of application of the mentioned methods will be analyzed for all types of PMSM faults in sections III-V, starting from the ITSCs detection, because these types of stator winding faults are especially critical, because they can spread out very fast and cause dangerous damage to the machine in a very short time.

III. SIGNAL ANALYSIS METHODS FOR INTER-TURN SHORT-CIRCUITS IN THE PMSM STATOR WINDING DETECTION

A. FREQUENCY DOMAIN METHODS

The most common methods for diagnosing ITSC faults are methods that perform frequency domain analysis. Signal processing in the frequency domain using FFT is established and still widely used as the basic diagnostic approach [11]. The popularity of this method is related to its simplicity, low cost, and online machine state monitoring capabilities [11]. In the literature, the successful application of this method to the extraction of PMSM stator winding fault symptoms from the stator phase current signal has been widely discussed in recent decades, among others, in [38]–[44]. The application of this approach consists of monitoring the amplitudes of the characteristic frequency components of the ITSCs in the spectrum of the diagnostic signal analyzed. According to [40], the frequency components, the amplitudes of which increase as a result of the failure of the stator winding, are calculated as follows:

$$f_{itsc_1} = f_s\left(1 \pm \frac{k}{p_p}\right), \qquad (1)$$

where: f_s – supply voltage frequency, k – consecutive positive integers, p_p – number of pole pairs.

Additionally, as proven in [41], the ITSC stator winding can cause an increase in the slot harmonics, which are calculated with the following equation:

$$f_{itsc_2} = f_s \left(1 \pm k \frac{N_{ss}}{p_p}\right), \tag{2}$$

where: N_{ss} – number of stator slots.

According to [20], the greatest and most obvious increase in the case of this fault is the increase in the amplitude of the $3f_s$ component, which has also been confirmed by the results presented by the authors in [42] and [43]. The impact of incipient ITSCs on the value of this component in a wide range of motor rotational speed and load torque was investigated. The improvement and expansion of the analysis of stator phase current signals with FFT is presented in [43], [45]–[47]. In these papers, the EPVA of the stator current is suggested as the detection tool for IM and PMSM stator winding faults. In all of these papers, the authors conclude that the increase of the $2f_s$ component amplitude in the stator phase current space vector module spectrum is a symptom of a stator winding fault. Greater sensitivity of this component to the stator winding fault is also emphasized compared to the FFT of the stator phase current.

Among the diagnostic methods that use frequency domain analysis, there are also methods that use FFT symmetrical components of the stator phase current. The use of instantaneous values of positive and negative stator current components is evaluated and compared in [48]. The authors have shown that in the case of the stator winding fault, the amplitude of the f_s component in the current negative sequence component increases significantly, while the positive sequence component is not sensitive to this type of failure. The experimental verification presented in [48] was carried out for a wide range of rotational speed and load torque, which also confirmed the robustness of this method to changes in motor operating conditions. In [49] the authors experimentally verified that both the current and voltage negative sequence harmonics should be considered for accurate detection of ITSC faults. In [50] the analysis of the negative sequence components of the current and voltage of the stator winding is combined with a fuzzy logic approach for the successful detection of ITSCs.

The application of spectral analysis of diagnostic signals other than the stator phase current to PMSM electrical faults has also been verified over the years. In [51] the authors proposed a three-step online stator winding fault detection approach for PMSMs based on the reference voltage in the *dq* frame analysis. The novel real-time PMSM stator winding fault detection method, which is based on the extraction of the second harmonic of the control voltages in the *dq* frame, is proposed and discussed in detail in [52]. The FFT analysis of the axial flux signal is also very effective for detecting ITSCs in the stator winding of PMSMs. In [54], a novel and robust stray flux analysis is proposed for the detection of ITSC for PMSM. This method utilizes the third-harmonic component of the stray flux as a reliable FI.

In the past, signals such as electromagnetic torque [55], [56], summation of phase voltage [56], and line voltage [57], were also combined with FFT analysis for electrical motor stator winding faults, including PMSMs. According to [57], in the case of ITSC of the PMSM stator winding, the amplitude of the $3f_s$ component in the line voltage spectrum and the $2f_s$ component of the electromagnetic torque increases significantly. In [58] the second harmonic of the active and reactive power spectrum is proposed as the FI independent of the motor control type.

In recent years, papers in which the authors proposed the use of ZSVC spectral analysis using FFT for the detection of PMSM stator winding faults have also been published [59]–[64]. The research discussed in [59] shows that the first, fifth, and seventh harmonics of the ZSVC spectrum are the components whose monitoring allows the detection of ITSCs in the PMSM stator winding. Compared to MCSA, this system provides better resolution even at low speed operation. The limitation of this approach is mentioned in [60], that is, to measure the ZSVC, it is necessary to access the neutral point of the stator winding. The method to detect ITSCs in PMSM operating under transient conditions is widely discussed in [61]. The interesting approach is presented in [63] where the novel VKF-OT algorithm is introduced and applied to track the third harmonic of the stator phase current and the first one of the ZSVC for online detection of this failure. Another effective online ITSC detection algorithm based on the injection of ZSVC and HF signals is proposed in [64]. There, ZVSC is used to detect the abnormal state of the PMSM drive, and then HF current signals are injected to discriminate between ITSC and resistive unbalance fault.

The most complex methods that perform frequency domain analysis are HOTs which are based on the HOS. So far, the application of the HOTs for the fault diagnosis of electric motors has also been discussed in the literature. The most popular HOTs are MUSIC, BS, PSD, and ESPRIT. In [65] the application of PSD, MUSIC, and BS of the stator phase current signal to PMSM stator short-circuit detection is evaluated and compared. The experimental results carried out in this work demonstrated that these HOTs can be successfully applied to detect and identify ITSC failures in PMSMs. The results are compared for different motor operating conditions and levels of stator winding fault, for undamaged winding, 4, 8 and 12 shorted turns. The authors' conclusions indicate that PSD and MUSIC can detect short-circuit for the whole speed range and can be used for preventive maintenance.

In the past, hybrid methods that combine statistical and frequency domain approaches have also been discussed in the field of PMSM electrical fault diagnosis. In [66] the extraction of PMSM fault symptoms performed by FFT is combined with PCA to reduce the dimensions of the samples and with Bayesian networks.

B. TIME-FREQUENCY DOMAIN METHODS

Despite many advantages and high efficiency in extracting electrical faults of PMSMs, FFT-based frequency domain analysis methods have several significant drawbacks. One of the disadvantages is that the FFT requires the signals to be stationary, which is a condition that is difficult to meet in modern drive systems. Moreover, this method requires a relatively long measurement time of the diagnostic signal and its processing is associated with the loss of information about the moment of occurrence of a given fault component.

The STFT is one of the most popular T-FMs that has been used in the diagnostics of electric motor failures. This method has also found application in the detection of PMSM electrical faults. In [67] the STFT-based method for the detection of electrical and mechanical faults of permanent magnet AC drives is discussed in detail and compared with wavelet analysis. The authors proved that this method is capable of identifying intermittent electrical and mechanical faults of this type of motor, also in transient states. A similar study, but extended by comparison with other signal processing methods, is also presented in [5]. Changes in the STFT spectrogram caused by ITSCs in the PMSM stator winding during variable motor speed are presented in [70]. In all of these works, the main idea of using STFT in fault diagnosis is discussed: observation of changes in spectrograms as a result of PMSM electrical fault. The components whose amplitudes increase are the same as in the case of FFT, but it is possible to observe their changes over time. However, in [67] the significant disadvantage of this method is mentioned. In the case of STFT, the time window width is constant, so a trade-off between time and frequency resolution must be made. The CWT does not have this disadvantage.

The CWT uses an adaptive time window, ensuring good resolution in both the time and frequency domains. This allows for a more accurate time-frequency response. The biggest advantage of the WT is that it works very well in the analysis of nonstationary signals. The CWT was successfully applied to PMSM electrical faults for hybrid and electrical vehicles in [69]. In this paper, the authors discuss the incipient diagnostics of stator faults and the monitoring of the stator winding based on the specific distortions in the stator currents, as well as in the reference voltages, extracted using WT. Similar research, but extended with the location of damage based on phase-to-phase voltage, is presented in [70].

Due to the much lower computational complexity, the discrete form of the WT (DWT) is more often used in the fault diagnostics field. The DWT performs multiresolution wavelet analysis. At each of its stages, the signal can be divided into two components, the detail and the approximation. In the case of this transform, the symptom of an electrical fault of PMSM is a change in the approximate and detailed waveforms, the range of which covers the components characteristic of this type of fault. In [43], the DWT stator phase current and the ENV stator phase current are proposed for the detection of ITSC in a very early stage of damage (1 shorted turn). The approach discussed is based on the RMS value of the selected details. The stator winding fault diagnosis method for model predictive-controlled PMSM based on cost function and DWT is proposed in [72]. The authors presented that by monitoring the normalized energy-related feature vector calculated from the DWT coefficients, it is possible to detect the ITSCs for different loads and rotation speeds. In [73] the authors proposed the WT of the reference voltage in the q-axis to detect incipient ITSCs in PMSM with a three-phase stator winding. In this work, it is also proven that the occurrence of this type of fault disturbs the stator currents and the reference voltages, leaving a specific fault signature. In [74] a wavelet analysis is successfully applied for the detection, localization and estimation of the number of shorted turns. DWT combined with an SVM based on the current waveform of the stators for automatic fault detection of the PMSM stator winding is discussed in [75].

Another approach to time-frequency domain analysis used for the extraction of PMSM electrical faults is HHT. In [76] the stator phase current HHT and energy calculation are proposed for the detection of PMSM stator winding fault. In this work, the advantage of this method, which is the possibility of detecting failure during transient conditions (rotation speed changes) is highlighted. The authors of [76] presented a method based on the online statistical analysis of the instantaneous frequency calculated by the HHT and demonstrated it through a simulation of the hardware-in-the-loop in real time and experimental results. In this work, it is also stated that HHT is well suited for stator winding fault detection because it is not affected by transient conditions, which introduce the possibility of false alarms. WVT, also known in the literature as WVD, is a time-frequency domain method that is based on the energy distribution. The detection of PMSM stator winding faults based on EMD and WVD is proposed in [78]. The authors presented that this approach is capable of providing short-circuit detection under dynamic transient conditions. It is also stated that the fault frequencies in nonstationary states of PMSM drive systems can be detected and tracked perfectly.

A novel hybrid method of stator winding fault diagnosis for LSPMSM based on MCSA and time-frequency analysis is proposed in [79]. In this work, the fault harmonic component was extracted from the motor current via Gabor order tracking. The results presented by the authors proved that the proposed method is successful and useful for detecting ITSCs in LSPMSMs, also during the transient conditions of the drives system, such as variable speed or variable load.

C. TIME DOMAIN (STATISTICAL) METHODS

Currently, methods that perform the diagnostic analysis in the time domain are not very common. In [80], an online time domain ITSC fault detection method is proposed, which is based on a residual analysis between the estimated stator currents obtained by a healthy model, taking into account the estimation of BEMF, the inverter model, and the unbalanced inductance matrix and the real currents of the PMSM. In this paper, an FI is defined on the basis of these residual currents. In [81], fault detection is carried out based on the difference between the estimated BEMF and the reference BEMF where the linear average value of the differences in the EMF normalized with the mechanical angular speed is introduced as FI. The authors in [82] proposed the novel stator current-based 1D-LBP method, which is compelling and distinctive, to detect short-circuit faults that occur in PMSM stators. In [83] the Park vector approach based on the stator phase current is combined with PCA for real-time condition monitoring of the PMSM stator winding. The results presented by the authors confirm the good detection performance and the localization of the faulted phase in addition to the presence of a strong signal noise.

All detection methods for PMSM drive ITSCs presented in Section III are gathered in Table 2 and categorized into groups based on signal analysis methods (frequency domain, time-frequency domain and time domain) and FI.

IV. SIGNAL ANALYSIS METHODS FOR MAGNETIC FAULTS OF PMSM

A. FREQUENCY DOMAIN METHODS

The appearance of disturbances in the PMSM magnetic field causes a distortion of the sinusoidal magnetomotive force. As a result, additional harmonics appear in the stator current spectrum around the fundamental supply frequency [15], [29], [32]:

$$f_{dem} = f_s \left(1 \pm \frac{k}{p_p}\right) = f_s \pm k f_r, \tag{3}$$

where: f_{dem} –DF frequency, $f_r = f_s/p_p$ –rotational frequency, $k = 1, 2, 3 \ldots$.

An increase in the degree of demagnetization of the rotor causes an increase in the amplitude of the stator current harmonics defined by (3), so it is an appropriate criterion for diagnosing this fault [84]–[88]. Therefore, the MCSA method can be easily used to detect the symptoms of demagnetization. However, the visibility of this symptom is strongly dependent on the configuration of the winding, and sometimes even in the case of demagnetization there are no harmonics or subharmonics other than those that occur in a healthy motor due to the existing natural asymmetries of the machine [19], [29], [84], [85]. However, the application of conventional FFT is limited to stationary motor conditions with respect to speed and load torque. Moreover, as a result of dependence (3), other motor damages depending on rotational speed, such as ITSCs (see (1)) and mechanical damages such as dynamic eccentricity, can be identified by the same frequencies in the stator currents [29], [32]. Therefore, in some cases, the MCSA does not distinguish between demagnetization and other motor faults, and therefore other techniques have been investigated using different signal analysis methods.

The study of the effect of permanent magnet demagnetization is a destructive test and there are many random factors, such as uncontrolled loss of magnetization due to artificial crushing of the magnet fragments. On the other hand, it is very expensive to prepare a motor with factory-supplied non-uniformly magnetized magnets. Therefore, most of the research was carried out with the use of simulation tests using various types of models, both circuit models and primarily in the field-circuit models using FEM. However, some of these research works have been verified experimentally.

In [88], MCSA/MVSA methods were tested in the case of three types of faults: partial demagnetization, static eccentricity, and ITSC fault. The analysis was based on two-dimensional FEA used to model and simulate the PMSM under healthy and faulted conditions and FFT was applied to the phase voltage or current signals. Without the additional technique, namely linear discriminant analysis, it was impossible to classify the fault type based only on frequency spectrum. Therefore, it is impossible to distinguish between the three types of failure by analyzing only the stator currents. In addition, fault detection accuracy based on current signal analysis is significantly influenced by inverter output harmonics, load fluctuations, and controller settings [87], [88].

For this reason, studies of different FIs were analyzed, namely ZSCC/ZSVC [87], [89], [90]. In [89] the DF detection method for a delta-connected PMSM based on the ZSCC method and FFT was proposed using the classical three-phase mathematical model of the machine with the introduced demagnetization factor for the magnetic flux, both for partial and uniform demagnetization. The method was experimentally verified and it was proven that the value of the fault severity index can provide reliable information on DF. Studies [87] and [89] proved that the stator current harmonics show the DF condition for medium and high speeds. On the contrary, the ZSCC makes it possible to determine PM demagnetization failure at high and low speeds with the correct accuracy. The correct combination of the analysis of stator current and zero sequence current, or zero sequence and q-axis current, enables the determination of faults for any range of speeds [87], [89].

In [90] the early demagnetization of the rotor in a SMPMSM was detected by online monitoring of the harmonic spectrum of the ZSVC of phase voltages. It was shown that local demagnetization reduces the amplitude of the ZSVC and this may enable fault identification. This method provides low computational complexity and high sensitivity of the FI to the DF. However, it is limited by the need to provide access to the neutral point of the stator windings, and an artificial neutral point must be created by a three-phase balanced resistor network connected to the motor terminals.

This drawback can be eliminated by using flux-based and BEMF methods that are capable of detecting both uniform and local demagnetization [15], [19], [29], [30], [32]. However, the flux-based method requires search coils mounted inside the motor [91] and is therefore a highly invasive method. The other solution consists of a properly designed measurement coil mounted on the motor housing to

TABLE 2. Classification of detection methods for ITSC faults in PMSMs.

Legend: **ON** – on-line detection algorithm, **RL/RS** – robust to load torque/speed changes, **SC** – steady-state condition required, **TC** – detection on transients available, **FL** – fault localization, **EV** – experimentally verified, **ACR** – additional measurement coils required, **TEM** – T_e measurement required, **AZP** – access to zero point required, **TR** - tradeoff must be made between t and f resolution,
(yellow box) – High Order Transforms, (green box) – Hybrid methods (Frequency domain + statistical),

Ref.	Diagnostic signal	Method	Fault index	Advantages	Disadvantages
Frequency domain methods					
[39], [41]-[46]	Stator current	FFT	Odd harmonics, especially $3f_s$ and others: $(1\pm k/p_p)\,f_s$, for k=1,3,5,7	EV, ON, RL, RS	SC
[45]-[47]		EPVA	$2f_s$	EV, SV	SC, measurement of currents in all phases necessary for the current EPV calculation
[43]	Stator current ENV	FFT	$2f_s$	EV, ON, RL, RS	SC, stator current ENV has to be calculated
[38]	Stator current in q-axis	FFT	$2f_s$	EV, ON, RL, RS	SC, stator current in q-axis has to be calculated
[48]-[50]	Stator current negative sequence component	FFT	f_s, $3f_s$	EV, ON, RL, RS	SC, current negative sequence component has to be calculated
[40]	Stator voltage	FFT	The first 14 harmonics	EV, ON, RL, RS	SC
[51]-[53]	Reference voltage in dq frame	FFT	f_{DC}, $2f_s$	EV, ON, RL, RS	SC, access to reference voltage in dq frame signal necessary
[50]	Stator voltage negative sequence component	FFT	f_s	EV, ON, RL, RS	SC, voltage negative sequence component has to be calculated
[59]-[64]	Zero sequence voltage component	FFT	f_s, $5f_s$, $7f_s$	EV, ON, RL, RS	SC, AZP
[54]	Axial flux	FFT	f_s, $3f_s$	EV, ON, RL, RS, FL	SC, ACR
[55], [57]	Electromagnetic torque	FFT	$2f_s$	EV, ON, RL, RS	SC, TEM
[42]	Rotational speed	FFT	$2f_s$	EV, RL, RS, FL Two control structures compared – scalar and vector control, high effectiveness for both	SC
[58]	Active and reactive power	FFT	$2f_s$	EV, ON, RL	SC, active and reactive power has to be calculated
[56]	Summation of phase voltages	DFT	f_s	EV, ON, RL, RS	SC, summation of phase voltages has to be calculated
[65]	Stator current	BS	Frequency pairs connected with $3f_s$ and $5f_s$,	EV, ON, RL, RS	SC, difficulty of calculation without zoom technique. It is difficult to analyze T-F figures
[65]		PSD	$3f_s$	EV, ON, RL, RS	SC, difficulty of calculation without zoom technique
[65]		MUSIC	$3f_s$	EV, ON, RL, RS Resolution is greater than MCSA.	SC, difficulty of calculation without zoom technique
[66]	Line-to-line voltage	FFT+PCA	Eigenvalues of line-to-line voltage components	EV, ON, RL, RS	SC for FFT
Time-Frequency domain methods					
[68]	Stator current	STFT	RMS values of the local maxima	EV, ON, RL, RS, TC, FL	TR
[41]		CWT	RMS value of the detail 1,2,3	EV, ON, RL, TC	It is difficult to analyze T-F figures
[74], [75]		DWT	f_{DC}, $2f_s$, RMS values of selected details coefficients	EV, ON, RL	SC
[76], [77]		HHT	$5f_s$ energy, standard deviation of the selected instantaneous frequencies	EV, ON, RL, RS, TC	It is difficult to analyze T-F figures Problems with fault detection at early stage
[78]		EMD+WVD	$3f_s$	EV, ON, TC, RL, RS	Fundamental frequency has to be filtered with EMD
[79]		GOT	$6f_s$	EV, ON, TC, RL, RS, electromagnetic noise in environment does not affect diagnosis accuracy.	The difficulty of calculation is a major drawback of this method

TABLE 2. *(Continued.)* **Classification of detection methods for ITSC faults in PMSMs.**

[71]		WPT	Second level approximates and details	EV, ON, TC, RL, RS	SC
[5], [67]	Stator current in q-axis	STFT	The first 31 harmonics	EV, ON, RL, RS, TC, FL	TR, stator current in q-axis has to be calculated
[73]	Torque current	DWT	WT coefficients for 1st frequency band	EV	SC
[69],[72]	Reference voltage in q-axis	CWT	Maximum value of the CWT positive coefficients	EV, ON, TC, RL, RS	Problems with fault detection at early stage and for very high short-circuit resistance Access to reference voltage in dq frame signal necessary
[73]		DWT	DWT positive coefficients values	EV, ON, TC, RL, RS	Access to reference voltage in dq frame signal necessary
[60],[72]	Zero sequence voltage component	DWT	f_s in DWT details, f_{DC}, $2f_s$ in DWT cost function spectrum	EV, ON, TC, RL, RS	AZP
[61]		HHT	f_s	EV, ON, TC, RL, RS	AZP
[78]	Rotational speed	EMD+WVD	$7f_s$, $9f_s$, $12f_s$	EV, ON, TC, RL, RS	Fundamental frequency has to be filtered with EMD
Time domain (statistical) methods					
[80]	Stator current	Residual analysis	FI based on the residual stator currents	EV, ON, TC, RL, RS	The detailed model of the healthy machine is necessary
[81]	BEMF	Residual analysis	FI based on the difference between the estimated and reference BEMF	EV, ON, TC, RL, RS	The estimation of the BEMF is necessary
[82]	Stator current	1D-LBP	Histogram of stator current 1D-LBP	EV, ON, TC, RL, RS	Long measurement time required (1 s)
[83]	Stator current	PVA+PCA	Eigenvalues of stator current PV components	ON, RL, RS Only 40 ms to collect enough data	Calculation of PVA and PCA of the stator current necessary

obtain the voltage induced in the coil by a stray flux [92]. In [91] the search coils are wound around each tooth so that the air gap flux density can be measured. Although the method is invasive, it enables detecting PM faults based only on first-order harmonics, making it robust to higher harmonics induced by power electronics devices. An additional advantage of this technique is that it does not require determining the load torque value to accurately diagnose the fault. Therefore, despite the invasive nature of this technique, it is very suitable for safety-enhanced applications such as offshore wind turbines, hybrid vehicles, and military applications, where early fault detection is of great importance. In the case of stray flux measurement, it has been shown in [93] that PM demagnetization can be detected through stray flux analysis similar to wound rotor synchronous machines by using both time and frequency analysis.

Since flux reduction as a result of demagnetization has a significant impact on the BEMF waveform of the PM machine, it is also used for fault diagnosis. BEMF can be measured directly in open circuit generator mode; thus, it is an noninvasive offline method [94]. The PM fault diagnostic methods are based on BEMF measurement and analysis of the harmonic spectrum of the induced voltage [94]–[96] or its ZSVC [97], [98]. The use of BEMF analysis is characterized by a lack of robustness to changes in PM temperature [3], but the method is simple to implement [29], [95].

Furthermore, vibration signal analysis [99] or noise and torque pulsation analysis [100] were used for the detection of partial demagnetization. The authors of [99] applied vibration acceleration to detect PDF and ITSC using both mode shape and vibration frequency information. The vibration and acoustic signals of the PM machine were used to detect PDF and static eccentricity according to the spectrum analysis in [100]. As FIs, the authors applied significant orders of harmonics extracted from the vibration signal by means of FFT.

The use of FFT analysis requires a compromise between the precision of the assessment of damage symptoms and the minimum computational effort [86], [88]. However, it does not provide information on the changes of each harmonic component over time and its instantaneous value. Additionally, the FFT can even mask components that appear at a given moment in time, but are of very short duration [10], [32]. Due to the aforementioned disadvantages of FFT-based methods, including the stationarity requirement, T-FMs are increasingly being used to detect demagnetization symptoms.

B. TIME-FREQUENCY DOMAIN METHODS

In order to eliminate the restrictions of the spectral analysis, the T-FMs are applied, e.g.: STFT [101], WT [102]–[106], WVD [101], [107], CWD [108], and HHT [109]–[112]. Some authors [5] focused their efforts on comparing and clarifying the capabilities of different time–frequency distributions. The main concept, advantages, and disadvantages of these linear and quadratic T-FM were briefly characterized in Section II*C*.

The STFT algorithm was applied for stator and rotor faults of the BLDC motor, including uneven asymmetric magnetization in [101]. It was highlighted that the fixed size of the chosen window and the difficulties in quantifying the fault extent remain the major drawbacks of this technique. However, the method is simple to implement in real time and according to the authors it can also be applied to other motors with PMs. It is also computationally less intensive than other T-FMs.

This problem can be solved using WT, as, e.g., in [102]–[106]. An advantage of WT over STFT is that the basic wavelet function is scalable. However, the parameters of this function must be adjusted to the specific fault. This allows WT to adapt to a wide range of frequency and time resolutions. In [102] and [103] the DF is analyzed using stator currents (obtained from FEM simulations and experimental tests) at different speeds using CWT and DWT. It was shown that both analyses enable identification of the DF by means of stator current even under speed or torque variations, at high, medium and low speeds. In [104] both the current and voltage signals of the stator winding were analyzed for a low level of vector-controlled PMSM using CWT. It was shown that the analysis of motor signals gives similar results. The work [105] proposes the application of WT to the BEMF signal of SMPMSM obtained from 2-D FEA simulations. It was shown that PMSM rotor faults caused by local and uniform demagnetization can be detected. In [106] online PM demagnetization fault diagnosis for IPMSM is proposed using CWT and GST. The use of GST facilitates the detection of demagnetization symptoms and energy pulsation associated with the torque ripples resulting from DF. The method was tested for partial demagnetization, but the authors claim that it can also be used for uniform DF detection.

Another T-FM to track the frequency components of the PMSM demagnetization fault used in the literature is quadratic time-frequency WVD. In [107] the PWVD and SPWVD have been tested for the BLDC motor drive; however, the authors recommend the PWVD for other motors, as the method suppresses cross-terms present in the original Wigner distribution and has much better resolution than STFT. This method was also mentioned by the same authors in [101] and recommended for the detection of uneven asymmetric DF.

As mentioned earlier, the WVD method, in addition to the frequency components characteristic of a fault, generates cross terms that may disturb these fault frequencies. This reduces the possibility of precisely determining the degree of fault. Suppression of these cross terms can be achieved by applying a modification of the WVD, namely the SPWVD. However, this comes at the cost of frequency resolution. Therefore, new methods such as CWD have been proposed that provide strong cross-term suppression while offering excellent frequency resolution characteristics.

The CWD was applied in [108] to detect DF in a SMPMSM operating under nonstationary conditions. The pre-processing of the transient current signals is done using CWD to determine the relevant characteristics of the DF. Then, these damage characteristics prepared with CWD are extracted using the box-counting method.

The HHT was applied to diagnose demagnetization in [109]–[112]. In conference papers [109], [110], and the following articles [111], [112] the HHT was applied to the stator current signal obtained from the FEM simulation model of the PMSM with DF with different speeds and load torque values.

In these investigations, the effectiveness of HHT was also proved in experimental tests for vector controlled PMSM with 50% DF in one pair of poles, for steady state and transient conditions under changes in motor speed at high, medium and low levels. The HHT enables the elimination of undesirable frequencies and concentrates the information characteristic of the DF in some IMFs, which then undergo the Hilbert transform. Compared to other quadratic T-FMs, the HHT spectrum is more accurate and easy to interpret. It does not contain cross frequencies and has no problem with the beginning and end boundaries. Additionally, in [111] it was concluded that the HHT algorithm is simple and easy to implement in a system for supervision, fault detection, and failure diagnostics.

C. OTHER METHODS

Some specific methods were also used for the detection of DFs. The partial DF of PMSM under nonstationary speed and load conditions was also analyzed in [113] using the VKF-OT algorithm. This method was applied to track the characteristic orders of the stator current. Only the harmonics related to the fault are tracked, while the remaining components are removed as noise. The ENV amplitude of the order of fault characteristics was used as FI. The obtained results show the potential of the proposed method to detect the PDF of the PMSM in the case of nonstationary processes, often found in industrial applications.

On the other hand, in [114], the torque ripple generated by the deformation of the magnetic flux in the motor air gap resulting from damage to the PMs in the SMPMSM was used for the detection of DF. The TDE method was applied to analyze the torque signal in the time domain. TDE belongs to the group of signal analysis methods that enable the extraction of hidden patterns in time series data (torque here). The TDE transforms the torque waveform into a reconstructed torque profile called the phase space. The radius of gyration around the center of mass of the points in a phase space was proposed as IF. Although this method does not require any additional equipment and is noninvasive (motor torque is estimated on the basis of current measurement and flux estimation in the control system), it has significant limitations. They result from the fact that, in the case of current (torque) signal analysis methods, different failures can induce the same characteristic frequencies and significantly impede the detection and distinguishing of failures.

Another time domain method was presented in [115] for the BLDC motor. Specifically, it focuses on the detection of ZCP in the BEMF waveform. It was shown in this work that

TABLE 3. Classification of detection methods for demagnetization faults in PMSMs.

Legend:	**INV/NINV** – invasive/non-invasive, **ON/OFF** – on-line/off-line detection algorithm, **PDF/UDF** – partial/uniform demagnetization fault, **LS/MS/HS** – low/medium/high sensitivity, **AOF/NAOF** – affected/not affected by other faults, **RL/RS** –robust to load torque/speed changes, **SC** – steady-state condition required, **TC** – detection on transients available, **ACR** – additional measurement coils required, **TEM** – T_e measurement/estimation required, **AZP** – access to zero point required, **VM** – vibration/noise measurement required, **TR** - tradeoff must be made between t and f resolution, **EV** – experimentally verified				
Ref.	**Diagnostic signal**	**Method**	**Fault index**	**Advantages**	**Disadvantages**
Frequency domain methods					
[84]–[88]	Stator current	FFT	$f_{dem} = f_s(1 \pm k/p_p)$, for k=1,3,5…	PDF, NINV, ON, EV	SC, LS, MS, AOF
[87], [89]	Zero sequence current component – ZSCC (+i_q)	FFT		PDF, UDF, ON, HS, EV	SC, INV, AOF
[90]	Zero sequence voltage component - ZSVC	FFT		PDF, ON, HS, EV	SC, INV, AOF
[91]-[93]	Axial flux	FFT		PDF, UDF, ON, HS, NAOF	SC, INV or ACR
[94]-[96]	BEMF	FFT		PDF, NINV, AOF	SC, OFF, MS
[97], [98]	Zero sequence BEMF component	FFT		PDF, HS, ON	SC, INV, AZP, AOF
[99]	Vibration	FFT		PDF, NINV, ON, NAOF	SC, VM, MS
[100]	Acoustic noise & torque	FFT		PDF, NINV, ON, NAOF	SC, VM, MS
Time-Frequency domain methods					
[101]	Stator current	STFT		PDF, NINV	LS
[102]-[104]		CWT/DWT		UDF, RS, RL, NINV, EV	MS
[101], [107]		WVD		PDF, NINV	MS
[108]		CWD		PDF, NINV	HS, TR
[109]-[112]		HHT		PDF, RS, RL, NINV, EV	HS
[104]	Stator voltage	CWT		RS. RL, NINV, EV	MS
[105]	BEMF	CWT		PDF, UDF, NINV	MS
[106]	Torque	CWT+GST		PDF, UDF, NINV, ON	
Other methods					
[113]	Stator current	VKF-OT	amplitude of ENVs of fault characteristic orders	PDF, NINV, ON	
[114]	Torque	TDE	radius of gyration in phase-space	PDF, UDF, NINV, ON	AOF, TEM, LS
[115]	BEMF	ZCP	zero-crossing point detection	PDF, NINV, NAOF, ON, HS	

this method enables the detection of very small DFs in the online mode.

All the methods discussed in this section are summarized in Table 3 and categorized into groups according to the type of signal analysis methods and FI.

V. SIGNAL ANALYSIS METHODS FOR MECHANICAL FAULTS DETECTION

A. BEARING FAULTS

Like every component of the drive, bearings have a defined life cycle. In addition to mechanical damage caused during assembly or due to improper storage, bearings are subject to fatigue damage. Spalling on the surfaces of components can lead to small pieces flaking off, resulting in asymmetries in the flux distribution inside the machine. Bearing damage leads to eccentricity, increased friction between the stator and rotor, and in extreme cases to ITSCs or insulation fire [15], [17], [24]. Damaged bearings manifest themselves by increased vibration and noise levels. The change in the flux distribution inside the machine can be visible as additional harmonics in the stator current. Therefore, the basic signals in the diagnostics of the bearing rolling element are mechanical vibration [116]–[127], noise [119], [128]–[130], and stator current [116], [122], [131]–[138].

In order to monitor the technical condition of the rolling bearings, characteristic symptoms are sought in the diagnostic signals. Thus, harmonics with frequencies described by the following formula appear in the mechanical vibration signal:

$$f_b = kf_u \pm lf_r, \tag{4}$$

and in the stator current signal respectively:

$$f_b = f_s \pm kf_u, \tag{5}$$

where: $k = 1, 2, 3 \ldots, l = 0, 1, f_u$ – frequencies specific for a given failure.

In order to determine the type of the damaged bearing component, it is necessary to know the damage frequency, f_u, which takes one of the forms:

$$f_{bc} = \frac{1}{2} f_r \left(1 - \frac{D_b}{D_c}\cos\beta\right), \quad (6a)$$

$$f_{or} = \frac{N_b}{2} f_r \left(1 - \frac{D_b}{D_c}\cos\beta\right), \quad (6b)$$

$$f_{ir} = \frac{N_b}{2} f_r \left(1 + \frac{D_b}{D_c}\cos\beta\right), \quad (6c)$$

$$f_{re} = \frac{D_c}{D_b} f_r \left(1 - \left(\frac{D_b}{D_c}\cos\beta\right)^2\right), \quad (6d)$$

where: N_b – number of rolling elements (balls), D_b – rolling element diameter, D_c – bearing pitch diameter, β – bearing working angle ($\beta = 0°$ for rolling bearing), f_{bc}, f_{or}, f_{ir}, f_{re} – frequencies specific for a given failure: bearing cage, outer race, inner race and rolling element.

There are also papers in which the authors use other diagnostic signals. Thus, in [138] it is shown that the stray magnetic flux spectrum contains more symptoms that indicate a damaged bearing than the current spectrum. The tests were carried out in both open and closed speed loops with different levels of magnetic field asymmetry. Furthermore, in a closed-loop speed control system, the effect of speed and load torque change on the amplitude of characteristic diagnostic symptoms was tested. In [139], the speed signal was subjected to a FFT and kurtosis analysis and compared with the results obtained from the mechanical vibration and stator current analysis over a wide range of PMSM motor speeds. The study showed that the analysis of the speed signal kurtosis spectrum can achieve results similar to those obtained for the vibration method. In [140], the ENV of the speed signal is analyzed. To suppress velocity ripples, the authors used additional resonant controllers in parallel with the existing proportional-integral controller. Furthermore, they compared the proposed method with the spectral kurtosis method of the velocity signal and three methods based on current analysis. In [141], an electromechanical model is presented for the modelling and detection of rolling element damage in PMSM motors. The simulation-modeled damage was diagnosed by means of FFT analysis of mechanical vibrations and FFT of the Park vector module of the stator current. Furthermore, it was shown that bearing damage is also visible in the electromagnetic torque.

In order to detect damage to a bearing component, it is necessary to process the measurement signals appropriately. Diagnostic methods used in PMSMs and reported in the literature for stator current signal analysis include: FFT [116], [131], [132], [135]–[137], ZFFT [133], OA [138], and EPVA [122], DWT [134]–[136], and CWT [136]. On the other hand, for mechanical vibration analysis: FFT [116], [117], [120], [121], ENV [117], [120], [121], [127], OA [117], [122], OA for vibration ENV [117], [118], [123]–[126] are used. The following methods are used with the acoustic signal, respectively: OA of noise [129], [130], and STFT [128]. Standard deviation, kurtosis, skewness, crest factor, clearance, shape factor [132], [137] are used to extract additional statistical characteristics of the analyzed signals.

To perform OA, information about the rotor speed is required, which is usually obtained by means of speed measurement. In [117], [122], [129] the information about the rotation direction is obtained from the phase current waveform, in [118] from a magnetic sensor mounted on the motor housing, in [123] from a mechanical vibration signal, and in [130] from an acoustic signal. In [124] the SWT is used to process the bearing vibration signal to extract the rotation phase from the time-frequency plane. In [126], the SWT method is used to process vibration from a triaxial sensor to obtain an accurate rotation angle waveform, and in [125], a method based on the SWT of the stator current is used.

In most of the articles reviewed, tests were performed in steady state. In [117], [118], [123]–[126], [128], [130], the tests were carried out in the dynamic state, while in [122], [135], [136], the tests were carried out in the steady state and with time-varying rotational speed. In [120] and [121], the effect of the load torque and the supply frequency of a PMSM motor on the change in the amplitudes of example diagnostic symptoms obtained from FFT and the analysis of ENV of mechanical vibration is presented. Depending on the diagnostic method used, the results are presented in the form of classical time courses, spectra, tables, or 3-D summaries, such as a 3-D color map of the relation between frequency, rotational speed, and sound level [128].

During the next industrial revolution, the approach to diagnosis is also changing. In [118], an efficient algorithm implemented in an industrial IoT node is proposed. To reduce the transmitted data between the node and the server, the signals from the magnetic sensor and accelerometer are processed and mixed in the IoT, sent as a new signal to the server, where they are decoded again. The proposed method can reduce about 95% of the transmission data compared to the traditional method, resulting in a reduction in power consumption in the battery-powered IoT node.

High noise levels can be a problem in industrial drives, so in [119] the wavelet threshold denoising and minimum entropy deconvolution methods are used to improve the signal-to-noise ratio. In [127], the Gaussian mixture model-based bearing fault band selection method is used to remove information indicative of bearing damage from the high frequency band, but without informing about the type of bearing component damaged. Experimental tests are carried out using artificially modelled damages. Most studies are carried out using physically damaged bearings by cutting, drilling, or electrically engraved pitting of the component [117], [120], [121], [125], [127], [129], [138]–[140]. In [116] the defective bearing was artificially aged by a burning grease process at 200° C for 60 hours and a broken cage.

Based on the literature review presented, it can be concluded that FFT analysis of mechanical vibrations has a high efficiency in rolling bearing damage detection; unfortunately, it requires a steady-state signal. On the contrary, the use of OA allows fault detection to be performed in dynamical drive states. Similarly, the ENV enables to detect the characteristic damage frequencies of the bearing. Noise is also a good diagnostic signal, which was confirmed by tests carried out on PM and BLDC motors.

It should be mentioned that stray magnetic flux analysis is highly effective; however, the method requires additional sensors. The tests showed a higher number of symptoms detected in this signal compared to the current analysis and effective bearing fault detection also for the motor with magnetic asymmetry. Analysis of the motor speed signal also enables the detection of damaged bearings even under low rotational speed conditions, which is its advantage compared to the spectral kurtosis of the speed signal and three current-based methods. Stator current analysis also allows for bearing condition monitoring, but detection may be slower than vibration-based analyzes. In addition, the signal is sensitive to low speeds and torque variations. The DWT of the stator current improves the efficiency of rolling bearing condition monitoring and also enables identification of both faults, eccentricity, and bearing damage. Diagnostics is possible at low, medium and high speeds as well as under speed changes.

The pros and cons of individual diagnostic signals and the methods used for fault detection in PMSM bearings are summarized in Table 4. The summary presented shows that symptoms obtained from several diagnostic signals are relatively rarely discussed or compared in one article.

B. ECCENTRICITY FAULTS

The eccentricity of electrical machines is a state in which there is an uneven distribution of the air gap between the stator and the rotor. The eccentricity of the air gap is the cause of the forces acting on the rotor. Among other things, an unbalanced magnetic pull causes the rotor to move in the stator bore, along the minimum length of the air gap. Distinguishing between the causes of magnetic field asymmetry can be difficult. In [142], a Hall sensor was proposed to detect magnetic asymmetry caused by dynamic or mixed eccentricity and local demagnetization.

A slight exceeding of the tolerance limits may aggravate the failure state caused by other unfavorable phenomena, such as power unbalance, demagnetization, misalignment, stator damage, work with excessive load, etc. In extreme cases, eccentricity may lead to friction of the rotor against the stator and, consequently, damage to the stator (including destruction of the windings' insulation) or the rotor (including damage to the magnets mounted on the rotor surface).

It is assumed that about 80% of mechanical failures lead to eccentricity [143]. It is also assumed that the manufacturing tolerance for eccentricity should not exceed 10% [31], [32]. Exceeding this limit adversely affects bearing operation (increasing its wear) and increases machine stress [32].

Three types of eccentricity can be distinguished: static (the minimum air gap length is constant and does not change its position during machine operation), dynamic (the minimum air gap length is constant but changes its position with rotor rotation) and mixed (the minimum air gap length changes its value and position with rotor rotation).

The basic diagnostic signal for eccentricity monitoring is the stator current, in which additional frequency components appear when the fault occurs, as described by the relation:

$$f_{ecc} = f_s \left(1 \pm \frac{2k-1}{p_p} \right) \tag{7}$$

where: $k = 0, 1, 2, 3, \ldots$

When dynamic eccentricity occurs, integer multiples of the frequency f_s/p_p appear in the stator current.

There are a great number of papers that deal with the modelling and study of eccentricity occurring in PMSMs. Eccentricity is most often modeled using FEM models [142]–[155]. In experimental studies, eccentricity is achieved by using bearings with off-center bushings [142], [144], [151], [156]–[158], shims mounted in the bearing housing [145] or on the motor shaft [147], [148], by modeling misalignment [159], by moving the rotor relative to the stator [153], [154], [160] or by eccentric shaft housings [152]. The level of modelled eccentricity can be controlled by measuring the radial force induced by the unbalanced magnetic pull, which is constant in space for static eccentricity and rotates with the rotor for dynamic eccentricity [160].

The basic diagnostic signals in eccentricity diagnosis are: stator current [135], [143]–[146], [150], [151], [156]–[159], [161], [162], mechanical vibrations [149], [155], [156], noise [155], an airgap search coil voltage [149], [152], [156], [160], stator voltage [159], speed [159], load torque [159], stator inductance in d-axis, L_d [147], [148], BEMF [160] and unbalanced magnetic pull [153], [154], [160].

The evaluation of the type and level of eccentricity is made based on the symptoms obtained mainly from the stator current analysis using a large number of methods: FFT [145], [156]–[158], [162], PSD [143], [144], [150], [151], [159], WT [135], [144], [146], [161], PCA [144], AD-OT method [158]. However, different analyses for other signals, e.g.: voltage PSD [159], speed PSD [159], load torque PSD [159], FFT of mechanical vibration [149], [155], [156], FFT of noise [155], FFT of voltage induced in a coil placed in the stator slots [152], FFT of unbalanced magnetic pull [153], [154] or OA of mechanical vibration and noise [155] were also applied for eccentricity detection. In [157], to distinguish eccentricity and demagnetization faults, the authors plotted the characteristic symptoms of both faults (amplitude and phase angle) in polar coordinates, obtained from stator current analysis. Some papers presented results obtained in dynamic states [135], [146], [152], [158], [161]. Focusing on eccentricity diagnosis, [31] cannot be omitted, in which the authors presented a critical analysis of various indices used for eccentricity detection. The presented literature review, which includes works from as early as 1986, can be an interesting position not only for beginning researchers.

TABLE 4. Classification of detection methods for bearing faults in PMSMs.

Legend:	**INV/NINV** – invasive/non-invasive, **LS/MS/HS** – low/medium/high sensitivity, **AOF/NAOF** – affected/not affected by other faults, **RL/RS** – robust to load torque/speed changes, **SC** – steady-state condition required, **TC** – detection on transients available, **ACR** – additional measurement coils or sensors required, **VM** – vibration/noise measurement required, **OS** – only simulation, **OD** – only one type of bearing damage, **EV** – experimental verification, **SM** – speed marker (**SM1** –from stator current waveform, **SM2** –from the magnetic sensor, **SM3** – from mechanical vibrations, **SM4** – from acoustic signal), **MDB** – method of damaging bearings (**MDB1** – aging in process of lubricant burning, **MDB2** – mechanical damage), **IoT** – method useful in IoT, **SBDB** – selection of bearing damage bands				
Ref.	**Diagnostic signal**	**Method**	**Fault index**	**Advantages**	**Disadvantages**
Frequency domain methods					
[116], [117], [120], [121]	Vibration	FFT	$f_b = kf_u \pm lf_r$ f_u – characteristic failure frequency of the bearing k=1,2,3… l=0,1	NINV, HS [116], SM1 [117], MDB1 [116], MDB2 [117], [120], [121], RL/RS [120], [121]	SC[120], [121], VM
[141]				Electromechanical model for rolling bearing fault detection	OS
[117], [141]		OA		NINV, SM1 [117], [122], MDB2 [117], SC and TC [122], TC [117], RL/RS [122], AOF (stator winding) [122]	VM
[117], [120], [121], [127]	Vibration ENV	FFT		NINV, SM1 [117], MDB2 [117], [127], RL/RS [120], [121], SBDB [127]	SC, VM
[117], [118], [123]-[126]		OA		NINV, SM2 [118], SM3 [123], [124], [126], SM1 [125], MDB2 [125], TC [117], [118], [123]-[126], IIoT [118], validated on BLDCM [125]	OD [123], [124], [126], VM
[116], [131], [132], [135]-[137]	Stator current	FFT	$f_b = f_s \pm kf_u$ f_u – characteristic failure frequency of the bearing k=1,2,3…	NINV, HS [116], MDB1 [116], cylindrical-roller bearing in a special test-bench housing [132], [137]	Detection slower than vibration indicator [116], OD [131], sensitive to low speed and torque change [135], [136], OS [135], [136], SC [135], [136]
[133]		ZFFT		NINV, needs smaller data and computational cost (in comparison with the FFT algorithm)	Simulated bearing failure
[138]		OA		NINV, EV, open and closed loop speed tests, MDB2	OD, LS
[141]	Stator current EPVA	FFT hodograph	kf_u	Electromechanical model for rolling bearing fault detection	OS
[141]		OA		NINV, SM1, SC and TC	
[129]	Noise ENV	OA		NINV, SM1, MDB2, TC	VM
[130]		FFT + OA		NINV, SM4, TC, simulation and EV, validated on PMSM, BLDCM and DCM	VM
[138]	Stray magnetic flux	OA		NINV, More symptoms than current analysis, open and closed loop speed tests, RL/RS, EV, effective detection with magnetic asymmetry, HS, MDB2	OD, ACR
[139]	Rotational speed Vibration Stator current	FFT + kurtosis spectrum	kf_u, k=1,2,3…	MDB2, wide speed range; similar effects for all three signals	OD, VM
[140]	ENV of rotational speed	FFT	kf_u, k=1,2,3…	EV, MDB2, method sensitive under low speed	SC
Time-Frequency domain methods					
[134]-[136]	Stator current	DWT	RMS values of the wavelet coefficient [134], Energy [135], [136]	NINV, SC and TC [135], [136], EV [135], [136], possible analysis and identification of both faults, eccentricities [135] and bearing damage [135], [136], RS	OS [134], OD [134]
[136]		CWT	Waveform plots	NINV, SC and TC, RS	
[128]	Noise	STFT	Three-dimensional color map	NINV, TC, black box developed for electric vehicles, AOF	VM
Time domain methods					
[132], [137]	Stator current	statistical features	standard deviation, kurtosis, skewness, crest factor, clearance, shape factor	NINV, MS, Cylindrical-roller bearing in a special test-bench housing	The fault diagnosis is impossible in small load conditions

As results from the presented literature review, apart from the commonly used FFT method with its known limitations, eccentricity detection is often performed on the basis of OA, AD-OT or WT, which enable the analysis of drive signals in steady states. Due to the long simulation time of mathematical models of drives with eccentricity and the complicated method of physical modeling of this failure, all types of eccentricity are analyzed only in a few studies. Moreover, it has been shown that there is a problem in distinguishing dynamic eccentricity from demagnetization or load unbalance. Only the analysis of the flux in the air gap makes it possible to distinguish these faults from each other, but requires the use of an additional measuring coil in the stator slots. In contrast, the analysis of the stator current and inductance L_d along the d-axis of the PMSM is characterized by high efficiency and reliability during changes in load and supplying frequency. This analysis is insensitive to DF and enables the detection of static and dynamic eccentricities regardless of the oscillating load torque. In addition, it does not require additional sensors.

In Table 5, the diagnostic methods applied for eccentricity detection of PMSM drive are summarized, with their advantages and disadvantages.

This summary shows that the primary diagnostic signal is the stator current. Numerous papers discuss mathematical models of a motor with eccentricity solved by the finite-element method. In most of them, simulation studies and proposed diagnostic methods are experimentally verified by physical modeling of eccentricity.

C. UNBALANCE FAULTS

Unbalance is the state of a rotating component when its mass distribution is uneven in relation to the axis of rotation. This results in unbalanced centrifugal forces and moments, which cause dynamic reactions in bearings, resulting in vibration and noise, thus leading to bearing damage. A symptom of unbalance is an increase in the amplitude of the rotational frequency that occurs in the diagnostic signal. Consequently, the f_r component is sought in mechanical vibrations, while the $f_s \pm f_r$ frequency is sought in stator current.

In [163], selected higher-order methods are presented to detect the umbalance of a PMSM drive system. The authors analyzed the mechanical vibration signal. The paper presents the influence of changes in the unbalance level on the value of amplitudes of characteristic frequencies obtained from FFT, BS and FS analysis. The changes in unbalanced mass and rotational speed were taken into account in the study. The highest sensitivity was obtained for the BS analysis of mechanical vibration acceleration. In [164], the mechanical vibration signal is subjected to FFT analysis. The effectiveness of unbalance detection is verified for a PMSM with modelled demagnetization and dynamic eccentricity. In [165] and [166], the stator current signal is analyzed, which, to eliminate the dominant fundamental component visible in the FFT analysis results, is subjected to the Park transform. The obtained signal was analyzed using DWT. The effectiveness of this method was confirmed by simulation and experimental results carried out under nonstationary conditions. In [167], the stator current is used to detect the unbalance. In this paper, two combined techniques are proposed: CWT and the distance approach. In the first step, the influence of the nonstationary condition is reduced in the wavelet coefficients, and then the distance of the residual signal from the distribution of the normal state is calculated. The effectiveness of the proposed method is confirmed by simulation studies for small loads under non-stationary conditions.

In [168] and [169] the detection of the unbalance in PMSG is discussed. In [168], the effect of the unbalanced mass and its mounting radius on the level of unbalance is investigated under stationary conditions. The stator current is analyzed for diagnostic purposes. The applied Bayesian method based on the current amplitude allows one to estimate the degree of damage. In [169], the focus is on the detection of unbalance in marine current turbines caused by plankton or biofouling adhering to the turbine blades under natural conditions.

In order to develop effective diagnostic methods, an experimental platform equipped with a direct-drive PMSG was built. The authors divided the methods into two groups, the first based on external sensors (e.g. accelerometers, cameras, temperature sensors) and the second based on phase current sensors embedded in the generator. The advantages and disadvantages of the different diagnostic methods used in the diagnosis of marine current turbines are presented in numerous tables.

In [170], mathematical models of rotor unbalance and magnetic asymmetry were presented. Vibration signals were used to evaluate the degree of unbalance and analyzed in the frequency domain. Experimental tests confirmed the correct operation of the developed simulation models.

The main features of the methods for detecting unbalanced PMSM rotors described in the reviewed literature are summarized in Table 6. It can be seen from the presented summary that the stator current and mechanical vibrations are the signals that are mostly used for unbalance detection. Moreover, only in [169] are both mentioned diagnostic signals discussed, while in the other works the authors focus on the analysis of only one of them. The use of HOS increases the efficiency of rotor unbalance detection while increasing computational power requirements. The discussed noninvasive unbalance detection methods require a steady-state condition. An exception to this rule is the use of FS or WT.

D. MISALIGNMENT FAULTS

The misalignment in the PMSM drive concerns the connection between the motor and the loading machine [171]–[176]. It is difficult to determine the level of misalignment when the drive is operating, as there are no measurement systems to measure it. The only way to detect it is to measure the secondary effects of forces acting on bearings, shafts, and couplings. For this purpose, the changes of amplitudes of characteristic frequencies related to the rotational speed of the motor are looked for in diagnostic signals, e.g. in the stator current, the symptoms of misalignment are the frequencies equal to $f_s \pm kf_r$. The misalignment of two shafts is divided into three basic types: parallel misalignment, angle misalignment, and a combination of both.

In [171] and [174], the FFT analysis of the PMSM motor speed signal is used to detect misalignment. The authors analyzed the amplitude of the characteristic frequency, $2f_r$. Furthermore, in [171], the authors proposed a

TABLE 5. Classification of detection methods for eccentricity faults in PMSMs.

Legend: **INV/NINV** – invasive/non-invasive, **ON/OFF** – on-line/off-line detection algorithm, **LS/MS/HS** – low/medium/high sensitivity, **AOF/NAOF** – affected/not affected by other faults, **RL/RS** – robust to load torque/speed changes, **SC** – steady-state condition required, **TC** – detection on transients available, **ACR** – additional measurement coils required, **VM** – vibration/noise measurement required, **MM** – mathematical model (FEM), **OS** – only simulation, **EV** – experimentally verified (**EV1** – use of bearings with off-centre bushings, **EV2** – use of shims, **EV3** – introducing misalignment, **EV4** – movement of rotor relative to stator, **EV5** – eccentric shaft housings), **SE/DE/ME** – only static/dynamic/mixed eccentricity, **PC** – fault signature in polar coordinates, **AaCPSD** – Auto and Cross Power Spectral Density, **DT** – dimensional tolerances of rotor and stator are considered

Ref.	Diagnostic signal	Method	Fault index	Advantages	Disadvantages
Frequency domain methods					
[145]	Stator Current	FFT	$f_{ecc} = f_s\left(1 \pm \frac{2k-1}{p_p}\right); k = 0,1,2,...$ 0.75th harmonic order*	NINV, MM, EV2, NAOF (broken magnet)	SE
[156]			f_s-f_r	NINV, EV1	DE, SC, LS, no fault identification (DE, partial demagnetization, load unbalance)
[157]			$f_{fault} = (1 \pm k/p_p)f_s$; k=1,2,3,…	NINV, EV1, NAOF (demagnetization), PC	DE, SC
[158]			$f_{ecc} = f_s\left(1 \pm \frac{2k-1}{p_p}\right); k = 0,1,2,...$ or 3rd and 5th order	NINV, EV1, SE, DE, ME	SC
[162]			$(1-l/p_p)f_s$; $(1+l/p_p)f_s$; l=1,3,5,..	NINV	SC, OS, ME
[143]		PSD	$f_{ecc} = (1 \pm l/p_p)f_s$; l=1,3,5,…	NINV, MM, EV	SC, SE, DE
[150]		PSD		NINV, MM	SC, OS, SE
[144]		PSD	$f_{ecc} = f_s\left(1 \pm \frac{2k-1}{p_p}\right); k = 0,1,2,...$	NINV, MM, EV1, RL	SC, SE, DE
[151]		PSD	$f_{mixed} = 2kf_s/p_p$	NINV, MM, EV1	SC, ME - detectable only at given load levels
[159]		PSD	$f_{SE} = f_s \pm kf_r$	NINV, EV3, AaCPSD, RL	SE
[158]		AD-OT		NINV, EV1, SC, TC, SE, DE, ME, RL, RS	
[149]	Vibration	FFT		NINV, MM, identification of SE and DE	SE, DE, OS
[155]		FFT, OA	$(2pk\pm1)^{th}$ order, k=1,2,3,…	NINV, MM, EV, in experiment the dynamic state (OA)	SE and DE in simulation, DE in experiment, VM
[156]		FFT	f_r (1X)	NINV, EV1	AOF, SC, DE, (DE, partial demagnetization, load unbalance), VM
[155]	Noise	FFT, OA	$(2pk\pm1)$th order, k=1,2,3,…	NINV, MM, EV, in experiment - dynamic state (OA)	SE, DE (simulation and experiment), VM
[159]	Voltage	PSD	$f_{SE} = f_s \pm kf_r$	NINV, EV3, AaCPSD	SE
[152]	Airgap flux	FFT	third- and fifth-frequency components	MM, EV5	DE, INV, ACR
[159]	Rotation speed	PSD	$f_{SE} = f_s \pm kf_r$	EV3, AaCPSD	SE
[159]	Load torque	PSD	$f_{SE} = f_s \pm kf_r$	EV3, AaCPSD	SE
[153], [154]	UMP	FFT	(1), (2)	MM, EV4, DT	SE, DE, force transducer required
Time-Frequency domain methods					
[144]	Stator Current	DWT	Peak of detail	NINV, MM, EV1	SC, SE, DE
[146]		CWT / DWT	Average ridges CWT / Energy	NINV, MM, EV, RL, RS, TC	DE
[135], [161]		DWT	Energy	NINV, TC, NAOF (short-circuited) [161]	undefined type of eccentricity [161]
Time domain methods					
[142]	Axial flux	Waveform plot		MM, EV1, SE, DE, ME	INV, ACR (Hall sensor)
[144]	Stator Current	PCA		NINV, MM, EV1, SE/DE identification	SC, SE, DE
[149]	Air-gap flux, EMF	Waveform plot		MM, more effective than vibration analysis in transient and asymmetrical conditions	SE, DE, OS, INV, ACR (airgap flux search coils)
[156]	Airgap flux	Waveform, Hexagon plots		EV1, damage identification (DE, partial demagnetization, load unbalance)	DE, SC, INV, ACR (airgap flux search coils)
[160]	UMP	RMS, Peak to peak of ENV		EV4, identify the type of SE or DE and its severity	SC, SE, DE, INV, ACR (airgap flux search coils)
[147], [148]	d-axis current and L_d	Waveform plot		EV2, MM, NAOF (demagnetization), HS, RL RS, detection of SE/DE independent of the oscillating load torque), low cost	DE, OFF, testing when the motor is stopped
Comments					

* the order spectrum depends on the determination of the fundamental harmonic and motor parameters

(1) SE generates the increase of electric orders 2, 4, 6, etc. (multiples of 2) without sideband peaks, and variations on the amplitudes of electric orders 2.4, 4.8, 7.2, etc. (multiples of Q_s/p_p) and especially their sideband peaks that are separated $1/p_p$, Q_s - number of slots of the stator.

(2) DE generates the increase of electric orders 2, 4, 6, etc. (multiples of 2) with sideband peaks that are separated $1/p_p$, and the increase of electric orders 2.4, 4.8, 7.2, etc. (multiples of Q_s/p_p) without sideband peaks.

proportional-integral resonant controller algorithm to suppress the periodic ripples of the speed signal caused by misalignment. In [172] several diagnostic methods based on stator current analysis are discussed: RMS, FFT, and DWT analysis of the stator current. The DWT of the stator current ENV and its space vector modulus were used to detect angular misalignment. The impact of the load torque on the values of the characteristic components was shown to be relatively small. In the case of changes in the frequency of the power supply, the components that are least dependent on its changes are $f_s - f_r$ and $f_s + f_r$. However, the influence of the f_s changes on the value of these symptoms is visible. The same applies to the RMS value of the stator current. On the contrary, the EPVA and current ENV analysis methods show that the fault index f_r is highly sensitive to misalignment, does not depend on the load torque and depends less on the stator frequency compared to the fault symptoms visible in the stator phase current spectrum. This makes this FI very useful for fault diagnosis and monitoring of the alignment of the drive system.

The DWT analysis of the stator current also shows that the RMS values are strongly dependent on the load torque and frequency of the supply voltage, which confirms their uselessness in misalignment detection. However, in the case of the RMS values of a5 and d5, the details obtained in the DWT analysis of EPVA and the ENV of the stator current increase significantly with increasing degree of angular misalignment, and do not depend on the loading torque and stator frequency. However, the influence of the supply voltage frequency changes is slightly greater for EPVA than in the case of DWT of current ENV. In [173], the effect of the misalignment on the torque generated is presented. Simulation and experimental studies showed that the torque amplitude is proportional to the level of parallel misalignment, and the frequency of torque pulsations depends on the motor speed. In [175], the frequency response of the PMSM drive tested with parallel misalignment was analyzed, while in [176] it was shown in simulations and experimental tests that the virtual phase torque diagram method (VPT) based on the self-sensing motor drive system enables detection of the offset angle of misalignment. VPT is a method that does not require additional sensors. Despite some limitations in mechanical system diagnostics (compared to vibration analysis), as a cost-free method, it can be used to assess gears and bearing condition.

Based on the literature review presented, Table 7 summarizes the diagnostic methods used to detect misalignment of PMSM drive systems. The summary shows that the misalignment is monitored on the basis of stator current and speed analysis.

VI. PMSM DIAGNOSTICS BASED ON CONTROL STRUCTURE SIGNALS

A. GENERAL REMARKS

In order to ensure high dynamics and precise regulation, PMSM must be controlled using an efficient control structure. As open-loop control is not applied in industrial applications, one of the specialized vector control methods must be used. Generally, they can be divided into FOC and DTC methods. Both methods are based on a series of regulators, which are usually PI-type controllers. The regulators are responsible for controlling the motor speed, torque, flux, and current space vector components using the relevant components of the voltage vector or a special switching table (in the case of the DTC method). Due to their compensating nature, control structures tend to compensate for the symptoms of the faults that can appear. The higher harmonics that would be present only in currents in the case of the open-loop control, when the ITSC and PD faults occur, are compensated with the counter response of the voltage controller, so the higher harmonics will be visible in voltages as well. Similarly, mechanical vibrations present in speed and torque due to bearing damages can be reduced by the action of the control structure and its regulators. Thus, the influence of the control structure and its compensatory nature must be taken into account when designing the diagnostic procedure [178].

The advantage of the control structure-based signal usage is that there is no need to apply any additional sensors (e.g. vibration sensors, additional resistance networks with voltage sensors) and in most cases the same microprocessor can be used to implement the control structure and to calculate necessary signal processing procedures and diagnostic algorithms. Most of the control structures applied in the papers cited in this section are based on the field-oriented approach with the reference direct-axis stator current component equal to zero. Only a few of them investigate the diagnostic procedure in the case of the DTC approach.

There are several signals, i.e. space vector components of the PMSM control variables, that can be utilized as diagnostic signals:

- reference voltage vector components, for example, [52]. Alternatively, estimated voltage vector components can be used (calculated on the basis of the DC-link voltage and duty cycle signals of the VSI modulator). However, in the case of a correctly designed voltage modulation, with dead-time compensation, both signals should be the same. Due to measurement problems, the usually measured voltage signal has not been taken as a diagnostic signal;
- reference or estimated stator vector components (in rotor flux-oriented frame, *d*-*q*), for example [38]. The torque-producing current component on the q-axis [38], [182] and the relationship between the components of the d and q axes [185] have been applied to design a diagnostic method so far;
- PI controller outputs in the case that the decoupling signals are applied in the control paths, e.g. [179] or when the control structure is extended with some additional PI regulators to compensate for the damage [180];
- voltage decoupling signals, not applied in the diagnostics so far.

TABLE 6. Classification of detection methods for rotor unbalance in drive system with PMSMs.

Legend:	**INV/NINV** – invasive/non-invasive, **LS/MS/HS** – low/medium/high sensitivity, **AOF/NAOF** – affected/not affected by other faults, **SC** – steady-state condition required, **TC** – detection on transients available, **VM** – vibration/noise measurement required, **OS** – only simulation, **EV** – experimentally verified, **EUM/ERS/EUR** – the effect of changing unbalance mass/rotational speed/unbalance radius was investigated, **LCC/HCC** – low/high computational complexity, **CT** – different control types (VC and DTC)				
Ref.	**Diagnostic signal**	**Method**	**Fault index**	**Advantages**	**Disadvantages**
Frequency domain methods					
[163]	Vibration	FFT	$1f_r$	NINV, EUM, ERS, LCC, MS	SC, VM
[164]			$1f_r$	NINV, NAOF, LCC	SC, VM
[170]			$1f_r$	NINV, EV, LCC	SC, VM
[169]		PSD	$1f_r$	NINV	SC, VM, fault detection is still a challenging task
[163]		BS	$(0, 1f_r); (1f_r, 1f_r)$	NINV, EUM, ERS, HS	SC, VM, HCC
[163]		FS	$1X$	NINV, EUM, ERS, TC, MS	VM, HCC
[165], [166]	Stator current	FFT	$f_s \pm f_r$	NINV, LCC	SC, LS
[169]		PSD	$f_s \pm f_r$	NINV	SC
[165], [166]	Stator current EPVA	FFT	$1f_r$	NINV, LCC	SC
Time-Frequency domain methods					
[167]	Stator current	CWT	Energy, Mahalanobis Distance	NINV, TC	OS, HCC
[165], [166]	Stator current EPVA	DWT	Normalized energy	NINV, TC, EV [165], CT	HCC
Time domain methods					
[168]	Stator current	Waveform plot		NINV, EUM, EUR	SC

TABLE 7. Classification of detection methods for misalignment faults in PMSMs.

Legend:	**INV/NINV** – invasive/non-invasive, **LS/MS/HS** – low/medium/high sensitivity, **RL/NRL/RS/NRS** – Robust/not robust to load torque /speed changes, **SC** - Steady-state condition required (signal stationarity), **EV** – experimentally verified, **EN** – required phase angle from encoder signal, **TW** – only time waveforms, **PM/AM** – only parallel/angular misalignment				
Ref.	**Diagnostic signal**	**Method**	**Fault index**	**Advantages**	**Disadvantages**
Frequency domain methods					
[172]	Stator current	FFT	$f_s \pm kf_r$	NINV, HS	SC, NRL, NRS, AM
[172]	Stator current EPVA	FFT	kf_r	NINV, HS, RL, RS	SC, AM
[172]	Stator current ENV	FFT	kf_r	NINV, HS, RL, RS	SC, RS, AM
[171], [174]	Rotational speed	FFT	$2f_r$	NINV, PM and AM [174]	SC, RS, AM [171]
Time-Frequency domain methods					
[172]	Stator current	DWT	RMS	NINV	SC, LS, NRL, NRS, AM
[172]	Stator current EPVA	DWT	RMS	NINV, MS, RL, RS	SC, AM
[172]	Stator current ENV	DWT	RMS	NINV, MS, RL, RS	SC, AM
Time domain methods					
[172]	Stator current	RMS		NINV	LS, NRL, AM
[173]	Torque	Waveform plot		EV, RL, RS	SC, TW, PM
[176]	Current i_q	VPT		EV, MS	SC, EN, AM

The signals mentioned above are available for the detection system, even if other control structures (DTC) are applied [134], [165], as they can be easily calculated, for example, with measured stator currents and rotor angle. However, in this section, it is assumed that methods based on phase current signals or current signals transformed into the stationary reference frame are not taken into consideration, as they are the signals that can be determined without knowledge of the control system structure.

B. ELECTRICAL FAULTS

Most diagnostic methods based on control structure signals utilize voltage signals. Signals have to be further processed, as their actual values vary with the operating point. However, the instantaneous value of the angle between the reference voltage components has been used directly as an efficient FI in [181]. This angle has also been used to distinguish between two different faults (ITSC and DF, as it decreases or increases with fault, respectively). Unfortunately, the value of the angle between the components for the undamaged motor must be known for the actual torque/speed/temperature operating point. This value can be estimated (based on motor parameters and signals) or determined experimentally, which can be both difficult and erroneous in the case of industrial applications. Additionally, the current controllers bandwidth seems to have an important influence on the proposed angle. Unfortunately, this aspect has not been verified in the literature.

Thus, in [52] the search for some characteristic frequencies in the components of the reference voltage vector has been proposed. It is shown that the ITSC introduces the second-order harmonic signal into the d-q rotating reference frame (they correspond to the third-order harmonics in the A-B-C frame; the classical Park transform reduces the order of the harmonic by one). The authors propose to transform the d-q frame voltage signals into a new frame rotating with triple synchronous speed. In this frame, the fault-related signals are constant in time and can be filtered by a low-pass filter. Therefore, there is no need to apply the FFT on-line. Finally, the filtered components create a vector whose amplitude becomes a fault indictor. This solution can be applied easily online, however, selecting a low-pass filter to obtain only the DC components can be problematic.

Voltage components are also used to detect ITSC faults in [179]. However, diagnostic signals are the output of the PI controllers, since the decoupling of BEMFs is included in the control paths. This paper proposes to use the instantaneous values of negative and positive sequence components obtained using a simple filtration and Fortescue transform. Finally, the ratio of negative to positive sequence component magnitudes, transformed into a stationary frame, is taken as FI. However, the complexity of the solution increases with the use of a statistical cumulative-sum algorithm to determine whether damage is present or not. Furthermore, similarly to [181], the operation point map (a table with 'healthy' FI values for many torque/speed values) must be determined before the diagnostic method is applied to compare the actual and initial values of the diagnostic index.

The quadrature component of the reference voltage vector is used as the diagnostic signal in [69] and [73]. Both propose to use an adapted WT to diagnose the ITSC fault. Both proposed methods require high computing power and a complex diagnostic algorithm. The interesting feature of the solution presented in [69] is the possibility of localizing the defective phase using high-pass-filtered phase-to-phase voltages.

The quadrature (torque producing) current component has been the only current component used as a diagnostic signal in the diagnosis of PMSM [38], [182]. In [38] the component was used to diagnose the ITSC fault. It is proposed to search for second-order harmonic amplitude variations and compare them with the healthy condition (the FI is the ratio of second-order harmonic amplitudes in faulty and healthy conditions). A lot of interest is paid to interpolating the FI according to the actual operating point – there is a necessity to know the amplitudes of the second-order i_{sq} harmonic for idle and rated torques for different speed values (only high speed operation is taken into account). As in the case of most diagnostic methods, the proposed method requires the FFT calculation, and thus steady-state operation. The fault is recognized when the FIFI exceeds a predefined threshold.

The estimation-based approach for the ITSC fault diagnosis method can be found in [182]. The difference between the measured and estimated quadrature current components, the number of winding turns, the measured voltage, the estimated voltage assuming the machine is healthy and the rotor angle is required. Therefore, perfect knowledge of motor parameters is necessary. However, all commonly known issues related to estimation quality can degrade the diagnostic process. (parameter determination mismatch, their changes in time and with temperature, measurement transducer offsets, noise, etc.). Additionally, the least-squares method must be applied to estimate the FI, which increases the complexity of the described method even more.

All of the above ITSC diagnostic methods act as a fault alarm for motor service personnel. However, if the fault is detected, the FTC method can be applied to decrease the level of oscillations that arise after the fault, for example, [183]. This method is based on the injection of the reference current signal. However, the proposed method is based on perfect knowledge of motor parameters, together with the actual number of shorted turns and short-circuit resistance, which is difficult to determine in an industrial application. Moreover, the fast dynamics of the damage and very high current in the short-circuit suggest that the drive should be stopped immediately, not operated after the fault is detected. More details on fault compensation methods and FTC algorithms will be discussed in Section IX*C*.

A simple and fast diagnostic method for single open phase fault detection based on control structure signals was first proposed in [184] and further developed in [185]. The FI relies on the ratio of the components of the real quadrature to the components of the direct axis. When the PMSM is healthy, the ratio is close to infinity (d-axis component close to zero), while the FI is close to zero. When the machine is faulty, the FI is no longer zero. When a predefined threshold is exceeded, a fault decision is made. Due to the nature of the fault, the diagnosis must be immediate, and preferably much faster than any RMS or FFT based algorithms. The diagnostic method shown in [185] can easily determine the faulty phase, based on the difference between the estimated and real electrical angles of the position of the rotor shaft.

C. MECHANICAL FAULTS

As noted above, most of the proposed diagnostic methods are designed to detect electrical faults (mostly ITSCs, but also single open-phase faults). However, virtual signals, which are part of the control structure, have also been used to diagnose mechanical-type damages. The inner and outer race faults of the motor bearing can be distinguished using the approach shown in [177]. Because it is applied to a general repetitive mechanical mechanism, a special harmonic speed controller is proposed instead of a traditional PI regulator. The diagnostic method is based on FFT analysis of the difference between the reference and estimated torques and the finding of increased amplitudes of the respective harmonic frequencies. The mentioned mechanism is driven by a sensorless PMSM drive. The diagnosis of bearing failure is also described in [134] for the DTC structure of the PMSM drive. The quadrature component of the stator vector is selected as the diagnostic signal, despite the fact that it is not part of the DTC algorithm but is additionally calculated for diagnostic purposes. The paper introduces a combination of DWT and NN analysis of the stator current component to determine bearing condition. This makes the proposed method quite complex. Moreover, the presented results are obtained with only simulation studies and are rather inconclusive.

An interesting comparison of the diagnostic efficiency of rotor unbalance for two main control structures (FOC and DTC) for PMSM is shown in [165]. A DWT is used to extract damage symptoms from the modulus of the stator current vector (expressed in a stationary frame). The proposed method is efficient in the case of both mentioned control strategies and also during nonstationary conditions, which is quite a rare situation.

Misalignment between the motor and the load can also be detected using control structure signals [176] without additional sensors. The q-axis current is proposed as a diagnostic signal. To extract the fault symptom from the current signal, the ensemble EMD method is proposed, which significantly increases the complexity of this method. Additionally, the proposed solution is able to efficiently detect misalignment and its severity level (right, left, angle of misalignment).

The control structure and its signals are also necessary in the case of eccentricity detection proposed in [147] and [148]. These two solutions suggest detecting the damage during the motor standstill, not during online operation. The reference voltage vector of the d-axis and the current vector, expressed in the field rotating reference frame, are used to determine the differential inductance, a decreasing value of which indicates eccentricity, while an increasing value indicates demagnetization [148]. To extract the inductance, it is necessary to induce an AC flux by injecting the d-axis current. A different idea based on online drive operation to detect eccentricity is shown in [178]. In this paper, the diagnostic is based on the 0.5 harmonics of current and voltage on the q-axis. Additionally, the authors propose a method to distinguish rotor fault and load torque variations. Demagnetization fault can also be diagnosed using control structure signals [180], in the case of a five-phase PMSM. The authors propose to include four additional PI regulators operating in a reference frame rotating with ten times the supply frequency, to reduce the oscillations in the BEMF signal due to the DF. Because of the applied reference frame the outputs of the regulators are constant in steady state and can be directly used as diagnostic signals (no FFT, filtration, RMS calculation, etc. is necessary); their increased values inform about the magnet fault.

D. INFLUENCE OF CONTROLLERS BANDWIDTH

Almost all of the FIs mentioned above are sensitive to the bandwidth of the applied controllers, the speed controller, and two current controllers in the case of the FOC. As shown in [178], [186], and [187], the symptoms of the fault are visible in voltage, current, or both, depending on the parameters of the regulator. Generally, if the bandwidth of the speed controller is low, the characteristic harmonics of a specific fault will be visible in the voltages [178]. On the contrary, if the bandwidth is high, they will be present in currents. This effect can be distorted by current controllers, if their bandwidth is low, the fault is visible in currents, and, if high, in voltages [186], [187]. In other words, the control structure tends to obtain clear sinusoidal current signals, and therefore higher harmonics must be present in voltages.

According to the above analysis, it seems that the FI, effective and insensitive to controller bandwidth, has to include both signals from the control structure, current, and voltage. An example of such a solution is shown in [186]. The amplitudes of the second harmonics in instantaneous active and reactive power signals are proposed to be diagnostic signals. It is shown that they are not sensitive to the current controller bandwidth. However, as stated in [187] the FI based on an active power signal does not adapt to the bandwidth. Therefore, the authors proposed a modified solution, using a Rayleigh quotient function [187] with four signals, second-order harmonic amplitudes of the voltage and current vector components on the d-q axes. Thus, the proposed quotient is a weighted sum of the mentioned signals (normalized to healthy values) and automatically adapts to the current controlled bandwidth. It is shown that its value is constant in a wide range of bandwidths.

As presented above, the control structure signals can be successfully applied to the diagnosis of several faults that can occur in PMSM drives. They are used mostly in the case of diagnosing electrical damage. More work is required on the diagnosis of mechanical faults using control structure signals, especially to evaluate the signals that can be used and to verify the influence of the controller bandwidth on fault detection.

VII. MODEL-BASED FAULT DETECTION OF PMSM DRIVE

A. GENERAL REMARKS

Increasing computational power and efforts to develop fault-tolerant systems lead to the use of software redundancy in drive systems in the form of mathematical models of an object. Additional information obtained from the mathematical model about the state of the machine at the current point of operation supports the drive system and can improve the quality of control, identify changes in the parameters of the drive, and also allows to determine the characteristic symptoms of fault, which are used in the diagnostics of drives.

Model-based fault detection methods use analytical models and FEM. Analytical models, written in the form of differential equations, are used to synthesize estimators or observers of state variables or motor parameters. Observers of state variables are used in fault detection tasks of components of the power system to calculate the residuals between the measured and estimated signals, showing the occurrence of a fault [16], [18], [22], [23]. A typical example is the detection of sensor faults in the drive system, which is studied in Section IX*B*. Estimators of parameters, e.g. stator resistance, as well as observers of state variables can infer inter-turn stator winding faults online, as discussed later in this section. However, the most common application is the use of mathematical models, in particular FEM-based, to model the electrical, magnetic, and mechanical faults of the PMSM. FEM models are used not only to analyze the influence of specific faults on the motor's state variables and to understand the phenomena occurring but also to test signal processing methods. Additionally, PMSM fault modeling can also be used to generate symptoms of different faults, providing data for training neural fault detectors. It is important to note that obtaining large enough databases of measurements for different failures and different operating conditions of the motor, serving as learning vectors in the training processes of neural networks, is difficult, and in the case of most PMSM failures requires tests on specially prepared machines (physical modeling of ITSC, partial or uniform demagnetization, eccentricity, or misalignment). The use of information on failure symptoms from mathematical models may allow one to abandon physical modeling of failures to extract their symptoms.

B. PARAMETER AND STATE OBSERVERS IN MOTOR DIAGNOSTICS

Among the methods that use parameter estimators to detect PMSM motor failures, extended Kalman filters (EKF) are the most frequently used – to diagnose ITSC faults [188], [189], open phase failure [190] and demagnetization failure [191]. In [188] it was proposed to use an interesting EKF algorithm to estimate the number of shorted turns in the stator winding. The algorithm is developed on the basis of a mathematical model with a damaged winding in the d-q coordinate system. The extended state vector of the proposed EKF contained three short-circuited turn ratios, which enabled not only fault detection, but also location of the damaged phase. This approach has also been adopted for a PMSG system in [189], where the unscented Kalman filter (UKF) was also applied on the same basis. It was shown that the UKF technique gives more precise values for the fault estimation than the EKF. The paper [190] proposed the open-phase fault diagnosis of the PMSM drive using EKF. Estimated stator resistance is used as a FI and it is added to the extended state vector of the estimator model described in a stationary reference frame. The EKF was also used to estimate the rotor flux of PMSM along the d-axis to detect PM demagnetization online [191].

In [81], the BEMF estimator developed on the basis of a mathematical model taking into account the influence of temperature and magnetic saturation is used to detect ITSC. The residuum calculated on the basis of the estimated and reference BEMF value after normalization with respect to the angular speed of the motor is used as the damage index.

A state observer for the estimation of the stator current of PMSM is proposed in [192] for ITSC fault detection. It was applied for the generation of residuals, calculated as a difference between the estimated and measured stator current vector under the stator winding fault. An additional mechanism based on the use of different reference frames for the calculation of the current vector allowed the correct detection of ITSC faults and quantification of the severity of the fault in any stator phase winding.

The online operation is an undoubted advantage of using state variable estimators or parameters for fault detection. On the other hand, the disadvantage is the need for a precise knowledge of the parameters of the mathematical model.

C. PMSM MODELS IN DIAGNOSTICS

As discussed earlier, mathematical models of PMSMs with faults are often used to analyze the magnetic field distribution and the waveforms of motor state variables when individual faults occur as well as to test the effectiveness of signal analysis methods.

The analytical models of PMSM are most commonly used to model ITSC [42], [44], [47], [64], [72], [83], [193]–[198]. The models presented in the literature are described by differential equations, in a three-phase system *A*-*B*-*C* [42], [47], [83], [195], [196], [198], in a synchronous reference frame d-q for 3-phase motors [44], [72], [193], [194], [197], and also for multiphase motors [213]. Models have been used in PMSM diagnostics to find symptoms of ITSC faults [42], [44], [47], to produce estimators showing the number of shorted turns [88], to design methods affecting the control system by injecting an additional signal [64], and to determine residuals in comparison methods [194] (residuals based on current signals in a synchronous reference frame compared to values obtained from the observer). However, the most popular use of the model is to test methods based on signal processing, such as ZSVC [195], PCA [83], DWT [72], Negative Sequence Voltage Component [193], [197], [198], Positive Sequence Voltage Component [193], [198].

A comparison of results obtained from analytical and FEM models in damage modeling can be found in [210]–[212]. These works attempted to improve the analytical models on the basis of additional information contained in the FEM models. They considered supporting analytical models by introducing non-linear characteristics of the machine model.

The analytical model is supported by a FEM simulation from which information on saturation and spatial harmonics is obtained.

The FEM models available in the literature deal with faults: ITSCs [64], [88], [199]–[201], [205], [209], eccentricity [88], [200], [201] and demagnetisation [88], [201]–[209]. The approach presented in [88], [200], [201], [208], [209] shows an overview of the symptoms that appear as a result of individual failures of PMSMs. In addition, the authors have considered the existence of more than one fault by verifying their behaviour for different drive operating conditions (i.e. temperature, speed variations, changing eccentricity, influence of ITSC, and level of demagnetization). Approaches are also encountered where synchronous machine designers attempt to select PMs in a way to achieve immunity against demagnetisation, for example, when an ITSC occurs. The authors of [202]–[204] performed an analysis of the effect of demagnetization on the FEM model where they proposed the selection of the PMs. The article [206] proposes a method affecting the antidemagnetization ability of PMs. The proposed solution affects the modulation of the fundamental harmonic. The simulation results obtained by the authors prove the effectiveness of the proposed method.

Similarly, the authors of [207] used machine learning based on the results of the simulation model, to detect demagnetization faults. The resulting voltage and current signals delivered from the simulation model for different load torque and speed values allowed the authors to build an effective diagnostic method. This shows that a properly designed PMSM mathematical model can serve as a symptom source for training machine learning-based damage detectors without the need for costly experimental studies with physically modeled failures.

VIII. ARTIFICIAL INTELLIGENCE-BASED PMSM FAULTS DETECTION

A. CLASSIFICATION OF AI-BASED METHODS

An important role in diagnostic systems based on signal analysis methods is played by the knowledge and experience of an expert, which is a limitation from the point of view of the automation of fault detection. The decision-making process is extended, and its precision is closely related to the experience of the diagnostician. Therefore, to limit the role of an expert in the diagnostic systems of electrical machines, AI methods, in particular NNs, are increasingly used. The methods and techniques of AI make it possible to a large extent to objective the process of classification and assessment of damage.

The main task of neural structures in diagnostics is to fully automate the process of classification and assessment of the technical condition of a machine. Based on the input information obtained from the analysis of diagnostic signals, the input vector of the NN is developed, which contains the damage symptoms. Therefore, the optimization of the detection system requires a thorough analysis of all the components of the information processing steps in terms of the assumptions regarding the operation of the diagnostic

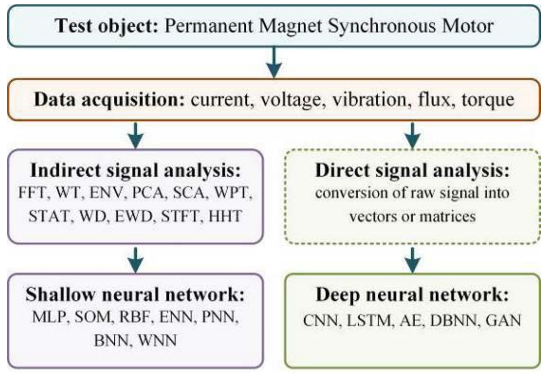

FIGURE 5. Classification of PMSM damage detection methods using shallow and deep learning neural networks.

application, such as possibly short time of preprocessing, precise assessment of the technical condition of the machine, the required computing power of the programmable system.

Also, an important point is the appropriate selection of the type and structure of the NN. Fig. 5 shows the division of the basic NN structures currently used in diagnostic systems, as well as methods for developing network input information. Currently, classic NNs, i.e. shallow neural networks (SNN), are still the most widely used structures in diagnostic tasks. Nevertheless, in recent years, usage of a new category of NNs based on DL techniques, namely DNNs has become possible.

As shown in Fig. 5, the use of SNN structures in the diagnostics of electrical machines makes it necessary to preprocess the measurement information (indirect signal analysis) to develop the network input vectors.

Therefore, increasing the precision of the detection systems is possible through the use of more and more computationally complex methods of signal analysis, e.g.: WT, STFT, and HHT, which significantly prolongs the diagnostic procedure (Fig. 5). Moreover, a significant limitation of shallow structures is the necessity of the existence of close relations between the symptoms of damage and the damage considered. The solution to the above problems may be the use of DNNs in diagnostics, in which the symptom extraction process using signal processing methods can be completely omitted. DNN input vectors are created based on the raw data contained directly in the measured signals (direct signal analysis), without the need for expert knowledge (Fig. 5).

B. SHALLOW NEURAL NETWORKS APPLICATION IN PMSM DRIVES

The analysis of the literature presented in Table 8 shows that the largest number of works related to the design of PMSM neural damage detectors refer to the application of the MLP structure.

The MLP network is characterized by an extremely simple mathematical description, thanks to which it is used in the case of mechanical damage: bearing damage [121], [231], eccentricity [231], and in the case of damage to the stator electrical circuits [215]–[218], [224], [225], [232], supply

TABLE 8. Artificial intelligence-based methods of PMSM faults detection–literature analysis.

No	Fault category 1	2	3	4	5	6	NN structure	Preprocessing method	Diagnostic signal
[120]			+				SOM	FFT+ENV	Vibrations
[121]			+				MLP	FFT+ENV	Vibrations
			+				RBF	FFT+ENV	Vibrations
			+				SOM	FFT+ENV	Vibrations
[214]	+						SOM	CWT	I_{sABC}
[215]	+						MLP	SCA	I_{sABC}
[216]	+						MLP	DIRECT	I_{sABC}
[217]	+			+			MLP	FFT	$I_{sABC}+T_e$
	+			+			MLP	STAT	$I_{sABC}+T_e$
[218]	+						MLP	FFT	I_{sABC}
[219]			+				CNN	WPT+FFT	I_{sABC}
[220]	+						CNN	DIRECT	I_{sABC}
	+						CNN	DIRECT	U_{sABC}
	+						CNN	DIRECT	*Flux*
[221]				+		+	MLP	FFT	I_{sABC}
[222]	+	+					CNN	DIRECT	I_{sABC}
[223]	+					+	LSTM	DIRECT	I_{sABC}
[224]	+						MLP	ENV	I_{sABC}
[225]	+						MLP+ENN	WD	$I_{sABC}+U_{sABC}$
[226]						+	MLP	RESIDUAL	I_{sABC}
[227]				+			MLP	STAT	$I_{sABC}+U_{sABC}$
[228]	+						LSTM	SCA	I_{sABC}
[229]	+						CNN	DIRECT	I_{sABC}
[230]	+	+					CNN	FFT	I_{sABC}
[231]			+		+		MLP	EWD	I_{sABC}
[232]	+	+					PNN	VMD	I_{sABC}
[233]		+	+				CNN	FFT	I_{sABC}
[234]	+						MLP	FFT+STAT	I_{sABC}
[235]	+						MLP	FFT	I_{sABC}
[236]		+					BNN	VKF-OT+WT	T_e
[237]	+	+					CNN	FFT	I_{sABC}

Fault categories:
1 – ITSCs-, **2** – demagnetization, **3** – bearing fault, **4** - unbalance supply, **5** – eccentricity of rotor, **6** – stator phase loss.

voltage imbalance [219], [221], [227] or phase loss of the stator winding [221], [226], and demagnetization faults [232].

In the case of MLP-based diagnostic systems described in the literature, the extraction of damage symptoms is performed using spectral analysis. This solution was presented, among others, in [218], [221] where the input vector of the MLP network contains the amplitudes of the characteristic components of the signal spectrum. The most common form of using FFT in the event of electrical circuit faults is the popular MCSA [218]. The authors in [217] showed that the configuration of the input vector in the form of simultaneous application of the results of FFT and statistical analysis allowed the high efficiency of fault detection of the PMSM stator windings. The combination of spectral analysis with additional signal processing methods was also presented in [120], [121].

In contrast, in [236] the VKF-OT and the dynamic Bayesian network were used for the detection of real-time rotor demagnetization from torque ripples. In this work, the torque transient obtained from the simulation model was processed by WT to eliminate electromagnetic disturbances. Next, the VKF-OT was applied to track the order of the torque ripple of the PMSM to extract the torque ripple characteristics as the feature that reflects changes in PM status. These features were used to train the BNN to detect demagnetization of the rotor magnet during motor operation over a wide speed range.

The limitations resulting from the selection of the network structure are partially ignored in the case of using neural networks with radial basis functions (RBFs) [121]. The architecture of the RBF is analogous to the multilayer perceptron, with the difference that only one hidden layer is assumed. The simplicity of the RBF training process compared to MLP and SOM is based on a predefined single hidden layer, as well as the need to select only the centres and shape parameters of the base functions used.

A separate group of neural structures used in diagnostic applications are recursive NNs. Contrary to the MLP, SOM, and RBF structures discussed, recursive networks are characterized by the existence of feedback between neurons. In addition, feedback affects the dynamics of the network, in which a change in the state of one of the neurons affects the operation of the entire network. The main representative of recursive structures in the field of technical diagnostics is the Elman network [225] which is characterized by partial recursion (one-step delays).

SNNs that are part of the PMSM neural fault detectors are currently implemented only in conjunction with methods of analysing diagnostic signals. Despite the examples presented, a small number of papers describing shallow structures are noticeable in the diagnosis of mechanical damage, as well as mixed damage. The fact that there is no description of applications for mixed failures may result from difficulties in separating the symptoms of electrical and mechanical failures. In summary, the applications of shallow neural structures in PMSM fault detection are still an unrecognized branch of diagnostic research that needs further development.

C. DEEP NEURAL NETWORKS APPLICATION IN PMSM DRIVES

The development of diagnostic systems in recent years is related to the concept of DNNs. The DNN structures require greater computing power and are characterized by automatic extraction of the input vector features. On the other hand, the development of neural structures that automatically extract the features of the input information, as well as the relationships between them, sheds new light on the design of diagnostic systems. The possibility of eliminating the preprocessing stage, which is a limitation of shallow structures, is a key argument determining the popularity of DNN in diagnostics.

The main representatives of DNNs used in diagnostic processes are CNN [219], [220], [222], [229], [230], [233], [237] and LSTM structures [223], [228]. The CNN structure allows higher-order features to be extracted from the input information using a mathematical convolution operation. LSTM constitute the development of the idea of recursive neural structures to DL techniques. Due to the much larger number of LSTM parameters (compared to CNN) and the more difficult training process, they are used mainly in the analysis of time sequences [223], [228]. The main applications of CNN, on the other hand, result from the high efficiency of feature extraction when the input data have a specific structure (matrices) or repeating sequences. The possibility of direct extraction of the input signal characteristics in the diagnostics of PMSM stator winding failures has been described in [220], [222], [223], [229], [237]. Nevertheless, the analysis of the literature shows that deep neural structures can also be based on preprocessed information [219], [228], [230], [233]. However, direct analysis provides a significant reduction in the reaction time of the diagnostic system to the resulting damage, which is its unquestionable advantage. In addition, it is characterized by the high precision of detection and assessment of the degree of damage, both in the case of single PMSM defects [220], [229], [237] and mixed defects [222].

DNNs transfer the task of extracting the symptoms of damage performed so far with the use of analytical methods to the structure of the NN. Due to this, the limitations resulting from analytical methods of signal processing are eliminated. The applications of direct analysis of measured signals shown in the literature ensure the achievement of precision of diagnostic systems that are not achievable for shallow structures, with a signal acquisition time several dozen times shorter.

However, DL methods in diagnostics are mainly used for the problem of detecting faults in IMs. In addition, there is little information in the literature on the impact of structure, learning methods, and network type on the effectiveness of DNN-based systems.

The accuracy of the fault classification obtained with the use of selected SNN and DNN structures based on the literature overview is presented in Table 9.

TABLE 9. Fault classification accuracy of the artificial intelligence-based diagnostic systems–literature analysis.

Nr	Fault category						NN structure	Fault classification accuracy	Diagnostic signal
	1	2	3	4	5	6			
[120]			+				SOM	93,00%	Vibrations
[121]			+				MLP	99,02%	Vibrations
			+				RBF	94,41%	Vibrations
			+				SOM	91,48%	Vibrations
[214]	+						SOM	93,30%	I_{sABC}
[215]	+						MLP	99,37%	I_{sABC}
[216]	+			+			MLP	98,50% (FFT)	$I_{sABC} + T_e$
	+			+			MLP	96,10% (STAT)	$I_{sABC} + T_e$
[219]			+				CNN	98,80%	I_{sABC}
[220]	+						CNN	88,92%	I_{sABC}
	+						CNN	94,76%	U_{sABC}
	+						CNN	99,38%	*Flux*
[229]	+						CNN	97,75%	I_{sABC}
[230]	+	+					CNN	99,28%	I_{sABC}
[231]			+		+		MLP	88,37%	I_{sABC}
[232]	+	+					PNN	91,70%	I_{sABC}
[233]		+	+				CNN	98,85%	I_{sABC}
[234]	+						MLP	96,00%	I_{sABC}
[235]	+						MLP	93,10%	I_{sABC}
Fault categories: **1** – ITSCs-, **2** – demagnetization, **3** – bearing fault, **4** - unbalance supply, **5** – eccentricity of rotor, **6** – stator phase loss.									

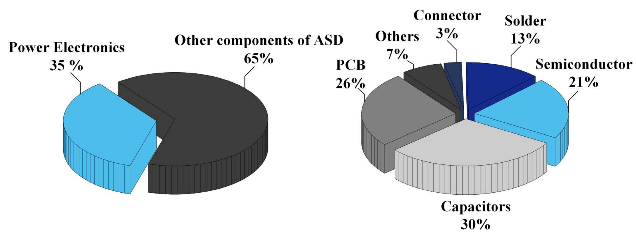

FIGURE 6. Distribution of faults in adjustable speed drives and in power converters.

IX. FAULT DETECTION OF PMSM DRIVE COMPONENTS AND FAULT-TOLERANT CONTROL

A. FREQUENCY CONVERTER FAULTS

Frequency converters are the closest link between digital control and power output in ASDs, including the PMSM drive. However, it is also the weak link where different faults occur frequently [19], [22], [23]. The failure modes of ASD have been studied in various surveys. According to [238], [239], damage to power semiconductor devices accounts for approximately 35% of all ASD failures. There are many types of faults in power converters, such as a power semiconductor device (21%), solder (13%), DC link capacitors (30%), printed circuit boards (PCB) (26%), sensors, etc. [240]. Thus, power device module failures comprise 35% of power converter faults, as shown in Fig. 6.

All of these failures result in deterioration of the drive performance or even an unplanned stoppage of the drive system.

About 30% of FC failures are related to abnormal operation of intermediate filter capacitors. As a result of aging, their capacity decreases and internal impedance increases [240]. As a consequence, they fail permanently, consisting of a short-circuit or inability to conduct current, i.e. a break. This is one of the reasons why systems consisting of many capacitors connected in series-parallel order are used. This protects the converter against the development of a failure to other elements in the event of a short-circuit of one of the capacitors and prevents the full loss of filter functionality when the failure is a break type.

In many FCs, electrolytic capacitors are mainly used in DC-links as a result of their low cost. However, the main disadvantage of electrolytic capacitors is their limited lifetime and high failure rate due to degradation of wear. The capacitor banks lose their initial operating characteristics because of aging effects, such as electrolytic reaction and the effects of temperature, frequency, and humidity. The increase in ESR is usually more significant than the decrease in capacitance. The lifetime of the capacitor is considered to be reached when the ESR of the capacitor increases more than twice the initial value [240]. Therefore, changes in the ESR value can be considered a key parameter to diagnose electrolytic capacitor failure. Methods of DC-link electrolytic capacitor fault detection based on ESR estimation are presented in [241]. They are online methods, realized using AC current injection in the q-axis of the AC/DC converter control system, indirect measurement of DC-link capacitor currents, direct measurement of the DC-link and capacitor voltage, or ESR calculation using the recursive least squares method. Off-line methods are also applied, as this is based on a capacitor model [242] or hardware-based ESR measurement [240].

The second most important types of the FC malfunctions are transistor failures in the inverter or rectifier, i.e. their open- breaks or short-circuits. They account for 12% of all electrical drive failures [240]. Transistors' abnormalities result mainly from aging changes, the speed of which may increase significantly with the increase of the intensity of the drive operation, i.e., its frequent overloads [19], [243], [244].

A review of the fault diagnosis and protection methods of inverter switches (IGBT, MOSFET, SiC MOSFET, and GaN FETs) considered as individual components is presented in [19], [245]. Whereas, in this paper, the focus is on the diagnosis of such faults at the drive system level.

In general, power semiconductor switch failures can be classified as short-circuit faults and open-circuit faults. When a short-circuit occurs, the inverter switch closes and remains on regardless of the gate control signal. A short-circuit of two transistor switches of an inverter leg causes the flow of a very large and destructive current on the following path: power supply – upper switch – lower switch – power supply. The consequences of such damage can be catastrophic. They can cause the drive system to stop or a short-circuit becomes an open-circuit fault, or even an open-phase failure due to damaged transistors or activation of the protection circuits. The effects of such damage are most severe for two-level inverters, which are used most frequently in drive systems with three-phase AC motors.

Shorted switch faults occur rapidly and need to be detected immediately, so hardware protection circuits are typically used in many modern PMSM drives [245]. Protection circuits are widely discussed and summarized in [246]. Moreover, a novel gate charge detection circuit for short-circuit fault detection of SiC MOSFETs is proposed in [247]. These circuits bypass the effect of such a fault in a very short time, without additional computational delay. Another way to deal with short-circuit faults in transistors is the application of fast fuses [248].

The development of software-based algorithms for the diagnosis of shorted switches has not been the main topic of academic research in the last few decades. In [249], PVA of the motor supply current is proposed for the diagnosis of short-circuit and open switch faults of VSI in variable speed AC drives. The authors confirmed that the switch short-circuit faults can be effectively diagnosed by monitoring the behavior of the average motor supply current Park's vector modulus. In [250], this method is successfully extended by the fuzzy logic approach to automate the fault diagnosis process of switches. The lack of papers in this field is due to the fact that, as already mentioned, such failures frequently become switch open-circuit faults, and this is where many researchers focus their attention.

The open-switch fault may result in current distortion, abnormal load operation, overheating, and decreased efficiency, resulting in a large torque ripple or even braking torque [22], [251]. Unlike the shorted switch failure, without the appropriate detection algorithm, the open-switch fault can remain undetected and can lead to secondary faults in other components of the drive system. Furthermore, this type of failure results in a degradation of drive performance, which can lead to disastrous accidents in applications that require increased robustness, such as electric vehicles [252]. Therefore, due to the hazardous effects of this type of damage, many methods of detection have been developed in recent decades [253].

Because open circuit fault causes incorrect output voltage, increase in current harmonics and torque pulsations, its diagnosis is of research interest so that the PM machine can operate safely in critical systems application [254].

The literature review shows that open-circuit FDD methods can be classified as current signatures [254]–[260], [267]–[272] and voltage signature-based methods [261]–[264], [273]. These methods can also be classified as model-free [184], [254]–[257], [261]–[263], [267]–[273] and model-based methods [252], [258]–[260], [264], [265].

In [254], a diagnostic algorithm was proposed that enables real-time detection and localization of multiple open-circuit faults of power switches in PMSM drives powered by VSI. The method is based on the difference between the measured phase currents and the corresponding reference signals, normalized using the absolute mean values of the motor phase currents.

The open-circuit fault detection in a FOC structure of a PMSM drive based on the signatures of the d-q current components along with the faulty phase localization is presented in [184]. The authors highlighted the simplicity of the proposed approach. In [255] and [256] a robust open-switch fault diagnostics technique is presented that combines the use of the normalized average value of the PMSM currents and three variables δ_{sj} ($j = a, b, c$), which correspond to the normalized average values of the product of two currents. In [257], an open-circuit fault diagnostic method based on symmetrical and DC components is discussed. The remaining phase currents under faulty conditions are theoretically analyzed on the basis of the FFT method and the torque generation mechanism. To assess the asymmetry and distinguish the type of fault, FI was proposed as the ratio of the magnitudes of the positive and negative sequence components of the phase currents.

The model-based diagnostic method for single and multiple open-switch failures in three-phase PMSM drives that utilize real-time estimation of motor currents using three Kalman filters is presented in [252]. The authors proposed an averaged normalized residual analysis of the measured and estimated currents as diagnostic criteria for the detection of this type of failure for both closed-loop and open-loop PMSM drives. In [258], the cross-correlation between estimated and measured phase currents is applied to evaluate the similarity that is used as a FI of the VSI for five-phase PMSM. In this investigation, the current is estimated using a SMO. The same approach, but improved with the adaptive fault detection threshold determination algorithm, is used in [259]. The open-switch fault detection and localization algorithm with model predictive control (MPC), based on the cost function, is proposed in [260]. To calculate the cost function, the stator currents in the d-q frame are utilized. Subsequently, the polarities of the normalized α -β frame current average values and the phase angles of the residual current vectors are used to locate the defective switch.

In [261] the model-free voltage method was proposed, which uses a direct comparison of the measured voltages with the appropriate reference values. The implementation of the voltage method using the differences between the measured and estimated voltage values, implemented in FPGA, is discussed in [262]. The authors proved that detection times shorter than 10 μs can be achieved.

Another model-free diagnosis method for the detection of open-switch faults of inverter-fed PMSM drives was introduced in [263]. It uses the residual as the sectoral average of the difference between the reference voltage and the measured pole voltage. This residual is directly compared with a threshold which is determined by analyzing measured voltage deviations from the reference voltage in the normal state. In [73] harmonic tracking of the ZSVC spectrum is introduced to detect open-phase faults in the PMSM drive system. This method enables not only to detect the fault, but also to distinguish the fault type: ITSC of the stator winding or inverter switch failure.

The model-based approach for the diagnosis of open-circuit faults in VSI with SVM supplying the DTC-based PMSM is presented in [264]. It involves the use of a flux observer based on the machine current model, which allows to estimate the voltage at the motor terminals. The proposed method utilizes the average values of the errors between the reference and estimated voltages. Different types of observers were also used for open-switch detection [265] for PMSM drives. These methods make a good diagnosis with a relatively short detection time. As they are based on residual generation between the observer model and motor signals, they are sensitive to variations in motor parameters. For these methods, the threshold selector remains the key issue in ensuring an effective and robust diagnosis.

Recently, active rectifiers are applied in FC to enable the regenerating operation mode of PMSM drives [255]. The open switch faults of these AC/DC converters are also diagnosed with current- and voltage-based methods, similar to those used in the inverters.

Current-based methods use current signals that can be measured directly or calculated using mathematical models. Some of them utilize solutions based on current hodograph analysis [266], [267] or algorithms consisting of calculating the DC component in phase currents [268]. Other solutions are based on the observation of the rotation of the current vector and average values of the phase currents. Transistor failure causes a lack of current flow in one of the receiver phases. In this situation, the current vector stops its rotation in a characteristic part of the $\alpha-\beta$ coordinate system, which can be easily detected when the position of the current vector does not change. When a single transistor fails, the mean values of the phase currents deviate from zero as the current does not flow half the period of the grid voltage. This observation provides sufficient information to detect faulty transistors in power converters [269], [270]. The main disadvantage of these methods is their sensitivity to changes in load.

Although in most cases the average values of measured currents are used as diagnostic variables, work [271] and [272] have shown that an effective diagnostic indicator may be the Euclidean distance between the estimated and measured diagnostic signals or the use of statistical analysis, e.g. correlation.

It should be noted that in most presented papers, the methods proposed for open-switch faults in active rectifiers are not validated under both rectifying and regenerating modes. It was shown in [273] that the open-circuit faults diagnostic technique of transistors based on the prediction of grid currents in the voltage-oriented controlled three-phase two-level rectifier can be used as well in rectifying as in regenerating modes. The proposed technique allows single- and multiple-transistor fault detection in a time shorter than one current fundamental period.

In the case of multilevel rectifiers, mainly voltage methods of transistor fault diagnostics are used, based on the voltage signals of DC-link capacitors. Failures of rectifier transistors lead to voltage asymmetry in capacitors, enabling simple detection of a damaged transistor based on additional information on phase polarization or switching state configuration defined by duty cycle factors [270].

The voltage-based method was also applied in [274] for open switch fault diagnosis in a voltage-oriented controlled AC/DC line side converter. Fault detection is based on the calculated rectifier phase voltage errors, compared with the assumed threshold, the value of which may be constant, independent of the line choke inductivity. On the other hand, for the location of a damaged transistor, the mean values of the rectifier voltage errors as well as information about their values and signs are used. The proposed method can be used in both AC/DC converter operation modes, rectifying, and regenerating. The method is characterized by a short diagnosis time and full effectiveness.

In the case of algorithms based on software solutions, it can be concluded that the fastest of them allow the identification of an inverter failure in less than one period of the fundamental harmonic of the stator current.

The average value of the diagnosis time largely depends on the definition of diagnostic thresholds, which are most often determined during failure-free operation of drives in such a way that their assumed value is not reached during various states of proper operation of the drive system. The adopted value of the diagnostic thresholds should constitute a compromise between the speed of diagnosis and the minimization of the risk of false alarms during the correct operation of the drives. Current-based methods are commonly used because their effectiveness does not depend on system parameters and does not require additional sensors. In contrast, voltage-based methods, despite the advantages such as fast fault detection and inherently higher false alarm immunity, are often excluded because they require additional equipment, sometimes with high requirements (voltage sensors and analog-to-digital converters), which increases the cost and complexity of the system.

The methods discussed in this section are listed in Table 10, together with the main information regarding each reference.

B. SENSOR FAULTS

The currents of the stator windings, the DC-link voltage of the frequency converter, and the rotor position are usually measured in a PMSM drive. Sensor failures may consist of a decrease in gain, an offset, intermittent sensor operation, or its complete outage. The last two failures are the most serious from the point of view of the drive because they cause a temporary or complete lack of information for the control system. Consequently, real-time sensor fault detection is essential.

Speed or position sensors and stator current sensors are crucial components of the PMSM drive system that transmit information from the motor to the control system. These sensors are prone to failures due to overcurrent, improper handling, or harmful environment. Therefore, it is necessary to monitor its proper operation and in the event that it fails to detect, isolate, and compensate for damage. Since hardware redundancy is expensive or sometimes impossible to implement, software redundancy is a good solution, which involves the use of various types of state variable estimators and replacing the signals from the damaged sensors with estimated ones [33], [274].

Signal analysis methods and model-based methods can be used to detect sensor failures [22]–[24]. Signal-based methods consist of extracting information on damage contained in the measured signal and evaluating the damage according to the characteristic fault symptom or comparing it with the behavior of an undamaged system. However, model-based methods, which require the mathematical models of the tested system, are more frequently used for sensor fault detection in AC motor drives, including PMSM drives. Model-based methods, using various types of state variable estimators, are applied to generate residuals by comparing the signals measured with sensors and estimated on an ongoing basis. These residuals are then compared with threshold values to obtain fault diagnostics. The main problem with model-based techniques is their robustness to changes in changes in system parameters and the choice of thresholds for particular failure types in a given system [275].

Failure of the DC-link voltage sensor can be easily identified, since the measured value of this voltage is much higher than zero under normal operating conditions. Thus, a sudden significant change in the measured value indicates a voltage sensor failure [276]. When the fault sensor is isolated, the actual DC link voltage signal is replaced with

TABLE 10. Detection methods for VSI and AC/DC converters in PMSM drives.

Ref.	Switch fault type	Switch Type	Diagnostic signal	Method
VSI				
[247]	Short-circuit fault	SiC MOSFET	---	Hardware protection circuits
[248]		IGBT		
[249]		IGBT	Stator phase current	PVA
[250]		IGBT		PVA + fuzzy logic
[184]	Open-circuit fault	MOSFET	Stator phase current	FI based on i_d,i_q currents
[249]		IGBT		PVA
[252]		IGBT		Residual analysis
[254]		IGBT		Normalized residual analysis
[255], [256]		IGBT		FI based on stator phase currents average
[258]		IGBT		Correlation of current residuum
[259]		IGBT		Residual analysis
[260]		IGBT		Cost function and residual analysis
[265]		IGBT		Residual analysis
[257]		IGBT	Negative and positive stator current sequence component	FFT
[261]		IGBT	Stator phase voltage	Residual analysis
[262]		IGBT	Pole voltage	Residual analysis
[263]		MOSFET	Pole voltage	Average residual analysis
[264]		IGBT	Stator phase voltage	Average residual analysis
[73]		IGBT	ZSVC	FFT
AC/DC converter				
[266]	Open-circuit fault	IGBT	Stator phase current	Modified Park's Vector Method
[267]				Normalized DC current method
[268]				Average values of current signals
[269]				Residual analysis
[270]				Topology symmetry analysis based on signal statistical parameters
[271]				Current kernel density estimation
[272]			Grid currents	Grid currents prediction
[273]			Rectifier phase voltage	Rectifier voltage error calculation
DC-link capacitor				
Ref.	**Diagnostic symptom**		**Method**	
[240], [241]	ESR calculation online		AC current injection (in q axis) Indirect DC link capacitor current estimation Direct measurement of DC link and capacitor voltage ESR estimation with RLS method	
[242], [240]	ESR calculation offline		Capacitor model Hardware measurement	

its estimated value. In [276] the simple method based on the calculated power balance was used. If the power balance exceeds a certain threshold, then the measured DC-link voltage is replaced by its nominal value. Such a correction is unacceptable in an application where the DC-bus voltage fluctuates, like e.g. in electric vehicles. Moreover, the proposed algorithm is difficult at low speed and in light-load condition because the power itself is too low. In work [277] an adaptive online observer is proposed for the simultaneous estimation of unknown DC link voltage, rotor fluxes, and rotor resistance, to make the observer more robust to parameter uncertainty. But this solution was designed only for induction motor drive systems. However, this methodology can also be adopted to the PMSM drive. A more interesting solution, which consists of a special kind of adaptive observer of the DC link voltage, is presented in [278]. This observer was reported to be robust to the stator winding parameters and performs well under different operating conditions.

Different types of PMSM speed/position estimators, which were previously designed for sensorless drives, can be used for speed sensor fault detection in sensor-based drives. Classical speed/position observers based on stator flux estimation, including the extended observer [279] or the sliding mode observer (SMO) [280], can be used for speed residuum generation. The other solution, based on the concept of a model reference adaptive system (MRAS), is proposed in [281]. The speed and position are determined at the output of the tuning mechanism of the adaptive model, which is the stator flux observer. The PMSM itself serves as the reference model. On the basis of the comparison of the motor current output and the tunable model, the stator current estimation error is calculated and processed by the adaptation algorithm. It should be mentioned that an additional estimate of stator resistance is required in these observers to ensure the proper accuracy of the position and velocity of the PMSM [276]. Also, Kalman filter-based speed/position estimator can be used; however, it is rather a time consuming algorithm. Nevertheless, the solution proposed in [282] can be a good candidate for speed sensor fault detection and compensation. In this paper, the authors proposed an EKF for the estimation of the position and rotor velocity of a PMSM. Speed and position were used as additional components of the extended state vector, and the original two-stage estimation algorithm was presented. This enabled to reduce the number of arithmetic operations, and thus obtain a higher sampling frequency and use a cheaper microcontroller.

More recently, some schemes based on SMOs have been proposed to estimate the speed of a PMSM [283]–[285]. In [283] the SMO was developed with the sign-type switching function replaced by a sigmoid function with some boundary layer, to avoid the time delay that occurs due to a low-pass filter usually used at the observer output. The rotor position and the angular speed of the motor are estimated from the BEMF. Some drawback of this solution is that the boundary layer and SMO gains selection are dependent on the motor speed. Furthermore, a modified SMO was presented in [284] to calculate the speed of the BEMF signal, which is estimated with a conventional SMO. The two-stage process of position and velocity estimation enables the elimination of the low-pass filter and the phase compensation module, and also improves the accuracy of the estimation.

Recently, higher-order sliding mode observers (HO-SMO) have been proposed for PMSM drives as well. In [285] HO-SMO is designed to estimate the unknown BEMF of PMSM. Fast and chattering-free estimation was obtained without low-pass filtering using this approach. On the basis of the estimated BEMF, an accurate speed estimate of PMSM was algebraically computed.

Signal-based methods are not used as often for the detection of current sensor (CS) faults in PMSM drives as the model-based method. However, attention should be paid to the method based on the locus of the current error vector, presented in [286]. However, the limitation of this method is that it can only be used for hysteresis current control and not for FOC with PI regulators, which is currently widely used. In [287], the FDD method with additional current sensors (five in total) is applied. This approach allows fault isolation to be performed on the whole speed range, including zero speed, and is inherently insensitive to the uncertainties of the drive parameter uncertainties; however, it requires significant redundancy of the sensors. The method proposed in [288] (for the PMSG) and in [289] (for the PMSM) uses average normalized current values, but is limited to failure of one of the three CSs present in the drive system.

On the contrary, in [290] a signal-based method was proposed for different types of CS faults, namely, for single or double signal loss faults (concurrent or independent), gain variation, and zero offset. In the proposed method, information about three-phase currents and the position of the rotor is required. The variation of the estimated stator current amplitude of the PMSM is used for fault detection. The authors of [292] present a method for CS fault detection based on so-called C_{ri} markers, which allows one to determine the components of the stator current differently, depending on which CS is actually faulted. The assumption was made that two of three CSs are used for the stator current reconstruction under a single sensor fault. In [292], DWT is applied to detect different types of CS faults in a PMSM drive. However, the robustness of the proposed algorithm was not discussed.

There are also works in which both damages: to the stator CSs and to VSI switches are analyzed. Based on previous work [288] and [289], the authors proposed an effective and robust diagnosis of CS faults and IGBT single and multiple open circuit faults of the inverter, where the same algorithm is used to detect, locate and discriminate both types of faults [255]. It is suitable for other than FOC strategies, such as MPC or V/f scalar control.

Regarding the use of model-based techniques for CS fault diagnosis in PMSM drives, different algorithms have been considered. In [296] simple tests were used to detect the CS failure and the state observer of the d-q components of the stator current vector was proposed for the estimation of the missing current. In [293] a model reference adaptive observer was proposed to estimate the phase current of PMSM using the information of position, speed and stator voltage in $\alpha - \beta$ frame. The authors of [294] and [295] suggested the use of SMO to diagnose CS faults in the PMSM drive. In [296] an encoderless control scheme is proposed using SMO with only one current sensor for fault diagnosis and the FTC of PMSM drives. Reconstruction of the faulted phase current is completed through SMO by using the current space vector error projection as the correction term. Then, the equivalent circuit of extended BEMF estimation is established. The authors of [297] introduced a current sensorless PMSM control structure, using only a single Luenberger observer based on the measured DC-link voltage and rotor speed for stator current reconstruction. The proposed method is based on a modification of the adaptive state observer to estimate line currents; however, only simulation results are presented. The concept is similar to those applied in the case of CS faults in the IM drive [298], [299]. Also, an EKF was proposed for CS fault detection in [300], however, the authors pointed out its sensitivity to variation of motor parameters.

The gain fault of CS was addressed in [301]. Sensor failure was treated as an additional variable that extended the observer state vector. The CS gain failure detection is based on the calculation of residuals between the PMSM model and a bank of three adaptive observers. Then a logical algorithm was proposed to identify the phase in which the damage occurred and to isolate the faulty sensor.

In [302] another FDD method for CSs is introduced using the parity space approach; however, the design procedure is mathematically complicated.

In recent years, methods that do not require exact knowledge of motor parameters have also been proposed. For example, the method based on d-q axis currents estimated from reference currents and healthy measured phase current is presented in [303]. However, in steady-state operation, especially at high speed, the estimated current errors are half the actual ones in steady-state postfault operation. Therefore, the response of the current command will be slowed. However, control targets can be achieved, as the direction of the current change is not affected. Another strategy for CS fault detection based on the residuum between the measured and estimated DC link current is presented in [304]. The damaged CS is isolated on the basis of the analysis of this residuum and the differences between the measured and estimated phase currents. Single and multiple sensor faults and current sensorless operation are covered by the proposed FDD method, as shown by simulation tests. However, an additional CS is required in the DC link of the frequency converter.

Some of the above presented methods for rotor position/speed and stator current sensors can be also directly used in postfault operation of the PMSM drive in FTC structures.

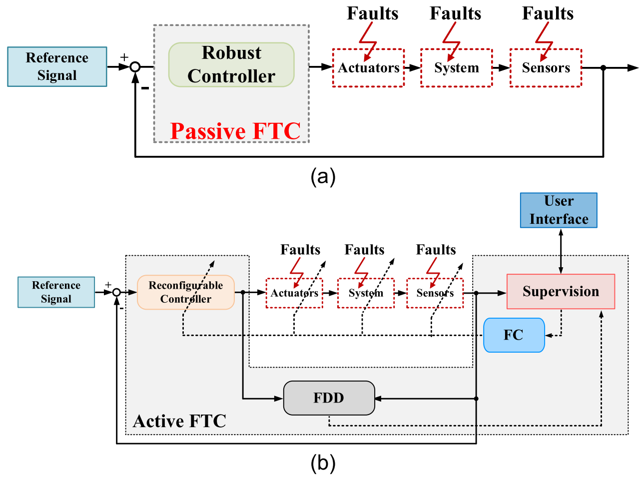

FIGURE 7. Passive (a) and active (b) FTC systems; FDD—fault diagnosis and detection, FC—fault compensation.

C. FAULT-TOLERNAT CONTROL

From the mid-2000s, as a result of intensively developing FDD methods for AC motor drives, the first FTC strategies for drive systems began to appear [33]. It also concerns PMSM drives, and examples of such control concepts can be found in [22], [23]. The goal of the FTC is to ensure the continued functionality, performance and, above all, stability of the system, even after a fault occurs, until it can be safely stopped for maintenance or repair.

In line with Isermann's groundbreaking work in this field [305], two types of FTC systems can be distinguished: passive and active. The general schemes of both control concepts are presented in Fig. 7.

The PFTC is based on robust controller design techniques that make the closed-loop system insensitive to different faults. The process continues operation under faulty conditions with the same structure and controller parameters (Fig. 7a). This approach does not require online FDD and is therefore computationally more attractive. The controller design for PFTC is based on advanced control techniques, such as adaptive theory, predictive control, and AI methods. However, the use of PFTC is limited in AC drives for the following reasons [33], [306]:

- when designing a PFTC system, only selected system failures can be taken into account, usually those that do not have a significant impact on the system operation, because only under such conditions the controller can be resistant to a failure;
- an increased robustness to selected faults can be achieved at the expense of reduced system ratings. Due to the fact that most failures do not occur very often, it is difficult to justify a significant reduction in system failure-free performance just to achieve some insensitivity to a limited failure class.

Unlike passive methods, AFTC is based on the controller reconfiguration or by using several switchable regulators. In this approach, fault compensation (FC) methods are also used. Therefore, this technique requires a system that realizes the task of detecting and localizing faults if they occur in the system. The structure of the AFTC system with a FDD unit is presented in Fig. 7b.

As PMSMs are often used in high-performance systems and safety-critical applications, AFTC solutions are paramount as they maintain a certain safe level of drive operation after detecting and locating faults (post-fault operation). The FDD system can also cooperate with the supervision system that can take an appropriate action to reconfigure the set of sensor and/or actuators to isolate the faults or tune the controller to minimize the impact of the fault (dashed lines in Fig. 7b). AFTC systems are based on hardware and/or software redundancy. In this last case they use dedicated fault detectors or special state or parameter observers that are applied not only for specific fault detection but also for their compensation. Some solutions applied to PMSM drives will be described below.

AFTC of voltage inverters mainly uses hardware-based solutions. There are several techniques for detection) and failure mitigation of semiconductor devices of VSI used in ASDs (presented in Section IX*A*). A detailed overview of fault-tolerant inverter topologies is presented in [307], [308]. Fault tolerance is typically achieved by introducing redundancy in the VSI components or additional complexity to the structure. The three most popular techniques are as follows:

1 – connecting the damaged phase to the midpoint of the DC-link using TRIACs;

2 – isolating the damaged phase and connecting the neutral line of the motor to the midpoint of the DC-link;

3 – introduction of an additional branch that is connected to the motor neutral line.

In all of these cases, the semiconductor devices are oversized, as are the DC link capacitors, and the output power of the inverter is limited during fault mode. The first and second approaches require access to the midpoint of the DC link, whereas the third approach handles open-phase-circuit only, and a fourth wire is needed, which increases the cost of the drive. Recently, phase redundancy approaches [239], [309] have gained popularity due to their ability to recover fully without oversizing the drive. A detailed comparison of the advantages and disadvantages of different fault-tolerant VSI topologies is presented in [307] and [308], including more cascaded multilevel converters or modular multilevel converters. However, it has been shown in [310], that also much less complicated solutions are possible due to proper modification of the modulation technique of the classical T-type three-level inverter under open circuit fault. The modulation strategies presented there can provide an FTC strategy for continuous operation with sinusoidal currents at no additional cost.

Due to the safety-critical applications of PMSM machines, high-fault tolerance design solutions are sought. The concept of a **PMfault-tolerant machine (PMFT)** is that it should satisfactorily maintain continuous operation after a fault has occurred. This concept appeared in the mid-1990s [311] and since then intensive research has been carried out on such design aspects of PMFT machines, such as:

- electrical insulation between phases,
- magnetic isolation between phases,
- unconditional limitation of short-circuit current,
- physical phase separation,
- effective thermal insulation between the phases,
- number of phases.

In [312] a detailed review and summary of the design concepts of the PMFT machine are presented, with an emphasis on limiting the short-circuit current. The latest results of research work in this area are presented in [313], with particular consideration of the design and analysis of machine topology, including modular design, short-circuit current limiting design, redundant design, ease of heat dissipation in PM and design techniques to increase torque. Based on the analysis of 143 references from more than 20 last years, it was concluded, among others, that the reduction or even closure of the slot opening is the best design solution leading to the reduction of the short-circuit current. In addition to modular design, multiphase technology has also been found to provide fault tolerance through redundancy. A new class of stator-PM machines has also been introduced, which not only provides fault tolerance but also improves PM heat dissipation, ensuring high power/torque density.

However, from the FTC point of view, the most commonly used motor structure includes multiphase and modular structures [314]. Although the multiphase motor can perform fault-tolerant operation, its control system and strategies are, in most cases, complicated. Different control strategies were used, including simple reconfiguration of the controller input and output [315], sliding mode controller (SMC) [316], or MPC [317]–[319]. All these solutions were proposed for the open-phase fault of multiphase motors and focused on minimization of torque ripples and the principle of unchanged magnetomotive force before and after the fault. On the other hand, the modular motor is designed to have several three-phase modules, each controlled by an independent three-phase inverter [320]. When a module fails (open-phase or short-circuit fault), it will be removed from the system without affecting the health modules that operate normally. But these solutions based on PMFT machines are costly.

In recent years, research on fault-tolerant strategies for PMSM stator winding failures appeared, as well for open-circuit faults – OC-FTC, as for ITSC faults – ITSC-FTC.

OC-FTC methods have been addressed in the literature, for example, in [321]–[323]. In [321] the reference frame transformation-based method is proposed for PMSM under open-circuit fault, allowing suitable torque control under healthy and faulted conditions, without modification of the control topology. The authors in [322] propose the open-circuit fault-tolerant algorithm based on FOC with a current prediction method together with an estimation of the threshold level for fault detection. These solutions show significant robustness against variation in motor parameters or load fluctuations and negligible implementation costs, since no hardware modifications are needed. In [323] an FTC strategy based on a finite control set MPC was proposed for a three-phase four-wire converter topology of the PMSM drive that connects the neutral point of the motor to the center of the DC link capacitor. The main advantage of this solution is that there is no need to modify the converter topology after the fault detection, and thus the transition from healthy to faulty state is smooth.

So far, **ITSC-FTC** strategies are relatively rare [324]–[327]. In [324] the dual current controller is used for separate control of the positive and negative sequence components of the stator current. The torque ripples are effectively minimized using a negative current component. The authors of [325] proposed a modification of the classical FOC structure with hysteresis controllers by injecting an unbalanced current component, which occurs in the PMSM under ITSC fault. It enabled the reduction of torque ripples. In [326] the ITSC fault-tolerant method is proposed, which consists in limiting internal motor copper losses. The control strategies presented in [324]–[326] mainly concern the reduction of electromagnetic torque ripple or copper losses, but they do not limit the value of short-circuit current, which is dangerous for the machine. Very few articles have been published on short-circuit fault current mitigation methods. In order to limit the ITSC current, a strategy based on the current injection technique was proposed for a triple redundant 3 × 3-phase PM synchronous reluctance machine [327]. However, this method cannot be directly adopted to three-phase PMSM. In [328] the three-phase current injection strategy was used to mitigate ITSC fault in PMSG with fractional-slot concentrated-winding. The proposed method enables one to limit the fault current to an acceptable level. The ITSC-FTC strategy dedicated to applications where it is desired to operate the PMSM drive after an ITSC fault, even if it means operation at lower power and lower speeds, was proposed in [329]. This method consists in a field-weakening strategy at speeds below nominal, to reduce the voltage induced in the faulted part of the winding. The proposed technique can be used to slow down the spread of damage and extend the service life of the machine after a failure. All of these methods were verified in simulations and experimental tests.

As was mentioned in Section IX*B*, the main sensors used in PMSM drive are: DC link voltage, stator current, and rotor speed/position sensors. In the case of DC link voltage sensor fault, the FTC strategy is usually based on the adaptive voltage observer [277], [278].

Speed sensor fault-tolerant control (SS-FTC) is nowadays based on relatively matured speed sensorless technology for PMSM drives. Presently existing sensorless methods are based mainly on the fundamental wave model; however, the method of an initial rotor position determination is needed for motor start-up. There are a lot of proposals for IPMSM and SMPMSM. Generally, these methods are based on the injection of voltage pulse signals, for example, [330], [331] and the injection of HF signals, for example, [332].

In SS-FTC solutions for drives with very high requirements as to the accuracy of operation or with an increased degree of safety, despite the use of a position/speed sensor, software redundancy is applied. In such arrangements as presented in Section IXB, the speed/position estimator is used to monitor and detect the speed sensor failure, and in the event of its failure, the system in the FTC mode immediately switches to the speed sensorless mode. Thus, all the solutions presented in Section IX*B* can be used in SS-FTC systems not only for speed sensor fault detection but also for fault compensation. These could be: extended observer [279], SMO [280], [283], [284] or super-twisting sliding mode observer (ST-SMO) [285], MRAS estimator [281], KF [282] or adaptive EKF [333]. Furthermore, speed estimation methods with higher accuracy in the range of low speeds, which combine classical observers with HF injection methods [334], [335], can be used in FTC strategies. Some authors propose the use of double software redundancy, as in [336]. In this work, in order to increase the reliability of the drive system in such critical applications as electric or hybrid vehicles or aircraft actuators, it is proposed to use two estimators of PMSM speed: a two-stage extended Kalman filter and BEMF adaptive observer which cooperate with a maximum likelihood voting algorithm and thus constitute a FTC strategy.

Only some of the position/speed estimators of the PMSM drive used in FTC systems are presented above. Of course, in the literature there are many articles discussing various modifications of the basic ideas of these estimators/observers, and practically all of them can be used in the speed sensorless systems as compensators for a damaged position/speed sensor.

The issue of **current sensor fault-tolerant control (CS-FTC)** is a bit different. Researchers have only recently begun to be interested in the possibilities of compensating damage to stator current sensors in PMSM drives. Chapter IX*B*, in a part concerning CS fault detection, presents, among others, the possibilities of using model-based stator current estimators in CS-FDD systems [317]–[322]. These current estimators are based on MRAS observer, LO, SMO or EKF, respectively, and for stator current reconstruction we need information on measured DC link voltage, as well as measured rotor speed. In most of the presented approaches, the stator current can be reconstructed with these models when minimum one CS is healthy. Only in work [321] the authors claim that all stator currents can be estimated using a single LO and a current sensorless drive system can be designed, but no experimental verification is given. It results from the paper analysis that, in the event of both CSs failure, the open-loop observer is applied (equivalent to the basic mathematical model of PMSM), which is sensitive to motor parameter changes.

In recent years, there have also been proposals for FTC strategies in case of failure of various sensors in the PMSM drive. The work [278] presents the FTC system taking into account speed, DC link voltage, and CS faults. Except for the adaptive observer for the DC link voltage (mentioned in Section IX*B*), the authors proposed a speed observer augmented with the HF signal injection method at low speeds and a LO to estimate the phase currents when a single-current sensor fault is detected. The observer then reduces to an open-loop observer in the event of failure of both CSs. The performance of the drive deteriorates significantly, but it is still a temporary remedy. When a sensor fault is detected, the drive system immediately isolates the faulty sensor while retaining the remaining functional ones. However, the authors assumed the failure of only one sensor at a time. It should be mentioned that for successful estimation of DC link voltage or stator currents, information on measured motor speed is required.

In [337] a dual SMO-based CS-FTC scheme is proposed for the encoderless PMSM drive. After CS fault detection (based on the residual of the measured current and the reference one, compared with the assumed threshold), one SMO is utilized to restructure the fault current and another SMO is utilized to estimate the rotor position/speed using the restructured current only for a single-phase CS fault.

SS-FTC and CS-FTC systems are also proposed for multiphase PMSM drives. A recently published paper [338] introduces such a technique for 5P-PMSM, based on SMO, developed for the case of damage to the CS and the speed sensor. The proposed FTC strategy is based on the residues between the estimated signals and the corresponding threshold values. The residual signals are sent to the FDD block, which, after detecting a fault, switches the signal from the sensor to the estimated signal. After the damage has been compensated for, the signals are sent to the backstepping controller. which ensures very good dynamic properties of the drive.

The FTC strategies belong to emerging topics in the field of PMSM drive control, as they are of great significance for improving the reliability of the systems and ensuring stable operation of the motor under long-term and high-intensity conditions, especially in EVs and other critical applications.

X. CONCLUSION

The presented review of diagnostic methods and techniques used for PMSM drives shows that a great deal of work has appeared in the literature in recent years. A significant number of them have been presented in this review, mainly taking into account papers published in reputable journals or scientific conference materials.

Nevertheless, the overview carried out on various diagnostic methods, based on signal analysis (including internal control structure signals), model-based, shallow, and deep learning neural networks, shows that some issues require more extensive elaboration and further improvement.

Based on the presented analyzes, several topics can be formulated that may be the subject of future research:

- **Diagnostics on transients**: In practical applications, the PMSM usually operates at variable speed and load, which leads to difficulties in isolating the failure symptoms from nonstationary signals. The existing time-frequency signal processing methods are very time-consuming, making online diagnostics difficult in transient states. The first attempts to use deep learning networks (CNNs) for this purpose show promising results, but their use is limited by the complexity of the neural structure. Moreover, this diagnostic should be extended to low-speed and light-load operation of PMSM drives.
- **Diagnostic based on control structure signals**: It is necessary to use the signals from the PMSM control structure to a greater extent not only to detect electrical failures, but also to detect mechanical damages, which will enable online diagnostics of these damages without the need to use additional sensors in the drives, i.e. vibration acceleration sensors.
- **Multiple fault diagnosis**: Diagnosis and classification of multiple faults is a difficult task because the same or similar failure symptoms can correspond to different failures. In the field of PMSM drives, an example is demagnetization failure and the need to differentiate it in the presence of damage to the stator winding or mechanical damage to the rotor. The choice of diagnostic signals and their processing methods is extremely important in the task of correct detection and classification of multiple failures.
- **Artificial intelligence–based diagnostics**: Research on AI-based methods in the emerging field of machine learning and deep learning should be further developed regarding fault diagnosis for greater accuracy and robustness, as well as online operation. This technology has many advantages and great potential in fault feature extraction and pattern recognition. However, related achievements in the field of PMSM fault detection and classification are relatively small compared to IM, and more research is needed.
- **Transfer learning**: It is a research problem in machine learning that focuses on storing the knowledge gained while solving one problem and applying it to a different but related problem. The application of the transfer learning (TL) technique in the field of electrical machine diagnostics, including PMSM drives, remains an unrecognized issue. Two research directions are possible in this field: 1 – TL from mathematical model to real motor; 2 – TL from one motor type to another (including different power range). Moreover, the problem of universality and scalability of diagnostic systems obtained in this way should be analyzed.
- **Real-time fault detection methods**: In many scientific papers, the developed diagnostic algorithms are not tested during the online (real-time) operation of the drive system. This is a significant lack because there are many additional demands connected with real-time operation, mainly related to signal processing methods and fault detector implementation, including the necessary processing power,

data storage capability, and disturbances. Data acquisition and processing are a major challenge for diagnostic systems.

- **Fault-tolerant systems:** Integrated solutions with the combination of fault detection and classification (especially in the case of multiple faults connected with IGBT, ITSC, demagnetization faults, sensor faults), fault isolation, and fault compensation using different strategies of fault-tolerant control, thus achieving the safe and reliable operation of PMSM drives dedicated to critical applications with high safety and reliability requirements.
- **Hardware implementation:** Most of the PMSM fault diagnosis methods presented in the literature do not contain a part on the possibility of hardware implementation, which would require no additional equipment and/or purchase of software associated with very high costs. More attention should be paid to the implementation of diagnostic algorithms on microcontrollers, preferably integrated with the motor control algorithm, to minimize the invasiveness of the diagnostic part in the operation of the entire drive system.
- **Failure prediction**: Increasing demands on process reliability and reducing the probability of unexpected failures require forecasting the evolution of failures and predicting when the machine will no longer operate as desired. These problems belong to prognostics, which is the next stage in the development of diagnostics. As the evolution of faults is a stochastic process, dependent on many factors, in order to assess the degradation rate it is necessary to use prognostic methods and tools that use methods of extrapolation of damage evolution trends or probability density functions estimating the probability of fault occurrence. Prognostics require continuous monitoring of system variables and parameters and next use this information to predict the time to failure, known as remaining useful life.
- **Data storage capability**: Today, the world is moving towards Industry 4.0 standards. Condition monitoring and predictive maintenance systems are also an essential part of the idea of Industry 4.0. More and more often, condition monitoring and motor fault diagnosis systems require the remote interface and the ability to collect massive amounts of data for later analysis. Due to the limited built-in memory of the microcontrollers, the ability to transfer real-time data to the cloud may be a key point in the future.

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