IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Date of publication xxxx 00, 0000, date of current version xxxx 00, 0000.

Digital Object Identifier 10.1109/ACCESS.2017.Doi Number

Fault diagnosis and fault-tolerant control of PMSM drives – state of the art and future challenges

T. Orlowska-Kowalska, Senior Member, IEEE, M. Wolkiewicz, P. Pietrzak, M. Skowron, P. Ewert, G.Tarchala, M. Krzysztofiak, C.T. Kowalski
Department of Electrical Machines, Drives and Measurements, Wroclaw University of Science and Technology, Wroclaw, 50-370, Poland

Corresponding author: T. Orlowska-Kowalska (e-mail: teresa.orlowska-kowalska@pwr.edu.pl).

This work was supported by the National Science Centre Poland under grant number 2017/27/B/ST7/00816.

ABSTRACT The issues of monitoring and fault diagnosis of drives with permanent magnet synchronous motors (PMSM) are currently very topical due to the increasing use of these drives in safety-critical devices. Every year, more and more articles on this subject are published. Therefore, the aim 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, 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 using the analysis of control structure signals 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 PMSM drives failures. Based on the presented literature analyses, 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	EKF/UKF	extended/unscented Kalman filter
AC	alternating current	EMD	empirical-mode-decomposition
AD-OT	angular domain-order tracking	ENN	Elman neural network
AE	autoencoder	ENV	envelope analysis
AFTC/PFTC	active/passive fault-tolerant control	EPVA	extended Park vector analysis
AI	artificial intelligence	ESPRIT	estimation of signal parameter by rotational invariance technique
ASD	adjustable speed drive		
BEMF	back electromotive force	ESR	equivalent series resistor
BLDCM	brushless direct current motor	EWD	equal width discretization
BNN	Bayesian neural network	FC	frequency converter
BS	bispectrum	FDD	fault detection and diagnosis
CNN	convolutional neural network	FEA/FEM	finite element analysis/method
CS	current sensor	FFT/DFT	fast/discrete Fourier transform
CWD	Choi–Williams distribution	FI	fault indicator
CWT	continuous wavelet transform	FOC	field-oriented control
DBNN	deep-belief neural network	FS	full spectrum
DC	direct current	FT	Fourier transform
DF	demagnetization fault	FTC	fault-tolerant control
DL	deep learning	GAN	generative adversarial network
DNN	deep neural network	GST	grey system theory
DTC	direct torque control	HF	high frequency
DWT	discrete wavelet transform	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, the rapid enhancement of “more electrical” drive system applications is observed, not only in such areas 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 reduces fuel consumption, operating costs, noise and pollution of the atmosphere. Thus, it is so important now to design electric drive systems so that they meet the following requirements: small dimensions, low weight, low cost, high efficiency and less efforts on 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 with 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 PMSMs in devices of a 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 topical issue [2], [3].

Because of the growing requirements of the 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 the ongoing monitoring of the drive condition and the observation of trends. This allows the detection of occurring failures at their initial stage and the prognosis of the drive system RUL [4]-[6].

B. CONTRIBUTION OF THIS PAPER

Over the last 30 years, many review articles on the FDD of electrical machines have been published, however, most of them concern the induction motors (IM) [7]-[13], due to the fact that, until recently, they accounted for more than 90% of all electric motors installed in industry [1]-[3]. Because of the growing interest in the usage of PMSM in various electric drives, especially in high performance drives, the methods of diagnosing failures of these drives have started to develop intensively in recent years and after 2010 some interesting reviews for the PMSM diagnostic methods have appeared in scientific literature [14]-[23]. Few conference papers were published as well [24], [25], presenting very preliminary review of condition monitoring and fault diagnosis techniques for PM motors. The most interesting surveys are summarized in Table I, taking into account whether or not the different issues are reviewed: description of the fault impact on the performance and state variables of the PMSM, more or less detailed analysis of different fault types, applied diagnostic methods, FTC concepts

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2022.3180153, IEEE Access

and future challenges. The period of the analyzed literature is given for each review, taking into account references concerning the PM drives only, as some of papers are also focused on IMs.

To the best authors' knowledge the first review on diagnostics of PM machines (BLDC and PMSM) was published in 2011 [14]. It presents a comprehensive information on fault influence on machine parameters and signals, some signature extraction methods and preliminary works 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 the analysis of phenomena and their impact on machine parameters.

TABLE I
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 publica-tion	Number of references all(only PMSM)	Period of references concerning PMSM drives only	Descri-ption of fault effects	Fault type diagnostics					Methods						FTC	Future challen-ges
					PMSM			Freq. Conv.	Sensors	Model-based		Signal-based		AI -based			
					Electri-cal	PMs	Mecha-nical			Sympt. gener.	Obser-vers	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	≈	√	√	√	√	√	√	√	√	√	√	√	√	√

With regard to diagnostic methods, by nature, only a limited number of examples has 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 paper 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 very wide and interesting review of PMSM faults, starting from fault types, mainly focusing on the electrical faults (resistive unbalance, inter-turn 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 overviewed, 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 fault diagnosis for PM machine are presented.

The two 2017 review articles [16], [17] are less comprehensive, also in terms of the works cited, but nevertheless focus on the diagnostic methods used to detect different fault symptoms. However, mechanical faults 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 about what specific symptoms are extracted with the use of a given method. In [17] the FDD methods are classified based on the source signal. The fault type and the most interesting application examples are described as well. 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 methods based on AI are not taken into account at all, while different categories of FIs for ITSC and irreversible demagnetization fault are discussed. Also 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 regarding the development of the FDD issue are formulated.

It seems that the most extensive overview of the literature on FDD methods applied for PMSM drive was presented in [19] in 2018. However, the authors did not take into account methods based on the analysis of internal signals of the PMSM drive control structures. Additionally, the methods based on AI were only mentioned, not discussed in detail. The state-of-the-art of diagnosis tools for PM damage and DFs, rotor eccentricity, UMP, open- and short-circuit faults of the stator winding is presented. 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 (over 33 references analyzed). Finally, an integrated methodology of PM machine condition monitoring is proposed, however FTC issues are not addressed.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2022.3180153, IEEE Access

In the subsequent review article from 2019 [20], the literature analysis 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 well as the FTC issues for PMSM drives. Compared to the already 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 servo drive systems with PMSM. The selected FDD methods of basic PMSM faults, as demagnetization, ITSC and rotor eccentricity faults are analyzed, as well as sensor fault and inverter fault of the servo drive are addressed. 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, the future development trends of PMSM servo system fault diagnosis technology are given.

Similarly, in [22] only selected FDD methods are analyzed for electrical faults occurring in 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 few works on NN application for PMSM fault detection are presented. It should be mentioned that model-based and observer-based methods are discussed for sensor faults as well as 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. 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 hardware design and software algorithm. The current problems are pointed out and the future development directions are defined.

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

One should also mention a very interesting review of existing FDD methods [32], that concerns the damage occurring 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, thus this paper is not included in Table I.

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 the recent trends in the advanced signal processing methods, NNs in fault detection and classification, including DL approach and FTC concepts. This paper 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 works in this topic, not only in in the field of diagnostics of rolling bearings (which is very common in the literature) in PMSM motors, but also in the damages 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 aim of this article is to present an overview of the 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 the damage occurs in the motor and drive system, according to the signal processing methods used and the type of diagnostic signals analyzed. In order to make it easier for the reader to follow these analyses, tabular summaries of individual methods and their assessments are presented. The contribution of this review is, inter alia, drawing attention to the emerging trends and challenges in the field.

The organization of the paper is as follows. Section II briefly describes the fault classification in PMSM drives, focusing on the motor failures and their 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 PMSM drive. The model-based fault diagnosis methods are discussed in Section VII. The particular attention to fault detection and classification using shallow and deep-learning NNs, is paid in Section VIII. The following Section IX is dedicated to frequency converter and sensor faults of the PMSM drive and the FTC issues are discussed there as well. This review paper ends with addressing 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 system using vector control methods: FOC or DTC. Motors are mainly supplied from two- or three-level VSIs with SVM. These inverters mostly use power switches based on IGBT, due to 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 sensor FTC concept, state estimators or observers are used, creating a software redundancy in the case of chosen sensor faults [32]. The general structure of such drive is presented in Fig. 1.

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

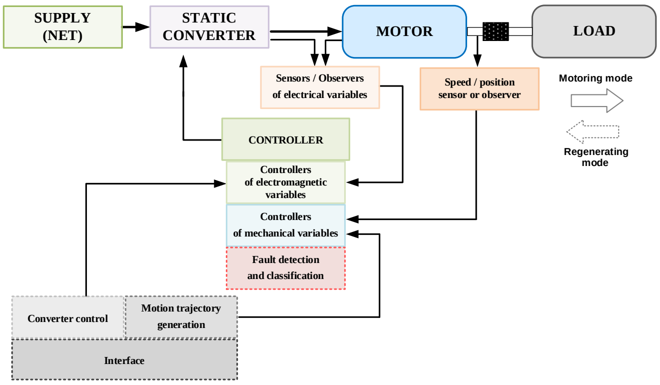


FIGURE 1. **Schematic diagram of modern PMSM drive with diagnostic option.**

B. PMSM FAULT CLASSIFICATION

The failures in PMSMs can be classified in a 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 approx. 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.

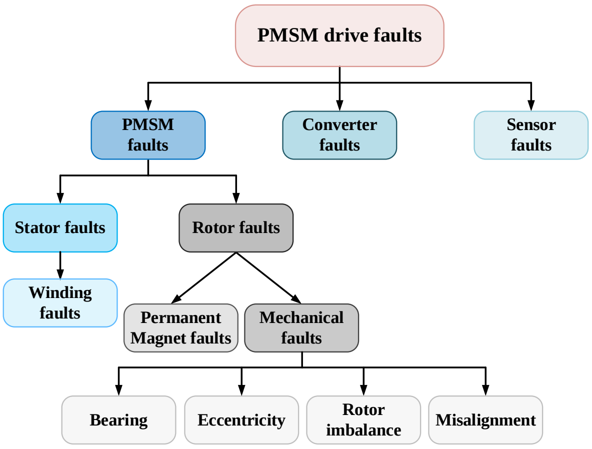
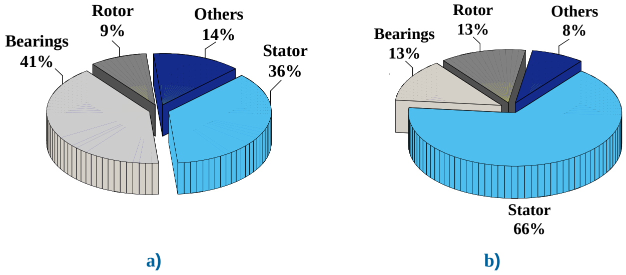


FIGURE 2. **Faults classification in PMSM drive.**

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



a) b)

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

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 lose their magnetization at high temperature and strong opposing magnetic fields, which leads to a reduction of the motor torque. For instance, the electrical faults of the stator windings, such as sudden 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 faults of the PMSM stator winding, which begin with single ITSCs, are usually caused by the insulation damage. Damage to the insulation 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 very destructive character as they are spreading-out very fast. Stator winding failure usually starts as an imperceptible single-turn short circuit, 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 measurement and processing of the diagnostic signals, enabling online monitoring of the 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. The damages may be mechanical in nature or related to the phenomenon of demagnetization [15], [18], [19], [20], [28]-[30], [32]. PM demagnetization 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. PM 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 the elements with increasing temperature [36]. The source of the PM temperature increase 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 PM damage [18], [19], [30]. Therefore, detection of ITSC at an early stage is very important in PMSM drives.

The PM demagnetization can be uniform over all poles or partial over certain region 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, re-increasing 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 faults of the PMSM are frequently occurring and concern 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 above sources constitute close to 41% of all low-voltage motor faults. They are mostly caused by wrong assembling, not proper lubrication, overloading of the motor 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 lead 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, overloading the PMSM can affect faster machine damage and these unexpected damage or failure of the drive can lead to very high motor repair or replacement costs. Therefore, the diagnostics seems to be necessary, e.g. it can help in planning preventive maintenance or even failure prognostics. Symptoms of the damages can be sought in electrical signals (current, voltage), magnetic quantities like 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 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.

The methods based on signal analysis use various methods of signal processing, which enable isolating the symptoms of drive system damage. 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 extensively developed nowadays, especially for IM drives [15], [20], [22], [24], while the NN are not so often used yet for PMSM drives as will be shown in Section VIII of this survey.

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

The diagnostics based on mathematical models (in particular, using different estimators of the 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 currently used diagnostic methods are based on processed electrical signals, especially current, voltage and leakage flux, as well as mechanical signals, such as vibration velocity and acceleration. The changes caused by electrical damages 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 non-invasive 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 the 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 symptoms (features) characteristic 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, kurtosis.

Currently, in the diagnosis of electric motors, including PMSMs, the most widely used methods are in the frequency domain and time-frequency domain [7]-[32]. The most common method belonging 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 as well as its improvement –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 vibrations processing in the event of mechanical damage.

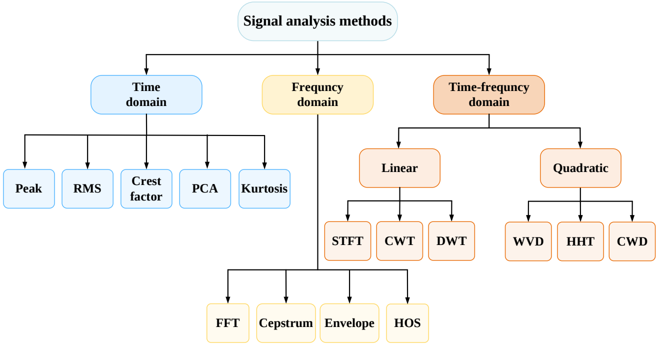


FIGURE 4. Signal analysis methods for AC motor drives.

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, 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 the 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*. Thus, depending on the application, a compromise must be made between time and frequency resolution, since the longer window has better frequency resolution and the smaller window has better time resolution [6]. Thus, the STFT method is better suited for non-stationary 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 non-adaptive nature. In the diagnosis of electrical machines, including PMSM, both CWT and DWT are used. By continuous variation of the resolution, CWT can provide 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. Nevertheless, the CWT is used for slowly developing failures such as e.g. demagnetization or bearing failures [15], [29], [32].

Other time-frequency signal analysis methods applied in the 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's 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 as 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 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 implementing WVD for discrete signals, an aliasing problem may arise.

Another transformation that analyzes the time-frequency energy of a signal is the HT. Since this transformation was developed for fully sinusoidal signals with a zero reference level, its modification is used for non-stationary signals – the HHT. This transformation uses the EMD method to decompose 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 derived IMF functions. The HHT enables the elimination of unwanted frequencies and focusing on those that are characteristic for 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

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2022.3180153, IEEE Access

there are no interactions of the frequency components distorting the spectrum, as e.g. in WVD. Therefore, in recent years, HHT has found application in the analysis of signals in transients [30].

The results of application the mentioned methods will be analyzed for all types of PMSM faults in sections III-V, starting from the ITSCs detection, as 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 the diagnosis of ITSC faults are the 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 frequency components characteristic for 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:

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

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

Additionally, as proven in [41], the stator winding ITSC may 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 the incipient ITSCs on the value of this component in a wide range of motor rotational speed and load torque was investigate in these articles. 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 of 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 compared to the FFT of the stator phase current is also emphasized.

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 for ITSC fault extraction is evaluated and compared in [48]. The authors have proven 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] authors verified experimentally that both the current and the voltage negative sequence harmonics should be considered for accurate ITSC faults detection. In [50] the analysis of the negative sequence components of the stator phase current and voltages is combined with a fuzzy logic approach for the successful detection of ITSCs.

The application of the spectral analysis of diagnostic signals other than the stator phase current to PMSM electrical faults has also been verified over the years. In [51] Authors proposed a three-step on-line stator winding fault detection approach for PMSMs based on the reference voltage in *dq* frame analysis. The novel real-time PMSM stator winding fault detection method, which is based on the extraction of the 2nd harmonic of the control voltages in *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 stator winding of PMSMs. In [54], a novel and robust stray flux analysis for ITSC detection for PMSM is proposed. This method utilizes the 3rd 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 the FFT analysis for electric 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 active and reactive power spectrum is proposed as the FI independent on the motor control type.

In recent years, the papers in which authors proposed the use of ZSVC spectral analysis using FFT for the detection of PMSM stator winding faults were also published [59]-[64]. The research discussed in [59] shows that the first, 5th and 7th harmonics of the ZSVC spectrum are the components whose monitoring allows for the detection of the ITSCs in the PMSM stator winding. Compared to the MCSA, this system provides better resolution even at low rotational speed operation. The limitation of this approach is mentioned in [60] – to measure the ZSVC, the access to the neutral point of the stator winding is needed. The method for ITSCs detection 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 3th harmonic of stator phase current and first one of the ZSVC for on-line detection of this failure. The another effective on-line ITSC detection algorithm based on the ZSVC and HF signal injection is proposed in [64]. There, ZVSC is used to detect the abnormal state of the PMSM drive, and then the HF current signals are injected to discriminate between the ITSC and resistive unbalance fault.

The most complex methods that perform frequency domain analysis are HOTs which are based on the HOS. Application of the HOTs for fault diagnosis of electric motors has also been discussed in the literature so far. The most popular HOTs are MUSIC, BS, PSD, and ESPRIT. In [65] the application of the PSD, MUSIC, and BS of the stator phase current signal to PMSM stator short-circuit detection is evaluated and compared. 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, the hybrid methods that combine the statistical and frequency domain approaches have been discussed also in the field of the PMSM electric 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 system. Moreover, this method requires a relatively long measuring 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 of detection of electrical and mechanical faults of permanent magnet AC drives is discussed in detail and compared with wavelet analysis. Authors proved that this method is capable of identifying intermittent electrical and mechanical faults of this type of motors, also in transient states. A similar study, but extended by comparison with other signal processing methods, is also presented in [5]. Changes in STFT spectrogram caused by ITSCs in the PMSM stator winding during the variable motor speed are presented in [70]. In all these works, the main idea of using STFT in fault diagnosis is discussed – observation of spectrogram changes 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 tradeoff 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 time and frequency domains. It allows for a more accurate time-frequency response. The biggest advantage of the WT is that it works very well in the analysis of non-stationary signals. The CWT was successfully applied to PMSM electrical faults for hybrid and electrical vehicles in [69]. In this paper, authors discussed the stator incipient fault diagnosis and monitoring of 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 localization of the damage based on the 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 fault diagnostics field. The DWT performs multiresolution wavelet analysis. At each of its stages, the signal can be divided into two components – detail and approximation. In the case of this transform, the symptom of an PMSM electrical fault is a change in the approximate and details waveforms, the range of which covers the components characteristic of this type of fault. In [43], the DWT of the stator phase current and the stator phase current ENV are proposed for the detection of ITSC at a very early stage of the damage (1 shorted turn). The discussed approach 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]. 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] Authors proposed the WT of reference voltage in *q*-axis to detect the incipient ITSCs in PMSM with three-phase stator winding. In this work, it is also proved that the occurrence of this type of fault disturbs the stator currents, as well as the reference voltages, leaving a specific fault signature. In [74] a wavelet analysis is successfully applied for detection, localization, and estimation of the number of shorted turns. DWT combined with a SVM based on the stators current waveform for automatic fault detection of PMSM stator winding is discussed in [75].

Another approach for time-frequency domain analysis used for the extraction of PMSM electric fault is HHT. In [76] the stator phase current HHT and energy calculation is proposed for the detection of PMSM stator winding fault. In this work the advantage of this method – possibility to detect the failure during the transient conditions (rotation speed) is highlighted. Authors of [76] presented a method based on the online statistical analysis of the instantaneous frequency calculated by the HHT and demonstrated it through real-time hardware-in-the-loop simulation and experimental results. In this work, it is also stated that HHT is well suited for stator winding fault detection because it is unaffected by transient conditions, which introduce the possibility of false alarms. The WVT, also known in the literature as WVD, is a time-frequency domain method which is based on the energy distribution. PMSM stator winding fault detection based on the EMD and WVD is proposed in [78]. Authors presented that this approach is able to provide short-circuit detection under dynamic transient conditions. It is also stated that the fault frequencies in non-stationary states of PMSM drive systems can be detected and tracked perfectly.

A novel hybrid method of stator winding fault diagnosis for LSPMSM based on the 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.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2022.3180153, IEEE Access

C. TIME DOMAIN (STATISTICAL) METHODS

Currently, methods that perform the diagnostic analysis in the time domain are not very common. In [80], an on-line 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, accounting for BEMF estimation, inverter model and unbalanced inductance matrix and the real currents of the PMSM. In this paper, a FI is defined based on these residual currents. In [81], the fault detection is carried out based on the difference between the estimated BEMF and the reference BEMF where linear average value of the EMF differences normalized with mechanical angular speed is introduced as FI. Authors in [82] proposed the stator current based novel 1D-LBP method, which is compelling and distinctive, to detect short-circuit fault that occurs 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 also in presence of a strong signal noise.

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

TABLE II.
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,
🟨 – High Order Transforms, 🟩 – 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

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2022.3180153, IEEE Access

[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
[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

IV. SIGNAL ANALYSIS METHODS FOR MAGNETIC FAULTS OF PMSM

A. FREQUENCY DOMAIN METHODS

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

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

where: f_{dem} –DF frequency, k=1,2,3….

An increase in the degree of rotor demagnetization causes an increase in the amplitude of the stator current harmonics defined by (3), so it is an appropriate criterion for diagnosis of this fault [84]-[88]. Therefore, the MCSA method can be easily used to detect the symptoms of the 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 natural existing asymmetries of the machine [19], [29], [84], [85]. However, the application of the conventional FFT is limited to the stationary motor conditions regarding speed and load torque. Moreover, as results from the dependence (3), other motor damages depending on the 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 magnets demagnetization is a destructive test and there are many random factors, such as uncontrolled loss of magnetization due to artificial crushing of the magnet’s 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], the MCSA/MVSA 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 on frequency spectrum only. 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 ZSCC method and FFT was proposed using classical three-phase mathematical model of the machine with introduced demagnetization factor for the magnetic flux, both for partial and uniform demagnetization. The method was verified experimentally and it was proven that the value of the fault severity index can provide the reliable information about the DF. The studies [87] and [89] proved that the stator current harmonics show the DF condition for medium and high speeds. On contrary, the ZSCC makes it possible to determine the PM demagnetization failure in high and low speeds with a correct accuracy. The proper combination of the analyses of stator current and zero sequence current, or zero sequence and *q*-axis current enables fault determination for any range of speeds [87], [89].

In [90] the early rotor demagnetization in a SMPMSM was detected through on-line 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 FI to DF. However, it is limited by the need to provide access to the stator windings neutral point and an artificial neutral point has to be created by a three-phase balanced resistor network connected to the motor terminals.

This drawback can be eliminated by using the flux-based and BEMF methods which 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 thus is a highly invasive method. The other solution consists in properly designed measurement coil mounted on the motor housing to obtain the voltage induced in the coil by a stray flux [92]. In [91] the search coils are wound up around each tooth so that the air-gap flux density can be measured. Although the method is invasive, it enable to detect PM faults on the basis of only the 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 the determination of the load torque value in order 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 high importance. In the case of stray flux measurement it has been shown in [93] that PM demagnetization can be detected through stray flux analysis similarly to wound rotor synchronous machines by using both time and frequency analysis.

Since flux reduction due to demagnetization has a significant impact on the BEMF waveform of PM machine, it is also used for fault diagnosis. The BEMF can be directly measured in open-circuit generator mode, thus it is off-line noninvasive 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 the lack of robustness to temperature changes of PMs [3], but the method is simple to implement [29], [95].

Also vibration signal analysis [99] or noise and torque pulsation analysis [100] were used for 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 based on spectrum analysis in [100]. As FIs, the authors applied significant orders of harmonics extracted from the vibration signal by means of FFT.

The usage 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 about 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 of time but are of very short duration [10], [32]. Due to the aforementioned disadvantages of FFT-based methods, including stationarity requirement, T-FMs to detect demagnetization symptoms are more and more often used.

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 to compare and clarify the capabilities of different time–frequency distributions. The main concept, advantages and disadvantages of these linear and quadratic T-FM were shortly 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 still remain the major drawbacks of this technique. However, the method is simple to implement in real time and according to the authors it can be also applied to other motors with PMs. It is also computationally less intensive than other T-FMs.

This problem can be solved by usingWT, 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 through 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 stator current and voltage signals were analyzed for a low (2.5-5)% demagnetization level of the vector-controlled PMSM using CWT. It was shown, that the analysis of signals of the motor gives similar results. The work [105] proposes the application of WT to

BEMF signal of SMPMSM obtained from 2-D FEA simulations. It was shown that PMSM rotor faults due to 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 the demagnetization symptoms and energy pulsation associated with the torque ripples resulting from DF. The method was tested for partial demagnetization but authors claim that it can be also used for uniform DF detection.

One other T-FMs for tracking 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 BLDC motor drive, however 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 the STFT. This method was also mentioned by the same authors in [101] and recommended for uneven-asymmetric rotor DF detection.

As it was 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 the 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] for detecting DFs 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 CWD-prepared damage characteristics are extracted using the box counting method.

The HHT was applied to diagnose the demagnetization in [109]-[112]. In conference papers [109], [110] and following articles [111], [112] the HHT was applied to stator current signal obtained from FEM simulation model of the PMSM with DF under different speed and load torque values. In these research the effectiveness of the HHT was proved also in experimental tests for vector controlled PMSM with 50% DF in one pole pairs, for both steady state and transient conditions under motor speed changes 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 the end boundaries. Additionally, it was concluded in [111] 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. Partial DF of PMSM under nonstationary speed and load conditions was also analyzed in [113] using 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 non-stationary 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 DF detection. 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). TDE transforms the torque waveform into a reconstructed torque profile called phase space. 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 non-invasive (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, which significantly impedes the detection and distinguishing of failures.

Another time domain method was presented in [115] for the BLDC motor. It consists in the detection of ZCP in the BEMF waveform. It was shown in this work that this method enables the detection of very small DFs in the online mode.

All methods discussed in this section are summarized in Table III and categorized into groups based on the type of signal analysis methods and FI.

TABLE III.
CLASSIFICATION OF DETECTION METHODS FOR DEMAGNETIZATION FAULTS IN PMSMS

<table>
<tr><td>Legend:</td><td colspan="5">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 <i>t</i> and <i>f</i> resolution, EV – experimentally verified</td></tr>
<tr><th>Ref.</th><th>Diagnostic signal</th><th>Method</th><th>Fault index</th><th>Advantages</th><th>Disadvantages</th></tr>
<tr><td colspan="6">Frequency domain methods</td></tr>
<tr><td>[84]–[88]</td><td>Stator current</td><td>FFT</td><td>$f_{dem} = f_s\,(1 \pm k/p_p)$, for k=1,3,5…</td><td>PDF, NINV, ON, EV</td><td>SC, LS, MS, AOF</td></tr>
<tr><td>[87], [89]</td><td>Zero sequence current component – ZSCC (+i_q)</td><td>FFT</td><td></td><td>PDF, UDF, ON, HS, EV</td><td>SC, INV, AOF</td></tr>
<tr><td>[90]</td><td>Zero sequence voltage component - ZSVC</td><td>FFT</td><td></td><td>PDF, ON, HS, EV</td><td>SC, INV, AOF</td></tr>
<tr><td>[91]-[93]</td><td>Axial flux</td><td>FFT</td><td></td><td>PDF, UDF, ON, HS, NAOF</td><td>SC, INV or ACR</td></tr>
</table>

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2022.3180153, IEEE Access

[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	

V. SIGNAL ANALYSIS METHODS FOR MECHANICAL FAULTS DETECTION

A. BEARING FAULTS

Like every component of the drive, bearings have a defined life-cycle. Apart from 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]. A damaged bearing manifests itself 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 diagnostics of 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 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…, 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:

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

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

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

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

where: N_b – number of rolling elements (balls), D_b – rolling element diameter, D_c – bearing pitch diameter, β – bearing working angle (β =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 indicating 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. Additionally, in a speed closed-loop 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 FFT and kurtosis analysis and compared with the results obtained from mechanical vibration and stator current analysis over a wide range of PMSM motor speeds. The study showed that the kurtosis spectrum analysis of the speed signal can achieve similar results to those obtained for the vibration method. In [140], the ENV of the speed signal is analyzed. In order to suppress velocity ripples, the authors used additional resonant controllers in parallel with 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 for modelling and detection of rolling element damage in PMSM motors is presented. The simulation-modelled damage was diagnosed by means of FFT analysis of the mechanical vibrations and the FFT of the Park's vector module of the stator current. Furthermore, it was shown that the bearing damage is also visible in the electromagnetic torque.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2022.3180153, IEEE Access

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]. The standard deviation, kurtosis, skewness, crest factor, clearance, shape factor [132], [137] are used to extract additional statistical features 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, while in [130] from an acoustic signal. In [124] the SWT is used to process the bearing vibration signal to extract the rotating phase from the time-frequency plane. In [126], the SWT method is used to process the vibration from a triaxial sensor in order 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 reviewed papers, the tests were conducted 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 load torque and supplying frequency of a PMSM motor on the change of amplitudes of example diagnostic symptoms obtained from FFT and mechanical vibration ENV analysis 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. In order 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 reduced 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 not informing about the type of damaged bearing component. 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 faulty bearing was artificially aged by a burning grease process at 200°C during 60 hours and a broken cage.

Based on the presented literature review, 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 contrary, the use of OA allows fault detection performed under dynamical states of the drive. 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 conducted on PM as well as 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. The analysis of the motor speed signal also enables the detection of damaged rolling bearings even at low rotational speed conditions, which is its advantage compared to 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 element 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.

Pros and cons of individual diagnostics signals and methods used for fault detection in PMSM rolling bearings are summarized in Table IV. The presented summary shows that it is relatively rare that symptoms obtained from several diagnostic signals are discussed and compared in one article.

TABLE IV.
CLASSIFICATION OF DETECTION METHODS FOR BEARING FAULTS IN PMSMS

<table>
<tr><td>Legend:</td><td colspan="5">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</td></tr>
<tr><th>Ref.</th><th>Diagnostic signal</th><th>Method</th><th>Fault index</th><th>Advantages</th><th>Disadvantages</th></tr>
<tr><td colspan="6">Frequency domain methods</td></tr>
<tr><td>[116], [117], [120], [121]</td><td>Vibration</td><td>FFT</td><td>$f_b = kf_u \pm lf_r$
f_u – characteristic</td><td>NINV, HS [116], SM1 [117], MDB1 [116], MDB2 [117], [120], [121], RL/RS [120], [121]</td><td>SC[120], [121], VM</td></tr>
</table>

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2022.3180153, IEEE Access

[141]			failure frequency of the bearing k=1,2,3… l=0,1	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	$f_b = f_s \pm k f_u$ 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

B. ECCENTRICITY FAULTS

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 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 to 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 the bearing operation (increasing its wear) and increases the stress in the machine [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,…

When the 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. The eccentricity is most often modelled using FEM models [142]-

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2022.3180153, IEEE Access

[155]. In experimental studies, the 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 modelling 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], d-axis stator inductance L_d [147], [148], BEMF [160] and unbalanced magnetic pull [153], [154], [160].

The evaluation of the type and level of the 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], PSD of load torque [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 symptoms characteristic of both faults (amplitude and phase angle) in polar coordinates, obtained from stator current analysis. A few 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.

As it 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 it requires the use of an additional measuring coil in the stator slots. On contrary, 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 V the diagnostic methods applied for eccentricity detection of PMSM drive are summarized, with their advantages and disadvantages.

TABLE V.
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 signa**	**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	$(2pk \pm 1)$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	(2*pk*±1)th order, *k*=1,2,3,…	NINV, MM, EV, in experiment - dynamic state (OA)	SE, DE (simulation and experiment), VM
[159]	Voltage	PSD	$f_{SE} = f_s \pm k f_r$	NINV, EV3, AaCPSD	SE
[152]	Airgap flux	FFT	third- and fifth-frequency components	MM, EV5	DE, INV, ACR
[159]	Rotation speed	PSD	$f_{SE} = f_s \pm k f_r$	EV3, AaCPSD	SE
[159]	Load torque	PSD	$f_{SE} = f_s \pm k f_r$	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.					

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 verified experimentally by physical modelling 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, and leading to bearing damage. A symptom of the unbalance is an increase in the amplitude of the rotational frequency occurring 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 for detecting the unbalance of a PMSM drive system are presented. 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. Changes of unbalance 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 the unbalance detection is verified for a PMSM with modelled demagnetization and dynamic eccentricity. In [165] and [166], the stator current signal is analyzed, which, in order 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 non-stationary conditions. In [167], 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 non-stationary condition is reduced in the wavelet coefficients, and then the distance of the residual signal from the distribution of 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 unbalance mass and its mounting radius on the unbalance level is investigated under stationary conditions. The stator current is analyzed for diagnostic purposes. The applied Bayesian method based on the current amplitude allows to estimate the degree of the 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 to detect PMSM rotor unbalance described in the reviewed literature are summarized in Table VI. It can be seen from the presented summary that stator current and mechanical vibrations are the signals that are mostly used for unbalance detection. Moreover, only in [169] both mentioned diagnostic signals are 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 the computational power requirements. The discussed non-invasive unbalance detection methods require a steady state condition. An exception to this rule is the use of FS or WT.

TABLE VI.
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

D. MISALIGNMENT FAULTS

The misalignment in PMSM drive concerns the connection between the motor and the loading machine [171]-[176]. The level of the misalignment is difficult to determine 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 $f_s \pm kf_r$. 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 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. DWT of the stator current ENV and its space vector modulus were used to detect angular misalignment. It was shown that the impact of the load torque on the values of the characteristic components is relatively small. In the case of the power supply frequency changes, the components that are the least dependent on its changes are $f_s - f_r$ and $f_s + f_r$. Nevertheless, the influence of the f_s changes on the value of these symptoms is visible. The same concerns the RMS value of the stator current. On contrary, the EPVA and current ENV analysis methods show that fault index f_r is highly sensitive to misalignment, does not depend on the load torque and depends less on the stator frequency in comparison with the fault symptoms visible in the stator phase current spectrum. It makes this FI very useful for fault diagnosis and drive system alignment monitoring. It was also shown form the DWT analysis of the stator current that RMS values are strongly dependent on the load torque and frequency of the supply voltage, which confirms their uselessness in misalignment detecting. However, in the case of the RMS values of a5 and d5 details obtained in DWT analysis of EPVA and stator current ENV increase significantly with the increasing degree of angular misalignment, and they do not depend on the loading torque and stator frequency. However, the influence of the supply voltage frequency changes is a little greater for EPVA than in the case of DWT of current ENV. In [173], the effect of the misalignment on the generated torque 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 tested PMSM drive with parallel misalignment was analyzed, while in [176] it was shown in simulations and in experimental tests that the virtual phase torque (VPT) diagram method based on self-sensing motor drive system enables the detection of the offset angle of misalignment. VPT is a method that does not require additional sensors. Despite some limitations in the diagnostics of mechanical systems (compared to the vibration analysis), as a cost-free method, it can be used to assess the condition of gears and bearings.

TABLE VII.
CLASSIFICATION OF DETECTION METHODS FOR MISALIGNMENT FAULTS IN PMSMS

<table>
<tr><td>Legend:</td><td colspan="5">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</td></tr>
<tr><th>Ref.</th><th>Diagnostic signal</th><th>Method</th><th>Fault index</th><th>Advantages</th><th>Disadvantages</th></tr>
<tr><td colspan="6">Frequency domain methods</td></tr>
<tr><td>[172]</td><td>Stator current</td><td>FFT</td><td>$f_s \pm k f_r$</td><td>NINV, HS</td><td>SC, NRL, NRS, AM</td></tr>
<tr><td>[172]</td><td>Stator current EPVA</td><td>FFT</td><td>kf_r</td><td>NINV, HS, RL, RS</td><td>SC, AM</td></tr>
<tr><td>[172]</td><td>Stator current ENV</td><td>FFT</td><td>kf_r</td><td>NINV, HS, RL, RS</td><td>SC, RS, AM</td></tr>
<tr><td>[171], [174]</td><td>Rotational speed</td><td>FFT</td><td>$2f_r$</td><td>NINV, PM and AM [174]</td><td>SC, RS, AM [171]</td></tr>
<tr><td colspan="6">Time-Frequency domain methods</td></tr>
<tr><td>[172]</td><td>Stator current</td><td>DWT</td><td>RMS</td><td>NINV</td><td>SC, LS, NRL, NRS, AM</td></tr>
<tr><td>[172]</td><td>Stator current EPVA</td><td>DWT</td><td>RMS</td><td>NINV, MS, RL, RS</td><td>SC, AM</td></tr>
<tr><td>[172]</td><td>Stator current ENV</td><td>DWT</td><td>RMS</td><td>NINV, MS, RL, RS</td><td>SC, AM</td></tr>
<tr><td colspan="6">Time domain methods</td></tr>
<tr><td>[172]</td><td>Stator current</td><td>RMS</td><td></td><td>NINV</td><td>LS, NRL, AM</td></tr>
<tr><td>[173]</td><td>Torque</td><td>Waveform plot</td><td></td><td>EV, RL, RS</td><td>SC, TW, PM</td></tr>
<tr><td>[176]</td><td>Current i_q</td><td>VPT</td><td></td><td>EV, MS</td><td>SC, EN, AM</td></tr>
</table>

Based on the presented literature review, Table VII 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 the open-loop control is not applied in industrial applications, one of specialized vector control methods must the 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 DTC method). Due to their compensating nature, the control structures tend to compensate 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. In a similar way, mechanical vibrations present in speed and torque due to the 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 signals 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 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, e.g. [52]. Alternatively, estimated voltage vector components can be used (calculated based on 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 the measurement problems, usually measured voltage signal has not been taken as the diagnostic signal;
- reference or estimated stator vector components (in rotor flux oriented frame, *d*-*q*), e.g. [38]. Torque-producing *q*-axis current component [38], [182] and a ratio between *d*- and *q*-axis components [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.

The above mentioned signals are available for the detection system, even if other control structures (DTC) are applied [134], [165], as they can be easily calculated, e.g. with measured stator currents and rotor angle. However, in this section, it is assumed that the 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 the knowledge about the control system structure.

B. ELECTRICAL FAULTS

Most diagnostic methods based on control structure signals utilize voltage signals. The signals have to be further processed, as their actual values are varying with the operating point. However, the instantaneous value of the angle between the reference voltage components has been directly used as an efficient FI in [181]. This angle has been also used in order to distinguish between two different faults (ITSC and DF, as it decreases or increases with the fault, respectively). Unfortunately, the value of the angle between the components for the undamaged motor must be known for actual torque/speed/temperature operating point. This value can be estimated (based on motor parameters and signals) or determined experimentally, which both can be 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, searching for some characteristic frequencies in the components of the reference voltage vector have been proposed in [52]. It is shown that the ITSC introduces the 2nd order harmonic signal into the *d*-*q* rotating reference frame (they correspond to the third-order harmonics in *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 three times the 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, 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.

The voltage components are used to detect the ITSC faults in [179] as well. However, the diagnostic signals are the outputs 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 to the stationary frame, is taken as the FI. However, the complexity of the solution is increased with the use of a statistical cumulative-sum algorithm to determine whether the damage is present or not. Additionally, in a similar way to [181], the operation points map (a table with "healthy" values of the FI for many torque/speed values) has to 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 of them 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 to locate the faulty phase with a usage of high-pass filtered phase-to-phase voltages.

The quadrature (torque-producing) current component has been the only current component used as the diagnostic signal in the diagnosis of PMSM [38], [182]. In [38] the component has been used in order to diagnose the ITSC fault. It is proposed to search for the second-order harmonic amplitude variations and compare it to the healthy condition (the FI is the ratio of 2nd order harmonic amplitudes in faulty and healthy conditions). A lot of interest is paid into interpolating the FI according to the actual operating point – there is a necessity to know the amplitudes of the 2nd 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 of the 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.

Estimation-based approach for the ITSC fault diagnosis method can be found in [182]. The difference between measured and estimated quadrature current components, number of winding turns, measured voltage, estimated voltage assuming that the machine is healthy and rotor angle are required. Therefore, a perfect knowledge of motor parameters is necessary. However, all of the 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, that increases the complexity of the described method even more.

All of the above ITSC diagnostic methods act as a fault alarm for the motor service personnel. However, if the fault is detected the FTC method can be applied in order to decrease the level of the oscillations arising after the fault, e.g. [183]. This method is based on the reference current signal injection. However, the proposed method is based on a perfect knowledge of motor parameters, together with actual number of shorted turns and short-circuit resistance, that 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 has been first proposed in [184] and further developed in [185]. The FI relies on the ratio of real quadrature to direct axis components. 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 the decision about the fault 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 estimated and real electrical angles of rotor shaft position.

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, the virtual signals, being a part of the control structure have been also used to diagnose mechanical-type damages. Motor bearing inner- and outer-race faults can be distinguished using the approach shown in [177]. Because it is applied for a general repetitive mechanical mechanism, a special harmonic speed controller is proposed instead of a traditional PI regulator. The diagnostic method is based on the FFT analysis of the difference between reference and estimated torque and finding increased amplitudes of respective harmonic frequencies. Mentioned mechanism is driven by a sensorless inverter-fed PMSM. Bearing fault diagnosis is also described in [134] for DTC structure of PMSM drive. The quadrature component of stator vector is selected as the diagnostic signal, despite the fact the it is not a 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 the condition of the bearing. 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 rotor unbalance diagnostic efficiency for two main control structures (FOC and DTC) for PMSM is shown in [165]. A DWT is used to extract the damage symptoms from the stator current vector modulus (expressed in stationary frame). Proposed method is efficient in the case of both mentioned control strategies and also during non-stationary conditions, that is quite a rare situation.

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

The control structure and its signals are also necessary in the case of the eccentricity detection proposed in [147] and [148]. These two solutions suggest to detect the damages during the standstill of the motor, not under the online operation. The *d*-axis reference voltage vector and current vector, expressed in 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]. In order to extract the inductance it is necessary to induce an AC flux by the *d*-axis current injection. Different, on-line operation based idea to detect the eccentricity is shown in [178]. In this paper, the diagnostic is based on the 0.5 harmonics of *q*-axis current and voltage. Additionally, the authors propose the method to distinguish the rotor fault and load torque time variations. The demagnetization fault can be also diagnosed using control structure signals [180], in the case of a five phase PMSM. 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 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 mentioned above FIs are sensitive to the bandwidth of the applied controllers, speed controller, two current controllers in the case of the FOC. As it is shown in [178], [186] and [187], the fault symptoms are visible in voltage, current or both of them, depending on the regulator parameters. Generally, if the speed controller bandwidth is low, the harmonics characteristic for a specific fault will be visible in voltages [178]. And the opposite, if the bandwidth is high, they will be present in currents. This effect can be distorted by the current controllers, if their bandwidth is low the fault is visible in currents, if high – in voltages [186], [187]. In other words, the control structure tends to obtain clear sinusoidal current signals, therefore higher harmonics must be present in voltages.

According to the above analysis, it seems that an effective and insensitive to controllers bandwidth FI has to include both signals from the control structure, current and voltage. An example of such solution is shown in [186]. The amplitudes of 2nd harmonics in instantaneous active and reactive power signals are proposed to be the diagnostic signals. It is shown that they are not sensitive to current controller bandwidth. However, as stated in [187] the active power signal based FI does not adapt with the bandwidth. Therefore, the authors proposed a modified solution, using a Rayleigh quotient function [187] with four signals, 2nd order harmonic amplitudes of: *d*-axis and *q*-axis voltage and current vector components. Thus, the proposed quotient is a weighted sum of mentioned signals (normalized to healthy values) and automatically adapt to the current controlled bandwidth. It is shown that its value is constant in a wide range of the bandwidth.

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 mostly applied in the case of electrical damage diagnosis. A further work on the diagnosis of mechanical faults using the control structure signals is required, especially to evaluate the signals that can be used and to verify the influence of the controllers bandwidth on the fault detection.

VII. MODEL-BASED FAULT DETECTION OF PMSM DRIVE

A. GENERAL REMARKS

Increasing computational power and efforts to develop fault-tolerant systems leads 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 power system components to calculate the residuals between measured and estimated signals, showing the occurrence of a fault [16], [18], [22], [23]. Typical example is the detection of sensor faults in the drive system, which is studied in Section IXB. Estimators of parameters, e.g. stator resistance, as well as observers of state variables can infer inter-turn stator winding faults on-line, as discussed later in this section. However, the most common application is the use of mathematical models, in particular based on FEM in modelling of 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. Moreover, PMSMs fault modelling can be also used to generate symptoms of different faults, which provide data for training neural fault detectors. It is important to note that the obtaining of 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 of the PMSM failures requires tests on specially prepared machines (physical modelling of ITSC, partial or uniform demagnetization, eccentricity or misalignment). The use of the information on failure symptoms from mathematical models may allow for the abandonment of physical modelling of failures in order 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 the fault detection but also the location of the damaged phase. This approach has been adopted also for a PMSG system in [189], where also the unscented Kalman filter (UKF) was 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 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 the PMSM along the *d*-axis to detect PM demagnetization on-line [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 the normalization with respect to the angular speed of the motor is used as the damage index.

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

The on-line 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.

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 multi-phase motors [213]. Models have been used in PMSM diagnostics to search for 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 additional signal [64], as well as to determine the residuals in comparison methods [194], where, based on the currents signals in synchronous reference frame compared to the 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 model by introducing nonlinear 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 literatures 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 PMSMs failures. 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. Authors of [202], [203], [204] performed an analysis of the effect of demagnetization on FEM model where they proposed selection of the PMs. The article [206] proposes a method affecting the anti-demagnetization 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 simulation model results, to detect demagnetization faults. The resulting voltage and current signals delivered from the simulation model for different load torque and speed values allowed 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

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2022.3180153, IEEE Access

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 objectify the process of classification and assessment of the 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, containing 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 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.

In addition, 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, the 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.

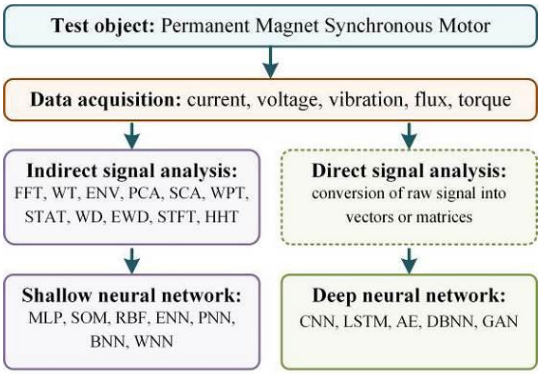


FIGURE 5. **Classification of the PMSM damage detection methods using shallow and deep-learning neural networks.**

As shown in Fig. 5, the use of the SNN structures in the diagnostics of electrical machines makes it necessary to pre-process 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, HHT, which significantly extends 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 considered damage. 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 VIII shows that the largest number of works related to the design of neural damage detectors of PMSMs concerns 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 damages: bearing damage [121, 231], eccentricity [231], and in the case of the damage to the stator electrical circuits [215-218], [224], [225], [232], supply voltage unbalance [219], [221], [227] or stator phase loss [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. Such a solution was presented, inter alia, 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 the simultaneous application of the results of FFT and statistical analysis made it possible to obtain a high efficiency of fault detection of the PMSM stator windings. The combination of spectral analysis with additional methods of signal processing was also presented in [120], [121].

TABLE VIII.
ARTIFICIAL INTELLIGENCE-BASED METHODS OF PMSM FAULTS DETECTION – LITERATURE ANALYSIS

No	Fault category						NN structure	Preprocessing method	Diagnostic signal
	1	2	3	4	5	6			
[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.

On the contrary, in [236] the VKF-OT and dynamic Bayesian network were employed for the real-time rotor demagnetization detection from torque ripples. In this work, the torque transient obtained from simulation model was processed by WT to eliminate the 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 reflecting changes in PM status. These features were used to train the BNN for the rotor magnet demagnetization detection during motor operation over the 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 (RBF) [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 discussed MLP, SOM and RBF structures, recursive networks are characterized by the existence of feedback between neurons. In addition, the 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 presented examples, a small number of papers describing shallow structures in the diagnosis of mechanical damage as well as mixed damage are noticeable. 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. To summarize, the applications of the shallow neural structures in the PMSM fault detection are still an unrecognized branch of diagnostic research that need further development.

C. DEEP NEURAL NETWORKS APPLICATION IN PMSM DRIVES

The development of diagnostic systems in recent years is related to the concept of the 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 more difficult training process, they are mainly used 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 has a specific structure (matrices) or repeating sequences. The possibility of direct extraction of the input signal features in the diagnostics of PMSM stator windings faults 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 pre-processed information [219], [228], [230], [233]. However, the direct analysis provides a significant reduction in the reaction time of the diagnostic system to the occurring damage, which is its unquestionable advantage. Moreover, 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. Thanks 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 unattainable for shallow structures, with a signal acquisition time several dozen times shorter.

Nevertheless, DL methods in diagnostics are primarily used in the problems of detecting faults in IMs. Moreover, there is little information in the literature on the impact of structure, learning methods and network type on the effectiveness of DNN-based systems.

Fault classification accuracy obtained with the usage of selected SNN and DNN structures based on the literature overview is presented in Table IX.

TABLE IX.

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.

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

A. FREQUENCY CONVERTER FAULTS

Frequency converters are the closest link between the digital control and power output in the ASDs, including PMSM drive. Nevertheless, 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], power semiconductor device damages account for approximately 35% of all ASD faults. There are many fault types of 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 modules failures compose 35% of power converter faults, as shown in Fig. 6. All these failures result in deterioration of the drive performance or even an unplanned stoppage of the drive system.

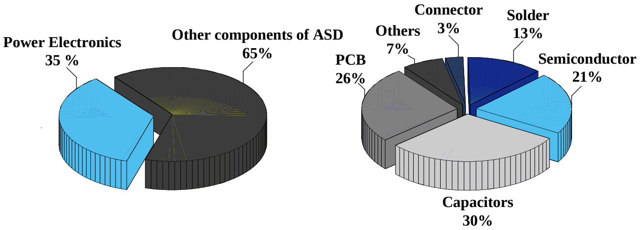


FIGURE 6. Distribution of faults in adjustable speed drives and in power converters.

About 30% of FC failures are related to abnormal operation of intermediate filter capacitors. As a result of aging their capacity decreases and the internal impedance increases [240]. As a consequence, they fail permanently, consisting in 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 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 due to their low cost. However, the main disadvantage of electrolytic capacitors is their limited lifetime and a high failure rate due to degradation of wear. The capacitor banks lose their initial operating characteristics because of the aging effects, such as the 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 for diagnosing electrolytic capacitor failure. The methods of the DC-link electrolytic capacitor fault detection based on estimation of ESR are presented in [241]. They are on-line methods, realized using AC current injection in *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 recursive least square method. The off-line methods are also applied, as this based on capacitor model [242] or hardware-based measurement of ESR [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 failures related to electric drives [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 the 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 categorized 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 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 most often used in drive systems with three-phase AC motors.

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

The development of software-based algorithms for the diagnosis of shorted switches has not been the main subject of the academic research in the last decades. In [249] the motor supply current PVA is proposed for the VSI short-circuit and open switch fault diagnosis in variable speed AC drives. 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 process of switch fault diagnosis. 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, decreased efficiency and the motor output irresistible torque gap, resulting in 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. Moreover, this type of failure results in the degradation of the drive performance, which may lead to disastrous accidents in application requiring increased robustness, such as electric vehicles [252]. Therefore, due to the hazardous effects of this type of the damage, many methods of its detection have been developed in last decades [253].

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

The literature review shows that the open-circuit FDD methods may be classified as current signatures [254]–[260], [267]-[272] and voltage signatures based methods [261]–[264], [273]. These methods can be also 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 PMSM drive based on the *d-q* frame current signatures along with the faulty phase localization is presented in [184]. Authors highlighted the simplicity of the proposed approach. In [255] and [256] a robust open-switch fault diagnostics technique 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 is presented. 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 based on the FFT method and the torque generation mechanism. In order to assess the asymmetry and to distinguish the fault type, FI was proposed as the ratio of the magnitude 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 the real-time estimation of motor currents using three Kalman filters is presented in [252]. The Authors proposed the averaged normalized residual analysis of the measured and estimated currents as diagnostic criteria for 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 which is used as a FI of the VSI for five-phase PMSM. In this research, 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, stator currents in *d-q* frame are utilized. Afterward, the polarities of normalized α -β frame current average values and phase angles of residual current vectors are utilized to locate the faulty 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]. Authors proved that detection times shorter than 10 μs can be achieved.

The 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 and the measured pole voltage. This residual is directly compared with a threshold, which is determined through analysis of measured voltage deviations from the reference in the normal state. In [73] the harmonic tracking of the ZSVC spectrum is introduced for a detection of the open phase fault in the PMSM drive system. This method enables not only to detect the fault, but also to

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2022.3180153, IEEE Access

distinguish the fault type: ITSC of the stator winding or switch failure of the inverter.

The model-based approach for diagnosis of open-circuit fault 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 the estimated voltages. Different types of observers were also employed for open-switch detection [265] for PMSM drives. These methods perform a good diagnosis with a relatively short detection time. As they are based on residual generation between observer model and motor signals, they are sensitive to motor parameters variations. For these methods, the threshold selector is still the key issue to insure effective and robust diagnosis.

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

The current-based methods use the current signals which can be directly measured or calculated using mathematical models. Some of them utilize the solutions based on the current hodograph analysis [266].]267] or the algorithms that consist in calculation of DC component in the phase currents [268]. Other solutions are based on the observation of the current vector rotation and average values of the phase currents. Transistor failure causes 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 α–β 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 period of 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 load changes.

Although in most cases average values of measured currents are used as diagnostic variables, the works [271], [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 noticed that in most presented papers the methods proposed for open switch faults in active rectifiers are not validated under both rectifying and regenerating mode. It was shown in [273] that the transistor open-circuit faults diagnostic technique based on the grid currents prediction 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 for single and multiple transistor faults detection in a time shorter than one current fundamental period.

In the case of multi-level rectifiers, mainly voltage methods of transistor fault diagnostics are used, based on the voltage signals of DC-link capacitors. Rectifier transistors failures lead to voltage asymmetry on capacitors, which enables simple detection of a damaged transistor on the basis of additional information about 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.

TABLE X.
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 on-line	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 off-line	Capacitor model Hardware measurement

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 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 the system parameters and do 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 as 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 X, 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 measured usually in a PMSM drive. Sensor failures may consist in: 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, a 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 their proper operation, and in the event of the failure, to detect, to isolate and compensate the 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]. The signal-based methods consist in extracting the information about the damage, contained in the measured signal and evaluating the damage in accordance with the characteristic fault symptom or comparison with a behavior of an undamaged system. However, the 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 for model-based techniques is their robustness to system parameter changes and the threshold choice for the particular failure types in a given system [275].

DC-link voltage sensor failure can be easily identified as the measured value of this voltage is much greater than zero under normal operating conditions. Thus, a sudden significant change in the measured value indicates a voltage sensor failure [276]. When the faulty sensor is isolated, the actual DC-link voltage signal is replaced with its estimated value. In [276] the simple method based on 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 the work [277] an on-line adaptive observer is proposed for simultaneous estimation of unknown DC-link voltage, rotor fluxes and rotor resistance, to make the observer more robust to parameters uncertainty. But this solution was designed only for induction motor drive systems. However, this methodology can be also adopted to PMSM drive. More interesting solution, which consists in a special kind of adaptive observer of the DC-link voltage is presented in [278]. It was reported that this observer is robust to stator winding parameters and performs well under different operating conditions.

Different type 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 extended observer [279] or sliding mode observer (SMO) [280], can be used for speed residuum generation. The other solution, based on a model reference adaptive system (MRAS) concept, 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. Based on 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 additional estimation of the stator resistance is required in these observers, to ensure the proper accuracy of PMSM position and velocity [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 authors proposed an EKF for the estimation of position and rotor velocity of a PMSM. Speed and position were used as additional components of the extended state vector and 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, a few schemes based on SMOs have been proposed for the speed estimation of a PMSM [283]-[285]. In [283] the SMO was developed with sign-type switching function replaced by a sigmoid function with some boundary layer, to avoid the time delay occurring 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 from 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 without low-pass filtering was obtained using this approach. Based on the estimated BEMF, an accurate speed estimate of PMSM was algebraically computed.

The signal-based methods are not used as often for the detection of current sensor (CS) faults in PMSM drives as the model-based method. Nevertheless, an 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, which is presently widely used. In [287], the FDD method with additional current sensors (five in total) is applied. This approach allows the fault isolation to be performed on the whole speed range including zero speed and is inherently insensitive to the drive parameter uncertainties, however it requires significant sensor redundancy. The method proposed in [288] (for PM synchronous generator) and in [289] (for PMSM) uses average normalized current values, but it is limited to failure of one of the three CSs present in the drive system.

On the contrary, in [290] a signal-based method for different CS fault types was proposed, namely for a single or double signal-loss faults (concurrent or independent), gain-variation and zero-offset. Information about three-phase currents and the position of the rotor is required in the proposed method. 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, that allows to determine the components of the stator current differently, depending on which CS is actually faulted. An assumption was made, that two of three CSs are used for the stator current reconstruction under the fault of a single sensor. 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 works [288] and [289] authors proposed an effective and robust diagnosis of CS faults, and IGBTs single and multiple open-circuit faults of the inverter, where the same algorithm is used to detect, localize, 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 the 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 *d*-*q* components of the stator current vector was proposed for missing current estimation. A model reference adaptive observer to estimate the phase current of PMSM by using the information of position, speed, and voltage in α-β frame was introduced in [293], whereas a SMOs were suggested to diagnose the CS faults of PMSM drive in [294] and [295]. In [296] an encoderless control scheme using SMO with only one current sensor for fault diagnosis and FTC of PMSM drives is proposed. The 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 currents 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]. The sensor failure was treated as an additional variable extending the observer state vector. The CS gain failure detection is based on the calculation of the 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 using the parity space approach is introduced, however, the procedure of the design is mathematically complicated.

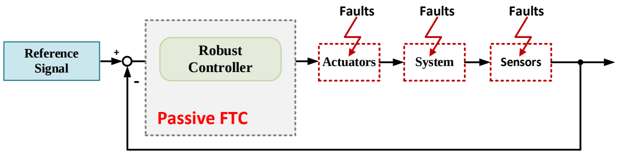
In recent years, the methods which do not need exact knowledge of motor parameters were also proposed. For example, the method based on *d*-*q* axis currents estimated from the reference currents and the healthy measured phase current is presented in [303]. However, in steady-state operation, especially at high speed, the estimated current errors are half the actual ones in steady-state post-fault operation. Hence, the response of the current command will be slowed. However, the control targets can be achieved since 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 using simulation tests. However, the additional CS in the DC-link of the frequency converter is required.

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

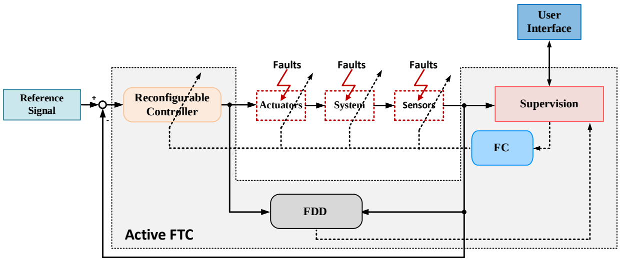
C. FAULT-TOLERNAT CONTROL

From the mid-2000s, as a result of intensively developing FDD methods for AC motor drives, first FTC strategies for drive systems began to appear [33]. It concerned also 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 works 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.



(a)



(b)

FIGURE 7. Passive (a) and active (b) FTC systems; FDD – Fault Diagnosis and Detection, FC – Fault Compensation.

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 parameters of the controller (Fig. 7a). This approach does not require on-line 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.

Contrary to passive methods, AFTC is based on the controller reconfiguration or by using several switchable regulators. Also the fault compensation (FC) methods are used in this approach. Therefore, this technique requires a system that realizes the task of detecting and localizing the 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 a hardware-based solutions. There are a number of techniques for the 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 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 these cases, the semiconductor devices are oversized, as are the DC-link capacitors, and the inverter output power is limited during fault-mode. The first and second approaches require access to the midpoint of the DC-link, while 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 full fault recovery 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 converter or modular multilevel converters. However, it has been shown in [310], that also much less complicated solutions are possible due to proper modification of modulation technique of the classical T-type three-level inverter under the open-circuit fault. The modulation strategies presented there can provide FTC strategy for continuous operation with sinusoidal currents without additional cost.

Due to the safety-critical applications of PMSM machines, high fault tolerance design solutions are sought. The concept of a **PM fault-tolerant (PMFT) machine** 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 on the PMFT machine design is presented, with an emphasis on limiting the short-circuit current. The latest results of research work in this area are presented in [313], with a particular consideration of the design and analysis of the machine topology, including: modular design, short-circuit current limiting design, redundant design, ease of heat dissipation in PM and design techniques for increasing the torque. Based on the analysis of 143 references from over 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. It has also been found that in addition to the modular design, multiphase technology can provide fault tolerance through its redundancy. A new class of stator-PM machines has also been introduced, which not only provides fault tolerance but also improved 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 realize the 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 outputs [315], sliding-mode controller (SMC) [316] or MPC [317]-[319]. All these solutions were proposed for open-phase fault of the multiphase motors and were focused on the minimization of the 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 a number of 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 cut off from the system without affecting the health modules operating normally. But these solutions based on PMFT machines are costly.

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

OC-FTC methods were addressed in the literature, e.g. in [321]-[323]. In [321] the reference frame transformations-based method is proposed for the PMSM under open-circuit fault, which enables the suitable torque control under healthy and faulted conditions, with no modifications of the control topology. 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 the fault detection. These solutions show significant robustness against motor parameter variation or load fluctuations, and negligible implementation costs, since no hardware modifications are needed. In [323] a FTC strategy based on a finite-control-set MPC was proposed for a three-phase four-wire converter topology of the PMSM drive which connects the neutral point of the motor to the middle of the DC-link capacitor. The main advantage of this solution is that there is no need to converter topology modification after the fault detection and thus the transition from healthy to faulty state is smooth.

So far, the **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. Authors of [325] proposed modification of the classical FOC structure with hysteresis controllers by an injection of unbalanced current component, which occurs in the PMSM under the ITSC fault. It enabled the reduction of the torque ripples. In [326] the ITSC fault-tolerant method is proposed, which consists in limiting internal copper losses of the motor. The control strategies presented in [324]-[326] concern mainly the reduction of the electromagnetic torque ripple or copper losses, but they do not limit the value of the short-circuit current, which is dangerous for the machine. There are very few articles on fault current mitigation methods. In order to limit the ITSC current, a strategy based on 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 the ITSC fault in PMSG with fractional-slot concentrated-winding. The proposed method enables limiting 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 reduced 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 damage spreading out 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 based nowadays 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 voltage pulse signal injection, e.g. [330], [331] and HF signal injection, e.g. [332].

In SS-FTC solutions for the 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 to 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 IXB can be used in the 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]. Moreover, speed estimation methods with increased accuracy in the range of low speeds, which combine classical observers with the 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 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. Only recently researchers have started to be interested in the possibilities of compensating damage to stator current sensors in PMSM drives. Chapter IXB, 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 need the information on measured DC-link voltage, as well as the 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] authors claims, that all stator currents can be estimated by single LO and 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 the speed, DC-link voltage, and CS faults. Except the adaptive observer for 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 both current sensor failures. The performance of the drive deteriorates significantly but still is a remedy temporarily. When a sensor fault is detected, the drive system immediately isolates the faulty sensor while retaining the remaining functional ones. However authors assumed the failure of only single sensor at one time. It should be mentioned, that for successful estimation of DC-link voltage or stator currents the information on measured motor speed is required.

In [337] a CS-FTC scheme based on dual SMOs is proposed for encoderless PMSM drive. After the 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 multi-phase PMSM drives. Recently published paper [338] introduces such technique for 5P-PMSM, based on SMO, developed for the case of damage to the CSs 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, the signals are sent to the back-stepping controller. which ensures very good dynamic properties of the drive.

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

X. CONCLUSIONS

The presented review of diagnostic methods and techniques used for PMSM drives shows that an immense amount of works have 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 miscellaneous 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.

On the basis of 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 non-stationary signals. The existing time-frequency signal processing methods are very time-consuming, which makes the on-line 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 diagnostics 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 on-line diagnostics of these damages without the need to use additional sensors in the drives, i.e. vibration acceleration sensors.

– **Multiple faults diagnosis:** diagnostic and classification of multiple faults is a difficult task because the same or similar failure symptoms may correspond to different failures. In the field of PMSM drives an example is the demagnetization failure and the need to differentiate it in the presence of the damage to the stator winding or mechanical damage to the rotor. The choice of diagnostic signals and methods of their processing 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 the fault diagnosis for higher accuracy and robustness as well as on-line operation. This technology has many advantages and big potential in fault feature extraction and pattern recognition. However, the related achievements in the field of PMSM fault detection and classification are relatively small compared to the IM and further research is needed.

– **Transfer learning:** it is a research problem in machine learning that focuses on storing 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, is still 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 on-line (real-time) operation of the drive system. This is a significant lack, because there are many additional demands connected with the real-time operation, related mainly to signal processing methods and fault detector implementation, including necessary processing power, data storage capability and disturbances. Data acquisition and processing is a major challenge for diagnostic systems.

– **Fault-tolerant systems:** integrated solutions with the combination of the fault detection and classification (especially in the case of multiple faults connected with the 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 concerning 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 requires forecasting the evolution of failures and predicting when the machine will no longer operate as desired. These issues 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:** Nowadays, the world is moving towards the 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 the 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.

REFERENCES

[1] Husain I., *Electric and Hybrid Vehicles*. Design Fundamentals, CRC Press, 2nd ed., 2011
[2] M. Hermance, Y. Gao, and J.M. Miller, “Hybrid electric vehicles: architecture and motor drives,” *Proc. IEEE*, vol. 95, no. 4, pp. 719-728, Apr. 2007.
[3] P.J. Tavner, “Review of condition monitoring of rotating machines,” *IET Electric Power Applications,* vol. 2, no.4, pp.215-247, 2008, 10.1049/iet-epa:20070280
[4] X. Wu, Y. Li, T. Lundell, and A. Guru, "Integrated prognosis of ac servo motor driven linear actuator using hidden semi-Markov models", *Proc. IEEE IEMDC*, pp. 1408-1413, 2009-May.
[5] E.G. Strangas, S. Aviyente, and S.S.H. Zaidi, “Time–frequency analysis for efficient fault diagnosis and failure prognosis for interior permanent magnet AC motors,” *IEEE Trans. Ind. Electron.*, vol. 55, no. 12, pp. 4191–4199, Dec. 2008.
[6] E.G. Strangas, S. Aviyente, J.D. Neely, and S.S.H. Zaidi, “The effect of failure prognosis and mitigation on the reliability of permanent-magnet AC motor drives,” *IEEE Trans. Ind. Electr.*, vol. 60, no.6, pp. 3519–3528, Nov. 2013.
[7] M. El Hachemi Benbouzid, “A review of induction motors signature analysis as a medium for faults detection,” *IEEE Trans. Industrial Electronics*, , vol. 47, no. 5, pp. 984-993, 2000.
[8] G. Singh, „Induction machine drive condition monitoring and diagnostic research–a survey“. *Electric Power Syst. Research,* vol. 64, pp. 145-158, 2003.
[9] S. Nandi, H.A. Toliyat, and X. Li, „Condition monitoring and fault diagnosis of electrical motors–A review,“ *IEEE Trans. Energy Conv.*, vol. 20, pp. 719-729, 2005.
[10] A. Bellini, F. Filippetti, C. Tassoni, and G.-A. Capolino, “Advances in diagnostic techniques for induction machines,” *IEEE Trans. Ind. Electron.*, vol. 55, no. 12, pp. 4109–4126, Dec. 2008.
[11] H. Henao,, G.A. Capolino, M. Fernandez-Cabanas, F. Filippetti, C. Bruzzese, E. Strangas, R. Pusca, J. Estima, M. Riera-Guasp, and S. Hedayati-Kia, “Trends in Fault Diagnosis for Electrical Machines: A Review of Diagnostic Techniques,” *IEEE Ind. Electron. Mag.* vol. 8, pp. 31-42, 2014.
[12] G. A. Capolino, J. A-. Daviu, and M. Riera-Guasp, „Modern diagnostics techniques for electrical machines, power electronics, and drives,“ *IEEE Trans. Ind. Electr.*., vol. 62, no. 3, pp. 1738–1745, March 2015.
[13] M. Riera-Guasp, J. Antonino-Daviu, and G.A. Capolino, “Advances in electrical machine, power electronic and drive condition monitoring and fault detection: State of the art,” *IEEE Trans. Ind. Electron*. vol. 62, no. 3, pp. 1746–1759, March 2015.
[14] Y. Da, X. Shi, and M. Krishnamurthy, “Health monitoring, fault diagnosis and failure prognosis techniques for Brushless Permanent Magnet Machines,” in: *Proc. 2011 IEEE Vehicle Power Prop. Conf.*, Sept. 2011.
[15] M. Cheng, J. Hang, and J.Zhang, “Overview of fault diagnosis theory and method for permanent magnet machine,” *Chinese Journal of Electrical Eng.*, vol. 1 no. 1, pp. 21-36, 2015..
[16] J. Zheng, Z. Wang, D. Wang, Y. Li and M. Li, "Review of fault diagnosis of PMSM drive system in electric vehicles," in: *2017 36th Chinese Control Conf. (CCC)*, pp. 7426-7432, July 2017.
[17] M. Krichen, N. Benhadj, M. Chaieb, and R. Neji, “Fault Detection and Diagnosis Methods in Permanent Magnet Synchronous Machines: A Review, “ *Int. Conf. Recent Adv. Electrical Syst. (ICRAES'17)*, Dec. 2017.
[18] Z. Ullah, and J. Hur, “A Comprehensive Review of Winding Short Circuit Fault and Irreversible Demagnetization Fault Detection in PM Type Machines,” *Energies*, vol. 11, no. 12, p. 3309, Nov. 2018.
[19] S. Choi, M.S. Haque, M.T.B. Tarek, V. Mulpuri, Y. Duan, S. Das, and H.A. Toliyat, „Fault diagnosis techniques for permanent magnet AC machine and drives—A review of current state of the art*.” IEEE Trans. Transportation Electrification*, vol. 4, no. 2, pp. 444-463, Feb. 2018.
[20] Y. Chen, S. Liang, W. Li, H. Liang, and C. Wang, “Faults and diagnosis methods of permanent magnet synchronous motors: A review.” *Applied Sciences*, vol. 9, no. 10, art. 2116, Oct. 2019.
[21] H. Wu, and J. Feng, “A Review of Fault Diagnosis Methods of Robot Joint Servo System.” *2020 IEEE Int. Conf. Mechatronics and Automation (ICMA)*, pp. 61-66, Oct. 2020.
[22] E.A. Bhuiyan, M.M.A. Akhand, S.K. Das, M.F. Ali, Z. Tasneem, M.R. Islam, and S.I. Moyeen, “A survey on fault diagnosis and fault tolerant methodologies for permanent magnet synchronous machines.” *Int. J. Automation and Computing*, vol. 17, no. 6, pp. 763–787, 2020.
[23] R. Li, Z. Wu and X. Li, "Review on fault diagnosis and active fault tolerant control of permanent magnet synchronous motor drive system," *Journal of Appl. Science and Eng.*, vol. 24, no 2, pp. 185-205, 2021.
[24] Z. Wang, J. Yang, H. Ye, W. Zhou, “A review of Permanent Magnet Synchronous Motor fault diagnosis,” *2014 IEEE Conf. and Expo Transportation Electrif. Asia-Pacific (ITEC Asia-Pacific)*, Aug. 2014.
[25] A. Usman, B.M. Joshi, and B.S. Rajpurohit, “Review of fault modeling methods for permanent magnet synchronous motors and their comparison,” *2017 IEEE 11th Int. Symp. Diagn. Electrical Machines, Power Electronics and Drives (SDEMPED)*, pp. 141-146, Aug. 2017.
[26] J. Faiz, H. Nejadi-Koti, and Z. Vlipour, “Comprehensive review on inter-turn fault indexes in permanent magnet motors,” *IET Electric Power Applications*, vol. 11, no.1, pp. 142-156, 2016.
[27] A.Gandhi, T. Corrigan, and L. Parsa, Recent Advances in Modeling and Online Detection of Stator Interturn Faults in Electrical Motors*,” IEEE Trans. Industrial Electronics*, vol. 58, no. 5, pp. 1564-1575, May 2011.
[28] J. Faiz, and H. Nejadi-Koti, “Demagnetization Fault Indexes in Permanent Magnet Synchronous Motors–An Overview,” *IEEE Trans. Magn.*, vol. 52, no. 4, pp. 1-11, Apr. 2016.
[29] J. Faiz, and E. Mazaheri-Tehrani, “Demagnetization Modeling and Fault Diagnosing Techniques in Permanent Magnet Machines Under Stationary and Nonstationary Conditions: An Overview,” *IEEE Trans Ind. Appl.*, vol. 53, no.3, pp. 2772-2785, May/June 2017.
[30] S.S. Moosavi, A. Djerdir, Y.A. Amirat, and D.A. Khaburi, “Demagnetization fault diagnosis in permanent magnet synchronous motors: A review of the state-of-the-art,” *Journal of Magnetism and Magnetic Materials*, vol. 391, pp. 203-212, Oct. 2015.
[31] J. Faiz, and H. Nejadi-Koti, “Eccentricity fault diagnosis indices for permanent magnet machines – state of the art,” *IET Electric Power Applications*, vol. 13, no. 9, pp. 1241-1254, 2019.
[32] L. Frosini, “Novel Diagnostic Techniques for Rotating Electrical Machines—A Review,” *Energies*, vol. 13, no. 9, art. 5066, 2020.
[33] T. Orlowska-Kowalska, C.T. Kowalski, and M. Dybkowski, “Fault Diagnosis and Fault-Tolerant-Control in Industrial Processes and Electrical

Drives," in: *Advanced control of electrical drives and power electronic converters*, Ed. by Jacek Kabziński. Springer, 2017, pp. 101-120
[34] P. O'Donell, "Report of Large Motor Reliability Survey of Industrial and Commercial Installations: Part I-II," *IEEE Trans Ind. Appl*., vol. IA 21, no. 4, pp. 853-872, 1985.
[35] H. Jiangbiao, C. Somogyi, A. Strandt, and N.A.O. Demerdash, "Diagnosis of Stator Winding Short-Circuit Faults in an Interior Permanent Magnet Synchronous Machine," in*: Proc. 2014 IEEE Energy Conv. Congr. Exp. (ECCE)*, Pittsburgh, USA, 14-18 Sept. 2014, pp. 3125-3130.
[36] C. W. Cheng, H. C. Man, and F. T. Cheng, "Magnetic and corrosion characteristics of Nd-Fe-B magnet with various surface coatings", *IEEE Trans. Magnetics*, vol. 33, no. 5, pp. 3910-3912, Sept. 1997.
[37] D. Hyun, T.-J. Kang, S. Lee, C. Kral, and A. Haumer, " Detection and classification of rotor demagnetization and eccentricity faults for PM synchronous motors," *in Proc. Energy, Covers. Cogr. Expo.*, Phoenix, AZ, USA, Sep. 2011, pp. 2512–2519.
[38] K. Kim, "Simple Online Fault Detecting Scheme for Short-Circuited Turn in a PMSM Through Current Harmonic Monitoring," *IEEE Trans. Industrial Electronics*, vol. 58, no. 6, pp. 2565-2568, June 2011.
[39] B. M. Ebrahimi and J. Faiz, "Feature Extraction for Short-Circuit Fault Detection in Permanent-Magnet Synchronous Motors Using Stator-Current Monitoring," *IEEE Trans. Power Electronics*, vol. 25, no. 10, pp. 2673-2682, Oct. 2010.
[40] R. Z. Haddad and E. G. Strangas, "Fault detection and classification in permanent magnet synchronous machines using Fast Fourier Transform and Linear Discriminant Analysis," *Proc. 2013 9th IEEE Int. Symp. Diagnostics for Electric Machines, Power Electronics and Drives (SDEMPED)*, 2013, pp. 99-104.
[41] J. A. Rosero, L. Romeral, J. Cusido, A. Garcia and J. A. Ortega, "On the short-circuiting Fault Detection in a PMSM by means of Stator Current Transformations*,"* in: *Proc. 2007 IEEE Power Electr. Spec. Conf.*, 2007, pp. 1936-1941.
[42] M. Krzysztofiak, M. Skowron, and T. Orlowska-Kowalska, "Analysis of the Impact of Stator Inter-Turn Short Circuits on PMSM Drive with Scalar and Vector Control," *Energies*, vol. 14, no. 1, p. 153, Dec. 2020.
[43] P. Pietrzak and M. Wolkiewicz, "Comparison of Selected Methods for the Stator Winding Condition Monitoring of a PMSM Using the Stator Phase Currents," *Energies*, vol. 14, no. 6, p. 1630, Mar. 2021.
[44] L. Romeral, J. C. Urresty, J. -R. Riba Ruiz and A. Garcia Espinosa, "Modeling of Surface-Mounted Permanent Magnet Synchronous Motors With Stator Winding Interturn Faults," *IEEE Trans. Ind. Electronics*, vol. 58, no. 5, pp. 1576-1585, May 2011.
[45] C. Bouchareb, and M.S. N. Said, "PMSM Model with Phase-to-Phase Short-Circuit and Diagnosis by ESA and EPVA," *Power Engineering and Electrical Engineering*, vol. 14, no. 5, pp. 522-530, 2016.
[46] M.A.S. Nejad and M. Taghipour, "Inter-turn stator winding fault diagnosis and determination of fault percent in PMSM," in: *Proc. 2011 IEEE Appl. Power Electron. Colloquium (IAPEC)*, 2011, pp. 128-131.
[47] D. S. B. Fonseca, C. M. C. Santos and A. J. M. Cardoso, "Stator Faults Modeling and Diagnostics of Line-Start Permanent Magnet Synchronous Motors," *IEEE Trans. Ind. Appl.*, vol. 56, no. 3, pp. 2590-2599, May-June 2020.
[48] P. Pietrzak and M. Wolkiewicz, "On-line Detection and Classification of PMSM Stator Winding Faults Based on Stator Current Symmetrical Components Analysis and the KNN Algorithm," *Electronics*, vol. 10, no. 15, p. 1786, Jul. 2021.
[49] F. Çira, M. Arkan, B. Gümüş and T. Goktas, "Analysis of stator inter-turn short-circuit fault signatures for inverter-fed permanent magnet synchronous motors," in:. *Proc. 42nd Ann. Conf. IEEE Ind. Elect. Soc.*, 2016, pp. 1453-1457.
[50] J. Quiroga, L. Liu and D. A. Cartes, "Fuzzy logic based fault detection of PMSM stator winding short under load fluctuation using negative sequence analysis," in: *Proc. 2008 Amer. Control Conf.*, 2008, pp. 4262-4267.
[51] G. Ahn, J. Lee, C. H. Park, M. Youn and B. D. Youn, "Inter-turn Short Circuit Fault Detection in Permanent Magnet Synchronous Motors Based on Reference Voltage," in: *Proc. 2019 IEEE 12th Int. Symp. Diagnostics for El. Mach., Power Electr. Drives* (SDEMPED), 2019, pp. 245-250.
[52] T. Boileau, N. Leboeuf, B. Nahid-Mobarakeh and F. Meibody-Tabar, "Synchronous Demodulation of Control Voltages for Stator Interturn Fault Detection in PMSM," in *IEEE Trans. Power Electronics*, vol. 28, no. 12, pp. 5647-5654, Dec. 2013.
[53] Y. Lee and T. G. Habetler, "An On-Line Stator Turn Fault Detection Method for Interior PM Synchronous Motor Drives," *Proc. 22nd Ann. IEEE Applied Power Electronics Conf. and Exp.*, 2007, pp. 825-831.
[54] V. Gurusamy, E. Bostanci, C. Li, Y. Qi and B. Akin, "A Stray Magnetic Flux-Based Robust Diagnosis Method for Detection and Location of Interturn Short Circuit Fault in PMSM," *IEEE Trans. Instr. Measurement*, vol. 70, pp. 1-11, art no. 3500811, 2021.
[55] Y. Laamari, S. Allaoui, A. Bendaikha, and S. Saad, "Fault detection between stator windings turns of permanent magnet synchronous motor based on torque and stator-current analysis using FFT and discrete wavelet transform," *Mathematical Modelling of Engineering Problems*, vol. 8, no. 2, pp. 315-322, April 2021.
[56] M. A. Awadallah, M. M. Morcos, S. Gopalakrishnan and T. W. Nehl, "A neuro-fuzzy approach to automatic diagnosis and location of stator inter-turn faults in CSI-fed PM brushless DC motors," *IEEE Trans. Energy Conv.*, vol. 20, no. 2, pp. 253-259, June 2005.
[57] J. Zhao, X. Guan, C. Li, Q. Mou and Z. Chen, "Comprehensive Evaluation of Inter-Turn Short Circuit Faults in PMSM Used for Electric Vehicles," *IEEE Trans. Intelligent Transportation Systems*, vol. 22, no. 1, pp. 611-621, Jan. 2021.
[58] T. Boileau, B. Nahid-Mobarakeh and F. Meibody-Tabar, "Back-EMF Based Detection of Stator Winding Inter-turn Fault for PM Synchronous Motor Drives," in: *Proc. 2007 IEEE Vehicle Power and Propulsion Conf.*, 2007, pp. 95-100.
[59] J. C. Urresty, J. R. Riba, and L. Romeral, "Application of the zero-sequence voltage component to detect stator winding inter-turn faults in PMSMs," *Elect. Power Syst. Res.*, vol. 89, pp. 38–44, Aug. 2012.
[60] J. Fang, Y. Sun, Y. Wang, B. Wei and J. Hang, "Improved ZSVC-based fault detection technique for incipient stage inter-turn fault in PMSM," *IET Electric Power Appl.*, vol. 13, no. 12, pp. 2015-2026, October 2019.
[61] J. Urresty, J. Riba, H. Saavedra and L. Romeral, "Detection of inter-turns short circuits in permanent magnet synchronous motors operating under transient conditions by means of the zero sequence voltage," *Proc. 2011 14th Eur. Conf. Power Electr. and Appl.*, 2011, pp. 1-9.
[62] J. Hang, J. Zhang, M. Cheng, and J. Huang, "Online Interturn Fault Diagnosis of Permanent Magnet Synchronous Machine Using Zero-Sequence Components," *IEEE Trans. Power Electronics*, vol. 30, no. 12, pp. 6731-6741, Dec. 2015.
[63] J. Urresty, J. Riba, and L. Romeral, "Diagnosis of Interturn Faults in PMSMs Operating Under Nonstationary Conditions by Applying Order Tracking Filtering," *IEEE Trans. Power Electron.*, vol. 28, no. 1, pp. 507-515, Jan. 2013.
[64] J. Zhang, Z. Xu, J. Wang, J. Zhao, Z. Din, and M. Cheng, "Detection and Discrimination of Incipient Stator Faults for Inverter-Fed Permanent Magnet Synchronous Machines," *IEEE Trans. Ind. Electron.*, vol. 68, no. 8, pp. 7505-7515, Aug. 2021.
[65] J. Rosero, J. Ortega, J. Urresty, J. Cardenas and L. Romeral, "Stator Short Circuits Detection in PMSM by means of Higher Order Spectral Analysis (HOSA)," in: *Proc. 2009 Twenty-Fourth Annual IEEE Applied Power Electronics Conf. Exp.*, 2009, pp. 964-969.
[66] B. Cai, Y. Zhao, H. Liu, and M. Xie, "A Data-Driven Fault Diagnosis Methodology in Three-Phase Inverters for PMSM Drive Systems," *IEEE Trans. Power Electron.*, vol. 32, no. 7, pp. 5590-5600, July 2017.
[67] W. G. Zanardelli, E. G. Strangas, and S. Aviyente, "Identification of Intermittent Electrical and Mechanical Faults in Permanent-Magnet AC Drives Based on Time–Frequency Analysis," *IEEE Trans. Ind. Applications*, vol. 43, no. 4, pp. 971-980, July-Aug. 2007.
[68] J. Rosero, J. Cusido, A. Garcia, L. Romeral, and J. A. Ortega, "Detection of Stator Short Circuits in PMSM by mean of joint Time-Frequency Analysis," in: *Proc. 2007 IEEE Int. Symp. Diagnostics for Electric Machines, Power Electronics and Drives*, 2007, pp. 420-425.
[69] N. Haje Obeid, A. Battiston, T. Boileau and B. Nahid-Mobarakeh, "Early Intermittent Interturn Fault Detection and Localization for a Permanent Magnet Synchronous Motor of Electrical Vehicles Using Wavelet Transform," *IEEE Trans. Transp. Electr*, vol. 3, no. 3, pp. 694-702, Sept. 2017.
[70] N. H. Obeid, A. Battiston, T. Boileau and B. Nahid-Mobarakeh, "Identification and localization of incipient intermittent inter-turn fault in the stator of a three phase permanent magnet synchronous motor," *Proc. 2017 IEEE 11th Int. Symp. Diagn. Electrical Machines, Power Electronics and Drives (SDEMPED)*, 2017, pp. 173-180.

[71] M. A. S. K. Khan and M. A. Rahman, "Development and Implementation of a Novel Fault Diagnostic and Protection Technique for IPM Motor Drives," *IEEE Trans. Ind. Electron.*, vol. 56, no. 1, pp. 85-92, Jan. 2009.

[72] J. Hang, J. Zhang, M. Xia, S. Ding and W. Hua, "Interturn Fault Diagnosis for Model-Predictive-Controlled-PMSM Based on Cost Function and Wavelet Transform," *IEEE Trans. Power Electronics*, vol. 35, no. 6, pp. 6405-6418, June 2020.

[73] N. H. Obeid, T. Boileau and B. Nahid-Mobarakeh, "Modeling and Diagnostic of Incipient Interturn Faults for a Three-Phase Permanent Magnet Synchronous Motor," *IEEE Trans. Ind. Appl.ications*, vol. 52, no. 5, pp. 4426-4434, Sept.-Oct. 2016.

[74] O. A. Mohammed, Z. Liu, S. Liu and N. Y. Abed, "Internal Short Circuit Fault Diagnosis for PM Machines Using FE-Based Phase Variable Model and Wavelets Analysis," *IEEE Trans. Magnetics*, vol. 43, no. 4, pp. 1729-1732, April 2007.

[75] P. Pietrzak and M. Wolkiewicz, "Application of Support Vector Machine to stator winding fault detection and classification of permanent magnet synchronous motor," in: *Proc. 2021 IEEE 19th Int. Power Elec. Motion Control Conf. (PEMC)*, 2021, pp. 880-887.

[76] J. Urresty, J. Riba, L. Romeral, J. Rosero and J. Serna, "Stator short circuits detection in PMSM by means of Hilbert-Huang transform and energy calculation," in: *Proc. 2009 IEEE Int. Symp. Diagn. Electric Machines, Power Electronics and Drives*, 2009, pp. 1-7.

[77] F. Alvarez-Gonzalez, A. Griffo, and B. Wang, "Permanent magnet synchronous machine stator windings fault detection by Hilbert-Huang transform," in: *Proc. Int. Conf. Power Electronics, Machines and Drives*, Liverpool, UK, 17–19 April 2018; pp. 3505–3509.

[78] J. A. Rosero, L. Romeral, J. A. Ortega and E. Rosero, "Short-Circuit Detection by Means of Empirical Mode Decomposition and Wigner–Ville Distribution for PMSM Running Under Dynamic Condition," *IEEE Trans. Ind. Electron.*, vol. 56, no. 11, pp. 4534-4547, Nov. 2009.

[79] Z. Dogan and K. Tetik, "Diagnosis of Inter-Turn Faults Based on Fault Harmonic Component Tracking in LSPMSMs Working Under Nonstationary Conditions," *IEEE Access*, vol. 9, pp. 92101-92112, 2021.

[80] N. Leboeuf, T. Boileau, B. Nahid-Mobarakeh, G. Clerc and F. Meibody-Tabar, "Real-Time Detection of Interturn Faults in PM Drives Using Back-EMF Estimation and Residual Analysis," *IEEE Trans. Ind. Applications*, vol. 47, no. 6, pp. 2402-2412, Nov.-Dec. 2011.

[81] A. Sarikhani and O. A. Mohammed, "Inter-Turn Fault Detection in PM Synchronous Machines by Physics-Based Back Electromotive Force Estimation," *IEEE Trans. Ind. Electron.*, vol. 60, no. 8, pp. 3472-3484, Aug. 2013.

[82] M. R. Minaz, "An effective method for detection of stator fault in PMSM with 1D-LBP," *ISA Transactions*, vol. 106, pp. 283-292, 2020.

[83] F. L. T. Guefack, A. Kiselev and A. Kuznietsov, "Improved Detection of Inter-turn Short Circuit Faults in PMSM Drives using Principal Component Analysis," *Proc. 2018 Int. Symp. Power Electronics, Electrical Drives, Aut. Motion (SPEEDAM)*, 2018, pp. 154-159.

[84] S. Rajagopalan, W. le Roux, T. G. Habetler, and R. G. Harley, "Dynamic eccentricity and demagnetized rotor magnet detection in trapezoidal flux (brushless DC) motors operating under different load conditions," *IEEE Trans. Power Electron.*, vol. 22, no. 5, pp. 2061–2069, Sep. 2007.

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

[86] J. Rosero, J. Cusido, A. Garcia, J. A. Ortega, and L. Romeral, "Study on the permanent magnet demagnetization fault in permanent magnet synchronous machines," in *Proc. IEEE IECON*, Nov. 2006, pp. 879-884.

[87] J. C. Urresty, J. R. Riba, and L. Romeral, "Influence of the stator windings configuration in the currents and zero-sequence voltage harmonics in permanent magnet synchronous motors with demagnetization faults," *IEEE Trans. Magn.*, vol. 49, no. 8, pp. 4885- 4893, Aug. 2013.

[88] R. Z. Haddad and E. G. Strangas, "On the accuracy of fault detection and separation in permanent magnet synchronous machines using MCSA/MVSA and LDA," *IEEE Trans. Energy Convers.*, vol. 31, no. 3, pp. 924–934, Sep. 2016.

[89] S. Ding, J. Hang, H. Li, and Q. Wang, "Demagnetisation fault detection in PMSM using zero sequence current components," *Electron. Lett.*, vol. 53, no. 3, pp. 148–150, 2017.

[90] J. C. Urresty, J.-R. Riba, M. Delgado, and L. Romeral, "Detection of demagnetization faults in surface-mounted permanent magnet synchronous motors by means of the zero-sequence voltage component," *IEEE Trans. Energy Convers.*, vol. 27, no. 1, pp. 42–51, Mar. 2012.

[91] Y. Da, X. Shi, and M. Krishnamurthy, "A new approach to fault diagnostics for permanent magnet synchronous machines using electromagnetic signature analysis," *IEEE Trans. Power Electron.*, vol. 28, no. 8, pp. 4104–4112, Aug. 2013.

[92] G.-A. Capolino, R. Romary, H. Henao, and R. Pusca, "State of the Art on Stray Flux Analysis in Faulted Electrical Machines" , in *Proc. IEEE Workshop on Electrical Machines Design, Control and Diagnosis (WEMDCD)*, Athens, Greece, 22-23 April 2019

[93] G.-A. Cappolino] T. Goktas, M. Zafarani, K.W. Lee, B. Akin, and T. Sculley, "Comprehensive Analysis of Magnet Defect Fault Monitoring Through Leakage Flux," *IEEE Trans. on Magnetics*, vol.53, n°4, art. no. 8201010, April 2017.

[94] D. Casadei, F. Filippetti, C. Rossi, and A. Stefani, "Magnets faults characterization for permanent magnet synchronous motors," in *Proc. IEEE Int. Symp. Diagnostics Electr. Mach., Power Electron. Drives*, Cargese, France, Aug./Sep. 2009, pp. 1–6.

[95] J. C. Urresty, J. R. Riba, and L. Romeral, "A back- EMF based method to detect magnet failures in PMSMs," *IEEE Trans. Magn.*, vol. 49, no. 1, pp. 591- 598, Jan. 2013.

[96] C. R. Ruschetti, C. J. Verucchi, G. R. Bossio, and G. O. Garcia, "A model for permanent magnet synchronous machines with demagnetization faults," *IEEE Latin Amer. Trans.*, vol. 11, no. 1, pp. 414–420, Feb. 2013.

[97] H.-K. Kim, D.-H. Kang, and J. Hur, "Fault detection of irreversible demagnetization based on space harmonics according to equivalent magnetizing distribution," *IEEE Trans. Magn.*, vol. 51, no. 11, art. no. 8109304, Nov. 2015.

[98] D. Casadei, M. Mengoni, G. Serra, A. Tani, and L. Zarri, "Behavior of a five-phase surface-mounted permanent magnet motor under magnet demagnetization," in *Proc. 8th IEEE Symp. Diagnostics Electr. Mach., Power Electron. Drives*, Bologna, Italy, Sep. 2011, pp. 265–271.

[99] Z. Yang, X. Shi, and M. Krishnamurthy, "Vibration monitoring of PM synchronous machine with partial demagnetization and inter-turn short circuit faults," in *Proc. 2014 IEEE Transp. Electr. Conf. Expo (ITEC)*, 15-18 June, 2014.

[100] D. Torregrossa, A. Khoobroo, and B. Fahimi, "Prediction of acoustic noise and torque pulsation in PM synchronous machines with static eccentricity and partial demagnetization using field reconstruction method," *IEEE Trans. Ind. Electron.*, vol. 59, no. 2, pp. 934-944, Feb. 2012.

[101] S.Rajagopalan, J. M. Aller, J. A. Restrepo, T. G. Habetler, and R. G. Harley, "Detection of rotor faults in brushless DC motors operating under non-stationary conditions," *IEEE Trans. Ind. Appl.*, vol. 42., no. 6, pp. 1464-1477, Nov./Dec. 2006.

[102] J. Rosero, L. Romeral, J. Cusido, and J.A. Ortega, Fault detection by means of wavelet transform in a PMSMW under demagnetization, in: *Proc. 33rd Ann. IEEE Ind. Electr. Soc. Conf., IECON*, Taipei, China, 5-7 Nov. 2007.

[103] J. R. Riba, J. A. Rosero, A. G. Espinosa, and L. Romeral, "Detection of demagnetization faults in permanent-magnet synchronous motors under nonstationary conditions," *IEEE Trans. Magn.*, vol. 45, no.7, pp. 2961-2969, Jul. 2009.

[104] T. Ishikawa, Y. Seki, and N. Kurita, "Analysis for fault detection of vector controlled permanent magnet synchronous motor with permanent magnet defect," *IEEE Trans. Magn.*, vol. 49, no. 5, pp. 2331-2334, May 2013.

[105] Y. Gritli, C. Rossi, D. Casadei, L. Zarri, and F. Filippetti, "Demagnetizations diagnosis for permanent magnet synchronous motors based on advanced wavelet analysis," in *Proc. 20th Int. Conf. Electr. Mach.*, Marseille, France, Sep. 2012, pp. 2397–2403.

[106] M. Zhu, W. Hu, and N. C. Kar, "Torque-ripple-based interior permanent-magnet synchronous machine rotor demagnetization fault detection and current regulation," *IEEE Trans. Ind. Appl.*, vol. 53, no. 3, pp. 2795–2804, May/Jun. 2017.

[107] S. Rajagopalan, J. A. Restrepo, J. M. Aller, T. G. Habetler, and R. G. Harley, "Wigner-Ville distributions for detection of rotor faults in brushless DC (BLDC) motors operating under non-stationary conditions," in *Proc. 5th IEEE Int. Symp. Diagn. El. Mach., Power Electr. Drives.*, 2005, pp. 1–7.

[108] D. Prieto, A. G. Espinosa, J.-R. R. Ruiz, J. C. Urresty, and J. A. Ortega, "Feature extraction of demagnetization faults in permanent-magnet synchronous motors based on box-counting fractal dimension," *IEEE Trans. Ind. Electron.*, vol. 58, no. 5, pp. 1594–1605, May 2011.

[109] J. Rosero, A. Garcia, J. Cusido, L. Romeral, and J.A. Ortega, Fault detection by means of Hilbert Huang Transform of the stator current in a PMSM with demagnetization, in: *Proc. IEEE Int. Symp. on Intelligent Signal Processing, WISP*, October 2007, pp. 1–6

[110] J.Rosero, L. Romeral,J.A. Ortega, and J.C. Urresty, Demagnetization fault detection by means of Hilbert Huang transform of the stator current decomposition in PMSM, *in Prof. of 2008 IEEE Intr. Symp. Industrial Electronics (ISIE)*, Cambridge UK 30-June-2July, 2008,

[111] A. G. Espinosa, J. A. Rosero, J. Cusido, L. Romeral, and J. A. Ortega, "Fault detection by means of Hilbert-Huang transform of the stator current in a PMSM with demagnetization," *IEEE Trans. Energy Convers.*, vol. 25, no. 2, pp. 312–318, Jun. 2010.

[112] J.-R. R. Ruiz, A. Garcia Espinosa, L. Romeral, and J. Cusido, "Demagnetization diagnosis in permanent magnet synchronous motors under nonstationary speed conditions," *Elect. Power Syst. Res.*, vol. 80, no. 10, pp. 1277–1285, Oct. 2010.

[113] C. Wang, M. Delgado, L. Romeral, Z. Chen, F. Blaabjerg, and X. Liu, "Detection of partial demagnetization fault in PMSMs operating under nonstationary conditions," *IEEE Trans. Magn.*, vol. 52, no. 7, art no. 8105804, pp. 1-4, July 2016.

[114] B. M. Ebrahimi and J. Faiz, "Demagnetization fault diagnosis in surface mounted permanent magnet synchronous motors," *IEEE Trans. Magn.*, vol. 49, no. 3, pp. 1185–1192, Mar. 2013.

[115] K.-W. Lee, J. Hong, S. Bin Lee, and S. Lee, "Quality assurance testing for magnetization quality assessment of BLDC motors used in compressors," *IEEE Trans. Ind. Appl.*, vol. 46, no. 6, pp. 2452–2458, Nov. 2010.

[116] A. Picot, Z. Obeid, J. Régnier, P. Maussion, S. Poignant, and O. Darnis, "Bearing fault detection in synchronous machine based on the statistical analysis of stator current". In: *2012-38th Ann. Conf. IEEE Ind. Electr, Soc. (IECON)*, pp. 3862-3867, October 2012.

[117] J. Guo, S. Lu, C. Zhai, and Q. He, "Automatic bearing fault diagnosis of permanent magnet synchronous generators in wind turbines subjected to noise interference", *Measurement Sciences and Technol.*, vol. 29, no. 2, 025002, 2018.

[118] X. Wang, S. Lu, W. Huang, Q. Wang, S. Zhang,and M. Xia, "Efficient Data Reduction at the Edge of Industrial Internet of Things for PMSM Bearing Fault Diagnosis", *IEEE Trans. Instrum. Measurement*, vol. 70, pp. 1-12, 2021.

[119] B. Cai, K. Hao, Z. Wang, C. Yang, X. Kong, Z. Liu, and Y. Liu, "Data-driven early fault diagnostic methodology of permanent magnet synchronous motor", *Expert Syst. with Appl.*, vol. 177, art. no. 115000, 2021.

[120] K. Jankowska, and P. Ewert, "Effectiveness Analysis of Rolling Bearing Fault Detectors Based On Self-Organising Kohonen Neural Network–A Case Study of PMSM Drive", *Power Electronics and Drives*, vol. 6, no. 41, pp. 100-112, 2021.

[121] P. Ewert, T. Orlowska-Kowalska, and K. Jankowska, "Effectiveness Analysis of PMSM Motor Rolling Bearing Fault Detectors Based on Vibration Analysis and Shallow Neural Networks", *Energies*, vol. 14, no. 3, 712, 2021.

[122] J.S.L. Senanayaka, and K.G. Robbersmyr, "Fault detection and classification of permanent magnet synchronous motor in variable load and speed conditions using order tracking and machine learning", *Journal of Physics: Conf. Ser.*, vol. 1037, no. 3, p. 032028, June 2018.

[123] Z. Wu, J. Niu, S. Lu, Y. Liu, F. Liu, "Fault Diagnosis of Wind Turbine Bearing Using Variational Nonlinear Chirp Mode Decomposition and Order Analysis", in: *2020 Int. Conf. Sensing, Meas. & Data Analytics in the era of Art. Intel. (ICSMD)*, pp. 479-484, Xi'an, China, Oct. 2020.

[124] J. Guo, X. Wang, C. Zhai, J. Niu, and S. Lu, "Fault diagnosis of wind turbine bearing using synchrosqueezing wavelet transform and order analysis", *2019 14th IEEE Conf. Ind. Electronics and Appl. (ICIEA)*, pp. 2384-2387, June 2019.

[125] J. Niu, S. Lu, Y. Liu, J. Zhao, and Q. Wang, "Intelligent bearing fault diagnosis based on tacholess order tracking for a variable-speed AC electric machine", *IEEE Sensors J.*, vol. 19, no. 5, pp. 1850-1861, 2018.

[126] X. Wang, J. Niu, S. Lu, F. Liu, and Y. Liu, "Improved Rotating Speed Estimation and Bearing Fault Diagnosis Using Multi-Channel Vibration Signals", *2020 Int. Conf. Sensing, Meas. & Data Analytics in the era of Art. Intel. (ICSMD)*, pp. 507-511, Oct. 2020.

[127] A.S. Maliuk, A.E. Prosvirin, Z. Ahmad, C.H. Kim, and J.M. Kim, "Novel Bearing Fault Diagnosis Using Gaussian Mixture Model-Based Fault Band Selection", *Sensors*, vol. 21, no. 19, 6579, 2021.

[128] C. Ma, and S. Zuo, "Black-box method of identification and diagnosis of abnormal noise sources of permanent magnet synchronous machines for electric vehicles", *IEEE Trans. Ind. Electron.*, vol. 61, no. 10, pp. 5538-5549, 2014.

[129] S. Lu, Q. He, and J. Zhao, "Bearing fault diagnosis of a permanent magnet synchronous motor via a fast and online order analysis method in an embedded system", *Mechanical Systems and Signal Processing*, vol. 113, pp. 36-49, 2018.

[130] S. Lu, X. Wang, Q. He, F. Liu, and Y. Liu, "Fault diagnosis of motor bearing with speed fluctuation via angular resampling of transient sound signals", *Journal of Sound and Vibr.*, vol. 385, pp. 16-32, 2016.

[131] P. Varal, V. Patole, S. Shinde, P. Deshmukh, and D. Srivastava, "Bearing Fault Analysis of Permanent Magnet Synchronous Motor (PMSM) using Current Signature Analysis", *Int. Research Journal of Engineering and Technology*, vol. 4, no. 4, pp. 410-415, 2017.

[132] C.P. Mbo'o, and K. Hameyer, "Bearing damage diagnosis by means of the linear discriminant analysis of stator current feature". *2015 IEEE 10th Int. Symp. Diagnostics for Electrical Machines, Power Electronics and Drives (SDEMPED)*, pp. 296-302, September 2015.

[133] J.S. Lee, T.M. Yoon, K.B. Lee, "Bearing fault detection of IPMSMs using zoom FFT", *Journal of Elec. Eng. and Technology*, vol. 11, no. 5, pp. 1235-1241, 2016.

[134] A.H. Abbas, A.A. Al-Saffar, and D.K. Shary, "Bearings fault diagnosis in direct torque control permanent magnet synchronous motor based on discrete wavelet transform and artificial neural network", *Int. Journal of Advances in Eng. & Technology*, vol. 7, no. 2, pp. 341-351, 2014.

[135] J. Rosero, J.L. Romeral, J. Cusido, J.A. Ortega, and A. Garcia, "Fault detection of eccentricity and bearing damage in a PMSM by means of wavelet transforms decomposition of the stator current", *2008 23rd Ann. IEEE Appl. Power Electronics Conf. Exp.*, pp. 111-116, February 2008.

[136] J. Rosero, L. Romeral, E. Rosero, and J. Urresty, "Fault Detection in dynamic conditions by means of Discrete Wavelet Decomposition for PMSM running under Bearing Damage", *2009 24th Ann. IEEE Applied Power Electronics Conf. Exp.*, pp. 951-956, February 2009.

[137] C.P. Mbo'o, and K. Hameyer, "Fault diagnosis of bearing damage by means of the linear discriminant analysis of stator current features from the frequency selection", *IEEE Trans. Industry Applications*, vol. 52, no. 5, pp. 3861-3868, 2016.

[138] V. Gurusamy, K.H. Baruti, M. Zafarani, W. Lee, and B. Akin, "Effect of Magnets Asymmetry on Stray Magnetic Flux Based Bearing Damage Detection in PMSM", *IEEE Access*, vol. 9, pp. 68849-68860, 2021.

[139] B. Ren, M. Yang, N. Chai, Y. Li, and D. Xu, "Fault Diagnosis of Motor Bearing Based on Speed Signal Kurtosis Spectrum Analysis", in: *22nd Int. Conf. El. Mach.& Systems (ICEMS)*, pp. 1-6, August 2019.

[140] M. Yang, N. Chai, Z. Liu, B. Ren, and D. Xu, "Motor speed signature analysis for local bearing fault detection with noise cancellation based on improved drive algorithm", *IEEE Trans. Industrial Electronics*, vol. 67, no. 5, pp. 4172-4182, 2019.

[141] A. Rezig, A. N'Diaye, M.R. Mekideche, and A. Djerdir, "Modelling and detection of bearing faults in Permanent Magnet Synchronous Motors", *2012 20th Int. Conf. El. Machines*, pp. 1778-1782, Sept. 2012.

[142] Y. Park et al., "Online Detection of Rotor Eccentricity and Demagnetization Faults in PMSMs Based on Hall-Effect Field Sensor Measurements", *IEEE Trans. Ind. Appl.*, vol. 55, no. 3, pp. 2499-2509, May-June 2019.

[143] B.M. Ebrahimi, and J. Faiz, „Configuration impacts on eccentricity fault detection in permanent magnet synchronous motors", *IEEE Trans. Magnetics*, vol. 48, no. 2, pp. 903-906, 2012.

[144] B.M. Ebrahimi, M.J. Roshtkhari, J. Faiz, and S.V. Khatami, "Advanced eccentricity fault recognition in permanent magnet synchronous motors using stator current signature analysis", *IEEE Trans. Ind. Electronics*, vol. 61, no. 4, pp. 2041-2052, April 2014.

[145] T. Goktas, M. Zafarani, and B. Akin, „Discernment of broken magnet and static eccentricity faults in permanent magnet synchronous motors", *IEEE Trans. Energy Conv.*, vol. 31, no. 2, pp. 578-587, 2016.

[146] J. Rosero García, J. L. Romeral, and E. R. García, "Detecting eccentricity faults in a PMSM in non-stationary conditions", *Ingeniería e Investigación*, vol. 32, no. 1, pp. 5-10, 2012.

[147] J. Hong, S.B. Lee, C. Kral, and A. Haumer, "Detection of airgap eccentricity for permanent magnet synchronous motors based on the d-axis inductance", *IEEE Trans. Power El.*, vol. 27, no. 5, pp. 2605-2612, 2011

[148] J. Hong, S. Park, D. Hyun, T.J. Kang, S.B. Lee, C. Kral, and A. Haumer, "Detection and classification of rotor demagnetization and eccentricity faults for PM synchronous motors", *IEEE Trans. Ind. Applications*, vol. 48, no. 3, pp. 923-932, 2012.

[149] K. Ahsanullah, E. Jeyasankar, A.N. Vignesh, S.K. Panda, R. Shanmukha, and S. Nadarajan, "Eccentricity fault analysis in PMSM based marine propulsion motors", in: *2017 20th Int. Conf. El. Mach. Syst. (ICEMS)*, pp. 1-6, Aug. 2017.

[150] M. Karami, N. Mariun, M. Rezazadeh Mehrjou, M.Z.A. Ab Kadir, N. Misron, and M.A. Mohd Radzi, "Static eccentricity fault recognition in three-phase line start permanent magnet synchronous motor using finite element method", *Mathematical Problems in Engineering*, vol. 2014, Article ID 132647, 2014.

[151] M. Karami, N.B. Mariun, M.Z.A. Ab-Kadir, N. Misron, and M.A. Mohd Radzi, "Motor Current Signature Analysis-based Non-invasive Recognition of Mixed Eccentricity Fault in Line Start Permanent Magnet Synchronous Motor", *Electric Power Comp. and Systems*, vol. 49, no. 1-2, pp. 133-145, 2021.

[152] K. Kang, J. Song, C. Kang, S. Sung, G. Jang, "Real-time detection of the dynamic eccentricity in permanent-magnet synchronous motors by monitoring speed and back EMF induced in an additional winding", *IEEE Trans. Ind. Electr.*, vol. 64, no. 9, pp. 7191-7200, 2017.

[153] U. Galfarsoro, A. McCloskey, S. Zarate, X. Hernández, and G. Almandoz, "Influence of manufacturing tolerances and eccentricities on the unbalanced magnetic pull in permanent magnet synchronous motors", in: *2020 Int. Conf. El. Mach. (ICEM)*, vol. 1, pp. 1363-1369, Aug. 2020.

[154] U. Galfarsoro, A. McCloskey, S. Zarate, X. Hernández, G. Almandoz, "Influence of manufacturing tolerances and eccentricities on the unbalanced magnetic pull in permanent magnet synchronous motors", *IEEE Trans. Ind. Appl.* (Early Access), 03 March 2022. doi: 10.1109/TIA.2022.3156075

[155] F. Lin, S. Zuo, and W. Deng, "2827. Impact of rotor eccentricity on electromagnetic vibration and noise of permanent magnet synchronous motor", *Journal of Vibroengineering*, vol. 20, no. 2, pp. 923-935, 2018.

[156] M.S.S. Rafaq, H. Lee, Y. Park, S.B. Lee, M.O. Zapico, D. Fernandez, and F. Briz, "Airgap search coil based identification of pm synchronous motor defects", *IEEE Trans. Ind. Elec.*, vol. 69, no. 7, pp. 6551-6560, 2021.

[157] M.B. Koura, A.H. Boudinar, A.F. Aimer, A. Bendiabdellah, and Z. Gherabi, "Diagnosis and discernment between eccentricity and demagnetization faults in PMSM drives", *Journal of Power Electronics*, vol. 21, no. 3, 563-573, 2021.

[158] M. Eker, and M. Akar, "Eccentricity fault diagnosis in a permanent magnet synchronous motor under nonstationary speed conditions", *Turkish Journal of Electrical Eng. Comp. Sc.*, vol. 25, no. 3, pp. 1881-1893, 2017.

[159] M. Akar, S. Taskin, S.S. Şeker, and I. Cankaya, "Detection of static eccentricity for permanent magnet synchronous motors using the coherence analysis", *Turkish Journal of Electrical Eng. Comp. Sc.*, vol. 18, no. 6, pp. 963-975, 2010.

[160] U. Galfarsoro, A. McCloskey, X. Hernández, G. Almandoz, S. Zarate, and X. Arrasate, "Eccentricity detection procedure in electric motors by force transducer and search coils in a novel experimental test bench", in: *2019 IEEE 12th Int. Symp. Diag. El. Mach., Power Electr. Drives (SDEMPED)*, pp. 220-226, August 2019.

[161] L. Romeral, J.A. Rosero, A.G. Espinosa, J. Cusido, and J.A. Ortega, "Electrical monitoring for fault detection in an EMA", *IEEE Aerospace and Electronic Syst. Mag.*, vol. 25, no. 3, pp. 4-9, 2010.

[162] Z. Gherabi, N. Benouzza, D. Toumi, and A. Bendiabdellah, "Eccentricity Fault diagnosis in PMSM using motor current signature analysis", in: *2019 Int. Aegean Conf. El. Mach. Power Electr. (ACEMP) & 2019 Int. Conf. Opt. El. Electronic Equip. (OPTIM)*, pp. 205-210, August 2019.

[163] P. Ewert, and M. Jaworski, "Application of selected higher-order methods to detect rotor unbalance of drive system with PMSM", in. *Proc. IEEE 19th Int. Power Electr. Motion Control Conf. (PEMC)*, pp. 874-879, April 2021.

[164] M.S.S. Rafaq, H. Lee, Y. Park, S.B. Lee, D. Fernandez, D. Diaz-Reigosa, and F. Briz, "A Simple Method for Identifying Mass Unbalance using Vibration Measurement in Permanent Magnet Synchronous Motors", *IEEE Trans. Ind, Electron.*, vol. 69, no. 6, pp. 6441-6444, 2021.

[165] J. Zhang, J. Hang, and M. Cheng, "Diagnosis of mechanical unbalance fault in permanent magnet synchronous machine drives", *Electric Power Comp. Syst.*, vol. 44, no. 12, pp. 1408-1417, 2016.

[166] J. Hang, J. Zhang, M. Cheng, and Z. Wang, "Fault diagnosis of mechanical unbalance for permanent magnet synchronous motor drive system under nonstationary condition". In *2013 IEEE Energy Conv. Congress and Exposition*, pp. 3556-3562, September 2013.

[167] C.H. Park, J. Lee, G. Ahn, M. Youn, and B.D. Youn, "Fault detection of PMSM under non-stationary conditions based on wavelet transformation combined with distance approach", in: *2019 IEEE 12th Int. Symp. Diag. El. Mach., Power El. Drives (SDEMPED)*, pp. 88-93, August 2019.

[168] P. Corbalan, L.E. Chiang, "Rotor Unbalance Fault Diagnosis in Wind Turbine by Markov Chain Monte Carlo Method", 2021; DOI: https://doi.org/10.21203/rs.3.rs-493595/v1

[169] T. Xie, T. Wang, Q. He, D. Diallo, and C. Claramunt, "A review of current issues of marine current turbine blade fault detection", *Ocean Engineering*, vol. 218, art. no. 108194, 2020.

[170] Y. Yinquan, "Fault Diagnosis of Permanent Magnet Synchronous Motor Based on Mechanical and Magnetic Characteristic Analysis", *A Thesis Submitted For The Degree Of Doctor Of Philosophy*, Department Of Electrical And Computer Engineering, National University Of Singapore, 2014.

[171] X. Huang, M. Yang, B. Ren, N. Chai, and D. Xu, "Angle misalignment detection and its suppression algorithm in motor system based on speed signal", in: *2020 IEEE 9th Int. Power Electr. Motion Control Conf. (IPEMC2020-ECCE Asia)*, pp. 3174-3179, 2020.

[172] P. Pietrzak, and M. Wolkiewicz, "Application of Spectral and Wavelet Analysis of Stator Current to Detect Angular Misalignment in PMSM Drive Systems", *Power Electr. and Drives*, vol. 6, no. 41, 42-60, 2021.

[173] X. Liu, D. Liang, J. Du, Y. Yu, X. Yang, and Z. Luo, "Effects analysis of misalignments on dynamic characteristics test for permanent magnet synchronous motor", *2014 17th Int. Conf. El. Machines and Syst. (ICEMS)*, pp. 1543-1547, October 2014.

[174] N. Chai, M. Yang, B. Ren, X. Huang, and . Xu, "Misalignment Detection of Rotor System Based on Adaptive Input-output Model Identification of Motor Speed", *2020 IEEE 9th Int. Power Elec. Motion Control Conf. (IPEMC2020-ECCE Asia)*, pp. 2266-2271, 29 Nov.-2 Dec. 2020.

[175] X. Liu, D. Liang, Q. Ze, and Y. Yu, "The frequency response of parallel misalignment in PMSM test bench", in: *2017 IEEE Int. Electric Machines and Drives Conf. (IEMDC)*, pp. 1-7, May 2017.

[176] Y. Yao, Y. Li, and Q. Yin, "A novel method based on self-sensing motor drive system for misalignment detection", *Mechanical Systems and Signal Processing*, vol. 116, pp. 217-229, 2019.

[177] V.T. Phung, and M. Pacas, "Sensorless harmonic speed control and detection of bearing faults in repetitive mechanical systems," in: *2017 IEEE 3rd Int. Future Energy Electr. Conf. and ECCE Asia (IFEEC 2017 - ECCE Asia)*, 2017, pp. 1646-1651.

[178] W.L. Roux, R.G. Harley, and T.G. Habetler, "Detecting faults in rotors of PM drives," *IEEE Ind. Appl. Mag..*, vol. 14, no. 2, pp. 23-31, March-Apr. 2008.

[179] F. Meinguet, E. Semail, X. Kestelyn, Y. Mollet, and J. Gyselinck, "Change-detection algorithm for short-circuit fault detection in closed-loop AC drives," *IET El. Power Appl.*, vol. 8, no. 5, pp. 165-177, 2014.

[180] D. Casadei et al., "Detection of magnet demagnetization in five-phase surface-mounted permanent magnet generators," in: *Proc.2012 3rd IEEE Int. Symp. Power Electr. Distrib. Gen. Syst. (PEDG)*, 2012, pp. 841-848.

[181] Z. Ullah, S.-T. Lee, and J. Hur, "A Novel Fault Diagnosis Technique for IPMSM Using Voltage Angle, " in: *2018 IEEE Energy Conv. Congr. Exp. (ECCE)*, 2018, pp. 3236-3243.

[182] S. Moon, H. Jeong, H. Lee, S. and W. Kim, "Interturn Short Fault Diagnosis in a PMSM by Voltage and Current Residual Analysis with the Faulty Winding Model," *IEEE Trans. Energy Conversion*, vol. 33, no. 1, pp. 190-198, March 2018.

[183] J. Zhang, W. Zhan, and M. Ehsani, "Fault-Tolerant Control of PMSM With Inter-Turn Short-Circuit Fault," *IEEE Trans. Energy Conversion*, vol. 34, no. 4, pp. 2267-2275, Dec. 2019.

[184] S.S. Kuruppu, and N.A. Kulatunga, "D-Q current signature based single winding open fault detection for SM-PMAC machine drives," in: *Proc. 2013 Int. Electric Machines & Drives Conf., 2013*, pp. 1343-1347.

[185] S.S. Kuruppu, and N.A. Kulatunga, "D-Q Current Signature-Based Faulted Phase Localization for SM-PMAC Machine Drives," *IEEE Trans. Industrial Electronics*, vol. 62, no. 1, pp. 113-121, Jan. 2015.

[186] B. Wang, J. Wang, A. Griffo, and B. Sen, "Stator Turn Fault Detection by Second Harmonic in Instantaneous Power for a Triple-Redundant

Fault-Tolerant PM Drive," *IEEE Trans. Ind. Electron.*, vol. 65, no. 9, pp. 7279-7289, Sept. 2018.

[187] S. Huang, A. Aggarwal, E.G., K. Li, F. Niu, and X. Huang, "Robust Stator Winding Fault Detection in PMSMs With Respect to Current Controller Bandwidth," *IEEE Trans. Power Electron.*, vol. 36, no. 5, pp. 5032-5042, May 2021.

[188] B. Aubert, J. Regnier, S. Caux, and D. Alejo, "Kalman filter-based indicator for online interturn short circuits detection in permanent-magnet synchronous generators," *IEEE Trans. Ind. Electron.*, vol. 62, no.3, pp. 1921-1930, Mar. 2015.

[189] W. El Sayed, M. Abd El Geliel, and A. Lotfy, "Fault Diagnosis of PMSG Stator Inter-Turn Fault Using Extended Kalman Filter and Unscented Kalman Filter," *Energies*, vol. 13, no. 11, p. 2972, Jun. 2020.

[190] B. G. Park, J. S. Jang, T. S. Kim, and D. S. Hyun, "EKF based fault diagnosis for open-phase faults of PMSM drives," in *Proc. 6th Int. Power El. Motion Contr. Conf. (IPEMC 2009)*¸17-20 May, 2009, Wuhan, China, pp. 418-422.

[191] X. Xiao, C. M. Chen, and M. Zhang, "Dynamic permanent magnet flux estimation of permanent magnet synchronous machines," *IEEE Trans. Appl. Supercond.*, vol. 20, no. 3, pp. 1085-1088, Jun. 2010.

[192] M. A. Mazzoletti, G. R. Bossio, C. H. De Angelo, and D. R. Espinoza-Trejo, "A Model-Based Strategy for Interturn Short-Circuit Fault Diagnosis in PMSM," *IEEE Trans. Ind. Electronics*, vol. 64, no. 9, pp. 7218-7228, Sept. 2017.

[193] F. Meinguet, E. Semail,X. Kestelyn, Y. Mollet, and J. Gyselinck, "Change-detection algorithm for short-circuit fault detection in closed-loop AC drives," *IET Electric Power Applications*, vol. 8, no. 5, pp. 165-177, May 2014.

[194] M. A. Mazzoletti, G. R. Bossio, C. H. De Angelo, and D. R. Espinoza-Trejo, "A Model-Based Strategy for Interturn Short-Circuit Fault Diagnosis in PMSM," *IEEE Trans. Ind. Electron.*, vol. 64, no. 9, pp. 7218-7228, Sept. 2017.

[195] J. Hang, D. Yan, M. Xia, S. Ding, and Q. Wang, "Quantitative Fault Severity Estimation for High-Resistance Connection in PMSM Drive System," *IEEE Access*, vol. 7, pp. 26855-26866, Feb. 2019.

[196] Y. Qi, E. Bostanci, M. Zafarani, and B. Akin, "Severity Estimation of Interturn Short Circuit Fault for PMSM," *IEEE Trans. Ind. Electron.*, vol. 66, no. 9, pp. 7260-7269, Sept. 2019.

[197] F. Gao, G. Zhang, M. Li, Y. Gao, and S. Zhuang, "Inter-turn Fault Identification of Surface-Mounted Permanent Magnet Synchronous Motor Based on Inverter Harmonics," *Energies*, vol. 13, no. 4, pp. 899, Feb. 2020.

[198] Y. Ge, B. Song, Y. Pei, Y. A. B. Mollet, and J. J. C. Gyselinck, "Analytical Expressions of Isolation Indicators for Permanent-Magnet Synchronous Machines Under Stator Short-Circuit Faults," *IEEE Trans. Energy Conv.*, vol. 34, no. 2, pp. 984-992, June 2019.

[199] F. Alvarez-Gonzalez, A. Griffo, and B. Wang, "Permanent Magnet Synchronous Machines Inter- Turn Short Circuit Fault Detection by Means of Model-Based Residual Analysis," in *Proc. 44th Ann. Conf. IEEE Ind. El. Soc. (IECON)*, 21-23 Oct., 2018, Washington, USA, pp. 647-652.

[200] Y. He, Y. Zhang, M. Xu, X. Wang, and J. Xiong, "A New Hybrid Model for Electromechanical Characteristic Analysis Under SISC in Synchronous Generators," *IEEE Trans. Ind. Electron.*, vol. 67, no. 3, pp. 2348-2359, March 2020.

[201] R. Z. Haddad, C. A. Lopez, S. N. Foster, and E. G. Strangas, "A Voltage-Based Approach for Fault Detection and Separation in Permanent Magnet Synchronous Machines," *IEEE Trans. Ind. Appl.*, vol. 53, no. 6, pp. 5305-5314, Nov.-Dec. 2017.

[202] D. Egorov, I. Petrov, J. Link, R. Stern, and J. J. Pyrhönen, "Model-Based Hysteresis Loss Assessment in PMSMs With Ferrite Magnets," *IEEE Trans. Ind. Electron.*, vol. 65, no. 1, pp. 179-188, Jan. 2018.

[203] A. Ibrayeva, F. Lopez, S. Eriksson, "Modelling of Permanent Magnet Synchronous Generator with Non-linear Magnets," in *Proc. 2021 22nd IEEE International Conference on Industrial Technology (ICIT)*, 10-12 March, 2021, Valencia, Spain, pp. 209-214.

[204] G. Bavendiek, F. Müller, S. Steentjes, and K. Hameyer "Modeling of history-dependent magnetization in the finite element method on the example of a postassembly rotor magnetizer." *Int J Numer Model.*, vol. 33, no. 5, Sep./Oct. 2020.

[205] H. Jeong, H. Lee, and S.W. Kim, "Classification and Detection of Demagnetization and Inter-Turn Short Circuit Faults in IPMSMs by Using Convolutional Neural Networks," in *Proc. 2018 IEEE Energy Conv. Congr. Exp. (ECCE)*, 23-27 Sept., 2018, Portland, USA, pp. 3249-3254.

[206] Y. Zhang, Z. Xiang, X. Zhu, L. Quan, and M. Jiang, "Anti-Demagnetization Capability Research of a Less-Rare-Earth Permanent-Magnet Synchronous Motor Based on the Modulation Principle," *IEEE Trans. Magn.*, vol. 57, no. 2, pp. 1-6, Feb. 2021.

[207] M. R. Mínaz, and E. Akcan, "An Effective Method for Detection of Demagnetization Fault in Axial Flux Coreless PMSG With Texture-Based Analysis," *IEEE Access*, vol. 9, pp. 17438-17449, Jan. 2021.

[208] A. C. Barmpatza, and J. C. Kappatou, "Study of the Total Demagnetization Fault of an AFPM Wind Generator," *IEEE Trans. Energy Conv.*, vol. 36, no. 2, pp. 725-736, June 2021.

[209] Y. Du, L. Wu, H. Zhan, and Y. Fang, "Influence of Dimensional Parameters on Three-Phase Short Circuit and Demagnetization in Surface-Mounted PM Machines," *IEEE Trans. Energy Conv.*, vol. 36, no. 3, pp. 2514-2523, Sept. 2021.

[210] A. Usman, N. T. Doiphode, and B. S. Rajpurohit, "Finite Element Modeling of Stator Winding Faults in Permanent Magnet Synchronous Motor: Part II," in *Proc. 2019 Int. Conf. El. Drives Power Elec. (EDPE)*, 24-26 Sept., 2019, pp. 169-176, The High Tatras, Slovakia.

[211] S. Moon, H. Jeong, H. Lee, and S. W. Kim, "Interturn Short Fault Diagnosis in a PMSM by Voltage and Current Residual Analysis With the Faulty Winding Model," *IEEE Trans. Energy Conv.*, vol. 33, no. 1, pp. 190-198, March 2018.

[212] C. Gao, M. Gao, J. Si, P. Su, and Y. Hu, "A Novel Analytical Method of Inductance Identification for Direct Drive PMSM with a Stator Winding Fault Considering Spatial Position of the Shorted Turns," *Appl. Sci.*, vol. 9, no. 17, pp. 3599, Aug. 2018.

[213] Y. Qi, E. Bostanci, V. Gurusamy, and B. Akin, "A Comprehensive Analysis of Short-Circuit Current Behavior in PMSM Interturn Short-Circuit Faults," *IEEE Trans. Power Electron.*, vol. 33, no. 12, pp. 10784-10793, Dec. 2018.

[214] C. Chuang, Z. Wei, W. Zhifu, and L. Zhi, "The Diagnosis Method of Stator Winding Faults in PMSMs Based on SOM Neural Networks," *Energy Procedia*, vol. 105, pp. 2295-2301, 2017.

[215] J. Quiroga, D.A. Cartes, C.S. Edrington, and L. Liu, "Neural network based fault detection of PMSM stator winding short under load fluctuation," in: *13th Int. Power El. Motion Contr. Conf.*, Budapest, Hungary, 2008.

[216] B.A. S., C.M.V. Barros, C.A. Siebra, and L.S.A. Barros, "A Multilayer Perceptron-Based Approach for Stator Fault Detection in Permanent Magnet Wind Generators," in" *Proc. 2019 IEEE PES Innovative Smart Grid Technologies Conf.– Latin America (ISGT Latin America)*, 2019.

[217] T. Shen, A. Kilic, C. Thulfaut, and H. Reuss, "An Intelligent Diagnostic Method for Permanent Magnet Synchronous Motors (PMSM) in the Electric Drive of Autonomous Vehicles," in" *Proc. 21st Europ. Conf. Power Electr. Appl. (EPE'19 ECCE Europe)*, 2019.

[218] S. Moosavi, A. Djerdir, Y. Ait-Amirat, and D. Khaburi, "ANN based fault diagnosis of permanent magnet synchronous motor under stator winding shorted turn," *Electric Power Syst. Research*, vol. 125, pp. 67-82, 2015.

[219] I. Kao, W. Wang, Y. Lai, and J. Perng, "Analysis of Permanent Magnet Synchronous Motor Fault Diagnosis Based on Learning," *IEEE Trans. Instrument. and Measurement*, vol. 68, pp. 310-324, 2019

[220] M. Skowron, T. Orlowska-Kowalska, and C.T. Kowalski, "Application of simplified convolutional neural networks for initial stator winding fault detection of the PMSM drive using different raw signal data," *IET Electric Power Applications*, vol. 15, no. 7, pp. 932-946, 2021.

[221] S.S. Refaat, H. Abu-Rub, M.S. Saad, E.M. Aboul-Zahab, and A. Iqbal, "Detection and discrimination between unbalanced supply and phase loss in PMSM using ANN-based protection scheme," in: *Proc. 7th IEEE GCC Conf. Exhibition (GCC)*, 2013.

[222] M. Skowron, T. Orlowska-Kowalska, and C.T. Kowalski, "Detection of permanent magnet damage of PMSM drive based on direct analysis of the stator phase currents using convolutional neural network," *IEEE Trans. Ind. Electr.*, 2022, (Early Access) doi: 10.1109/TIE.2022.3146557.

[223] Y. Luo, J. Qiu, and C. Shi, "Fault Detection of Permanent Magnet Synchronous Motor Based on Deep Learning Method," in: *Proc. 21st Int. Conf. Electrical Machines and Systems (ICEMS)*, 2018.

[224] Y. Nyanteh, C. Edrington, S. Srivastava, and D. Cartes, "Application of Artificial Intelligence to Real-Time Fault Detection in Permanent Magnet Synchronous Machines," *IEEE Trans. Ind. Appl.*, vol. 49, pp. 1205-1214, 2013.

[225] Z. Wang, J. Yang, C. Cao, and Z. Gu, “Phase-phase short fault analysis of permanent magnet synchronous motor in electric vehicles,” *Low Carbon Cities and Urban Energy Systems*, 2016.

[226] K. Urbanski, and D. Majchrzak, “Faults detection in PMSM drive using Artificial Neural Network,” *Przeglad Elektrot.*, vol. 1, no. 6, pp. 24-27, 2017.

[227] S.S. Moosavi, A. Djerdir, Y. Aït-Amirat, and D.A. Kkuburi, “Artificial neural networks based fault detection in 3-Phase PMSM traction motor,” in: *Proc. 2012 XXth Int. Conf. Electr. Mach.*, pp. 1579-1585, 2012.

[228] H. Lee, H. Jeong, G. Koo, J. Ban, and S.W. Kim, “Attention Recurrent Neural Network-Based Severity Estimation Method for Interturn Short-Circuit Fault in Permanent Magnet Synchronous Machines,” *IEEE Trans. Industrial Electronics*, vol. 68, no. 4, pp. 3445-3453, 2021

[229] L.S. Maraaba, A.S. Milhem, I.A. Nemer, H. Al-Duwaish, and and M.A. Abido, “Convolutional Neural Network-Based Inter-Turn Fault Diagnosis in LSPMSMs,” *IEEE Access*, vol. 8, pp. 81960-81970, 2020

[230] H. Lee, H. Jeon, and S.W. Kim, “Detection of Interturn Short-Circuit Fault and Demagnetization Fault in IPMSM by 1-D Convolutional Neural Network,” in: *Proc. 2019 IEEE PES Asia-Pacific Power and Energy Eng. Conf. (APPEEC)*, pp. 1-5, 2019.

[231] M. Akar. M. Hekim, and U. Orhan, “Mechanical fault detection in permanent magnet synchronous motors using equal width discretization based probability distribution and a neural network model,” *Turkish Journal of Electr. Eng. Comp. Sc.*, vol. 23, no. 3, pp. 813-823, 2015.

[232] X. Dai, Y. Zhang, L. Qiao, and D. Sun, “Fault Diagnosis of Permanent Magnet Synchronous Motor Based on Improved Probabilistic Neural Network,” in: *Proc. 40th Chinese Control Conf. (CCC)*, pp. 2767-2772, 2021.

[233] C.S. Wang, I.H. Kao, and J.W. Perng, “Fault diagnosis and fault frequency determination of permanent magnet synchronous motor based on deep learning,” *Sensors*, vol. 21, no. 11, 2021.

[234] L.S. Maraaba, Z.M. Al-Hamouz, and M.A. Abido, “An Accurate Tool for Detecting Stator Inter-Turn Fault in LSPMSM,” *IEEE Access*, vol. 7, pp. 88622-88634, 2019.

[235] L.S. Maraaba, Z.M. Al-Hamouz, A.S. Milhem, and M.A. Abido, “Network-Based Diagnostic Tool for Detecting Stator Inter-Turn Faults in Line Start Permanent Magnet Synchronous Motors,” *IEEE Access*, vol. 7, pp. 89014-89025, 2019.

[236] M. Zhu, B. Yang, W. Hu, G. Feng, and N.C. Kar. “Vold-Kalman Filtering Order Tracking Based Rotor Demagnetization Detection in PMSM,” *IEEE Trans. Ind. Appl.*, vol. 55, pp. 5768–5778, Nov. 2019.

[237] Z. Chen, K. Liang, T. Peng, and Y. Wang, “Multi-Condition PMSM Fault Diagnosis Based on Convolutional Neural Network Phase Tracker,” *Symmetry*, vol. 14, no 2, pp. 295, 2022,

[238] S. Yang, D. Xiang, A. Bryant, P. Mawby, L. Ran, and P. Tavner, “Condition Monitoring for Device Reliability in Power Electronic Converters: A Review,” *IEEE Trans. Power Electr.*, vol. 25, no. 11, pp. 2734-2752, 2010.

[239] R. R. Errabelli and P. Mutschler, “Fault-tolerant voltage source inverter for permanent magnet drives,” *IEEE Trans. Power Electron*., vol. 27, no. 2, pp. 500–508, Feb. 2012.

[240] Kyo-Beum Lee, and Ui-Min Choi, Faults and diagnosis systems in power converters. In: A*dvanced and Intelligent Control in Power Electronics and Drives*. Orłowska-Kowalska T, Blaabjerg F, Rodriguez J (ed) Springer, Heilderberg, pp 143-178, 2014.

[241] X.S. Pu, T.H. Nguyen, D.C Lee, K.B. Lee, and J.M. Kim,”Fault Diagnosis of DC-Link Capacitors in Three-Phase AC/DC PWM Converters by Online Estimation of Equivalent Series Resistance,” *IEEE Trans. Ind. Electronics*, vol. 60, no. 9, pp. 4118-4127, Sept. 2013.

[242] A.M.R. Amaral, and A.J.M. Cardoso, “A simple offline technique for evaluating the condition of aluminum-electrolytic-capacitors,” *IEEE Trans. Ind.. Electron*., vol. 56, no. 8, pp. 3230–3237, Aug. 2009.

[243] V. Smet, F. Forest, J. Huselstein, A. Rashed, F. Richardeau, “Evaluation of VCE Monitoring as a Real-Time Method to Estimate Aging of Bond Wire-IGBT Modules Stressed by Power Cycling,” *IEEE Trans. Ind. Electronics*, vol. 60, no. 7, pp. 2760-2770, July 2013.

[244] Z. Zhang, G. Luo, Z. Zhang, and X. Tao, "A hybrid diagnosis method for inverter open-circuit faults in PMSM drives," *CES Trans. Electrical Machines and Systems*, vol. 4, no. 3, pp. 180-189, Sept. 2020.

[245] S. Lee, K. Kim, M. Shim, and I. Nam, "A Digital Signal Processing Based Detection Circuit for Short-Circuit Protection of SiC MOSFET," *IEEE Trans. Power Electr.*, vol. 36, no. 12, pp. 13379-13382, Dec. 2021.

[246] H. Yan, Y. Xu, F. Cai, H. Zhang, W. Zhao, and C. Gerada, "PWM-VSI Fault Diagnosis for a PMSM Drive Based on the Fuzzy Logic Approach," *IEEE Trans. Power Electr.*, vol. 34, no. 1, pp. 759-768, Jan. 2019.

[247] B. Lu, and S. K. Sharma, "A Literature Review of IGBT Fault Diagnostic and Protection Methods for Power Inverters," *IEEE Trans. Ind. Applications*, vol. 45, no. 5, pp. 1770-1777, Sept. 2009.

[248] I. Jlassi, J. O. Estima, S. K. El Khil, N. M. Bellaaj, and A. J. M. Cardoso, "A Robust Observer-Based Method for IGBTs and Current Sensors Fault Diagnosis in Voltage-Source Inverters of PMSM Drives," *IEEE Trans. Ind. Appl.*, vol. 53, n-o. 3, pp. 2894-2905, May-June 2017.

[249] A. M. S. Mendes, and A. J. Marques Cardoso, "Voltage source inverter fault diagnosis in variable speed AC drives, by the average current Park's vector approach," in: *Proc. IEEE Int. Electric Machines Drives Conf.. IEMDC'99*, 1999, pp. 704-706.

[250] H. Merabet, T. Bahi, K. Bedoud, and D. Djalel, "Real-Time Switches Fault Diagnosis for Voltage Source Inverter Driven Induction Motor Drive," *Int. Journal of Electr. Eng. & Telecom.*, Seatle, WA, USA, March 2019.

[251] Y. Liang, R. Wang, and B. Hu, "Single-Switch Open-Circuit Diagnosis Method Based on Average Voltage Vector for Three-Level T-Type Inverter," *IEEE Trans. Power Electr.*, vol. 36, no. 1, pp. 911-921, Jan. 2021.

[252] F. Naseri, E. Schaltz, K. Lu and E. Farjah, "Real-time open-switch fault diagnosis in automotive permanent magnet synchronous motor drives based on Kalman filter," *IET Power Electr.*, vol. 13, no 12, pp. 2450-2460, 2020.

[253] M. Trabelsi, E. Semail, and N. K. Nguyen, "Experimental Investigation of Inverter Open-Circuit Fault Diagnosis for Biharmonic Five-Phase Permanent Magnet Drive," *IEEE Journal of Emerging and Selected Topics in Power Electronics*, vol. 6, no. 1, pp. 339-351, March 2018.

[254] J. O. Estima, and A. J. Marques Cardoso, “A New Algorithm for Real-Time Multiple Open-Circuit Fault Diagnosis in Voltage-Fed PWM Motor Drives by the Reference Current Errors,” *IEEE Trans. Ind. Electronics*, vol. 60, no. 8, pp. 3496-3505, Aug. 2013.

[255] S. Khojet El Khil, I. Jlassi, A. J. Marques Cardoso, J. O. Estima, and N. Mrabet-Bellaaj, "Diagnosis of Open-Switch and Current Sensor Faults in PMSM Drives Through Stator Current Analysis," *IEEE Trans. Ind. Appl.*, vol. 55, no. 6, pp. 5925-5937, Nov.-Dec. 2019.

[256] S. K. E. Khil, I. Jlassi, J. O. Estima, N. Mrabet-Bellaaj, and A. J. M. Cardoso, "Detection and isolation of open-switch and current sensor faults in PMSM drives, through stator current analysis," in: *Proc. 2017 IEEE 11th Int. Symp. Diagnostics El. Machines, Power Electr. and Drives (SDEMPED)*, Tinos, Greece 2017, pp. 373-379.

[257] W. Huang, J. Du, W. Hua and Q. Fan, "An open-circuit fault diagnosis method for PMSM drives using symmetrical and DC components," *Chinese Journal of El. Eng.*, vol. 7, no. 3, pp. 124-135, Sept. 2021.

[258] M. Salehifar, R. Salehi Arashloo, M. Moreno-Eguilaz, V. Sala, and L. Romeral, “Observer-Based Open Transistor Fault Diagnosis and Fault Tolerant Control of Five-Phase Permanent Magnet Motor Drive for Application in Electric Vehicles,” *IET Power Electr.*, vol. 8, no. 1, pp. 76-87, 2015.

[259] X. Zhou, J. Sun, P. Cui, Y. Lu, M. Lu, and Y. Yu, "A Fast and Robust Open-Switch Fault Diagnosis Method for Variable-Speed PMSM System," *IEEE Trans. Power Electr.*, vol. 36, no. 3, pp. 2598-2610, March 2021.

[260] W. Huang et al., "Current-Based Open-Circuit Fault Diagnosis for PMSM Drives With Model Predictive Control," *IEEE Trans. Power Electronics*, vol. 36, no. 9, pp. 10695-10704, Sept. 2021.

[261] R. Ribeiro, C. Jacobina, E. da Silva, and A. Lima, “Fault detection of open-switch damage in voltage-fed PWM motor drive systems,” *IEEE Trans. Power Electronics*, vol. 18, no. 2, pp. 587– 593, March 2003.

[262] S. Karimi, A. Gaillard, P. Poure, and S. Saadate, “FPGA-Based Real-Time Power Converter Failure Diagnosis for Wind Energy Conversion Systems”, *IEEE Trans. Ind. Electr.*, vol. 55, no. 12, pp. 4299-4308, Dec. 2008.

[263] C. Choi, and W. Lee, "Design and evaluation of voltage measurement-based sectoral diagnosis method for inverter open switch faults of permanent magnet synchronous motor drive," *IET Electric Power Applications*, vol. 6, no. 8, pp. 526-532, 2012.

[264] N. M. A. Freire, J. O. Estima, and A. J. M. Cardoso, “A voltage-based approach without extra hardware for open-circuit fault diagnosis in closed loop PWM AC regenerative drives,” *IEEE Trans. Ind. Electron*., vol. 61, no. 9, pp. 4960–4970, Mar. 2014.

[265] Q.T. An, L. Sun, and L.Z. Sun, “Current residual vector-based open switch fault diagnosis of inverters in PMSM drive systems,” *IEEE Trans. Power Electron*., vol. 30, no. 5, pp. 2814–2827, May 2015.

[266] Won-Sang Im, Jang-Sik Kim, Jang-Mok Kim. Dong-Choon Lee, and Kyo-Beum Lee, “Diagnosis Methods for IGBT Open Switch Fault Applied to 3-Phase AC/DC PWM Converter”, *Journal Pow. Electron*., vol. 12, no. 1, pp. 120-127, 2012.

[267] K. Rothenhagen, and F. W. Fuchs, “Performance of diagnosis methods for IGBT open circuit faults in voltage source active rectifiers”, in: *IEEE 35th Ann. Conf. Pow. Electron. Spec. (PESC)*, vol.6, pp. 4348-4354, June 2004.

[268] P. Duan, K. Xie, L. Zhang, and X. Rong, “Open-switch fault diagnosis and system reconfiguration of doubly fed wind power converter used in a microgrid”, *IEEE Trans. Pow. Electr*., vol. 26, no. 3, pp. 816-821, 2011.

[269] I. Jlassi, J.O. Estima, S.K. El Khil, N.M. Bellaj, and A.J. Marques Cardoso, “Multiple Open-Circuit Faults Diagnosis in Back-to-Back Converters of PMSG Drives for Wind Turbine Systems”, *IEEE Trans. Pow. Electron*., vol. 30, no. 5, pp. 2689–2702, 2015.

[270] F. Wu, and J. Zhao, “Current Similarity Analysis Based Open-Circuit Fault Diagnosis for Two-Level Three-Phase PWM Rectifier”, *IEEE Trans. Pow. Electron*., vol. 32, no. 5, pp. 3935-3945, May 2017.

[271] L. Tian, F. Wu and J. Zhao, “Current kernel density estimation based transistor open-circuit fault diagnosis in two-level three phase rectifier”, *Electron. Letters*, vol. 52, no. 21, pp. 1795-1797, 2016.

[272] P. Sobanski, and T. Orlowska-Kowalska, "IGBT open-circuit fault diagnosis based on the current prediction in the line-side AC/DC converter," in: *2017 IEEE Int. Conf. Ind. Technol. (ICIT)*, Toronto, 2017, pp. 113-118.

[273] P. Sobanski, and T. Orlowska-Kowalska, "Open switch fault diagnosis methods for an AC/DC line-side converter," in: *2017 IEEE Int. Conf Ind. Technol. (ICIT)*, Toronto, 2017, pp. 1580-1585.

[274] M. Bourogaoui, H. B. A. Sethom, and I. S. Belkhodja. “Speed/position sensor fault tolerant control in adjustable speed drives –a review.” *ISA Transactions*, vol. 64, pp. 269–284, 2016.

[275] D. U. Campos-Delgado, D. R. Espinoza-Trejo, and E. Palacios. Fault-tolerant control in variable speed drives: A survey. *IET Electric Power Appl*., vol. 2, no. 2, pp. 121–134, 2008.

[276] Y.-S. Jeong, S.-K. Sul, S.E. Schulz, and N.R. Patel, “Fault detection and fault tolerant control of interior permanent-magnet motor drive system for electric vehicle,” *IEEE Trans. Ind. Appl*., vol. 41, no. 1, pp. 46–51, Jan./Feb. 2005.

[277] F.R. Salmasi, T.A. Najafabadi, and P. J. Maralani, “An adaptive flux observer with online estimation of DC-link voltage and rotor resistance for VSI-based induction motors,” *IEEE Trans. Power Electron.*, vol. 25, no. 5, pp. 1310–1319, May 2010.

[278] G.H.B. Foo, H. Beng, X. Zhang, and D.M. Vilathgamuwa, “Sensor Fault Resilient Control of Interior Permanent-Magnet Synchronous Motor Drives,” *IEEE/ASME Trans. Mechatronics*, vol. 20, no. 2, pp.855-864, April 2015

[279] G.H.B. Foo, and M.F. Rahman, “Sensorless direct torque and flux controlled IPM synchronous motor drive at very low speed without signal injection,” *IEEE Trans. Ind. Electr*., vol. 57, no. 1, pp. 395–403, Jan. 2010.

[280] G.H.B. Foo, and M.F. Rahman, “Direct torque control of an IPM synchronous motor drive at very low speed using a sliding mode stator flux observer,” *IEEE Trans. Power Elec.*, vol. 25, no. 4, pp. 933–942, Apr. 2010.

[281] A. Piippo, M. Hinkkanen, and J. Luomi, “Analysis of an adaptive observer for sensorless control of interior permanent magnet synchronous motors,” *IEEE Trans. Ind. Electron*., vol. 55, no. 2, pp. 570–576, Feb. 2008.

[282] A. Akrad, M. Hilairet, and D. Diallo, “A sensorless PMSM drive using a two stage extended Kalman estimator,” in *Proc. IEEE IECON*, Orlando, FL, 2008, pp. 2776–2781.

[283] H. Kim, J. Son, and J. Lee, "High-speed sliding-mode observer for the sensorless speed control of a PMSM", *IEEE Trans. Ind. Electron*., vol. 58, no. 9, pp. 4069-4077, Sep. 2011.

[284] Z. Qiao, T. Shi, Y. Wang, Y. Yan, C. Xia, and X. He, "New sliding mode observer for position sensorless control of permanent magnet synchronous motor", *IEEE Trans. Ind. Electron*., vol. 60, no. 2, pp. 710-719, Feb. 2013.

[285] S. Kommuri, J. J. Rath, K. C. Veluvolu, and M. Defoort, "Robust fault-tolerant cruise control of electric vehicles based on second-order sliding mode observer", in: *Proc. 2014 14th Int. Conf. Control, Automat. Systems (ICCAS)*, pp. 698-703, Oct 2014, Gyeonggi-do, South Korea. pp.698-703.

[286] H. Berriri, M.W. Naouar, I. Slama-Belkhodja. and E. Monmasson, "Field programmable gate array-based fault-tolerant hysteresis current control for AC machine drives", *IET El. Power Appl.*, vol. 6, no. 3, pp. 181-189, 2012.

[287] F. Meinguet, and J. Gyselinck, "Fault detection isolation and reconfiguration of three-phase AC drive with current sensor fault", in: *Proc. IEEE Int. Elect. Mach. Drives Conf.*, pp. 200-205, Aug. 2011.

[288] N. M.A. Freire, J.O. Estima, and A.J.M. Cardoso, "A new approach for current sensor fault diagnosis in PMSG drives for wind energy conversion system", *IEEE Trans. Ind. Appl.*, vol. 50, no. 2, pp. 1206-1214, Mar. 2014.

[289] S.K. El Khil, I. Jlassi, and J.O. Estima, "Current sensor fault detection and isolation method for PMSM drives using average normalized currents", *Electron. Lett.*, vol. 52, no. 17, pp. 1434-1435, Jul. 2016.

[290] C. Wu, C. Guo, Z. Xie, F. Ni, and H. Liu, “A signal-based fault detection and tolerance control method of current sensor for PMSM drive,” *IEEE Trans. Ind. Electron*., vol. 65, no. 12, pp. 9646–9657, Dec. 2018.

[291] K. Jankowska, and M. Dybkowski, “Design and Analysis of Current Sensor Fault Detection Mechanisms for PMSM Drives Based on Neural Networks,” *Designs*, vol. 6, no. 1, Feb. 2022.

[292] S. Ben Slimen, M. Bourogaoui, and H. Ben Attia Sethom, “Abrupt current sensor faults signatures in a salient PMSM drive using the multiresolution analysis technique,” in *Proc. Int. Conf. Elect. Sci. Technol. Maghreb*, Marrakech, Morocco, Oct. 26–28, 2016.

[293] S. Diao, Z. Makni, J. F. Bisson, D. Diallo, and C. Marchand, "Sensor fault diagnosis for improving the availability of electrical drives", in: *Proc. 39th Ann. Conf. IEEE Ind. Electr. Soc. (IECON)*, pp. 3108–3113, Nov. 2013.

[294] G. Huang, Y. Luo, C. Zhang, Y. Huang, and K. Zhao, "Current sensor fault diagnosis based on a sliding mode observer for PMSM driven systems", *Sensors*, vol. 12, pp. 11027-11049, May 2015.

[295] S. K. Kommuri, S. B. Lee, and K. C. Veluvolu, ``Robust sensors-fault-tolerance with sliding mode estimation and control for PMSM drives, "*IEEE/ASME Trans. Mechatronics*, vol. 23, no. 1, pp. 17-28, Feb. 2018.

[296] G. Zhang, H. Zhou, G. Wang, C. Li, and D. Xu, "Current Sensor Fault-Tolerant Control for Encoderless IPMSM Drives Based on Current Space Vector Error Reconstruction," in *IEEE Journal of Emerg. Selected Topics in Power Electr*., vol. 8, no. 4, pp. 3658-3668, Dec. 2020.

[297] Y. Azzoug, M. Sahraoui, R. Pusca, T. Ameid, R. Romary, and A. J. M. Cardoso, "A Variable Speed Control of Permanent Magnet Synchronous Motor Without Current Sensors," in: *2020 IEEE 29th Int. Symp. Ind. Electr. (ISIE)*, 2020, pp. 1523-1528.

[298] Y. Azzoug, M. Sahraoui, R. Pusca, T. Ameid, R. Romary, and A. J. Marques Cardoso, “Current sensors fault detection and tolerant control strategy for three-phase induction motor drives,” *Electrical Engineering*, vol. 103, no. 2, pp. 881–898, Apr. 2021.

[299] M. Adamczyk and T. Orlowska-Kowalska, “Self-correcting virtual current sensor based on the modified Luenberger observer for fault-tolerant induction motor drive,” *Energies*, vol. 14, no. 20, 2021.

[300] G. H.B. Foo, X. Zhang, and B. M. Vilathgamuwa, "A sensor fault detection and isolation method in interior permanent-magnet synchronous motor drives based on an extended Kalman filter", *IEEE Trans. Ind. Electron*., vol. 60, no. 8, pp. 3485-3495, Aug. 2013.

[301] F. Grouz, L. Sbita, and M. Boussak, "Current sensors gain faults detection and isolation based on an adaptive observer for PMSM drives," *10th Int. Multi-Conf. Syst., Signals and Devices (SSD13)*, 2013, pp. 1-6.

[302] H. Berriri, M. W. Naouar, and I. Slama-Belkhodja, "Easy and fast sensor fault detection and isolation algorithm for electrical drives", *IEEE Trans. Power Electron*., vol. 27, no. 4, pp. 490-499, Feb. 2012.

[303] W. Wang, Y. Feng, Y. Shi, M. Cheng, W. Hua, and Z. Wang, "Fault-Tolerant Control of Primary Permanent-Magnet Linear Motors With Single Phase Current Sensor for Subway Applications," *IEEE Trans. Power Electronics*, vol. 34, no. 11, pp. 10546-10556, Nov. 2019

[304] H. Li, Y. Qian, S. Asgarpoor, and H. Sharif, "Machine Current Sensor FDI Strategy in PMSMs," *IEEE Access*, vol. 7, pp. 158575-158583, 2019.

[305] R. Isermann, *Fault-Diagnosis Systems. An Introduction from Fault Detection to Fault Tolerance.* Springer, Berlin–Heidelberg, 2006.

[306] M. Verhaegen, S. Kanev, R. Hallouzi, C. Jones, J. Maciejowski, and H. Smail. “Fault Tolerant Flight Control - A Survey.” In: Edwards C, Lombaerts T, Smaili H (ed) *Fault Tolerant Flight Control*. Springer, Berlin-Heidelberg, pp 47–85, 2010.

[307] B. A. Welchko, T. A. Lipo, T. M. Jahns, and S. E. Schulz, “Fault tolerant three-phase AC motor drive topologies: A comparison of features, cost, and limitations,” *IEEE Trans. Power Electron.*, vol. 19, no. 4, pp. 1108–1116, Jul. 2004.

[308] W. Zhang, D. Xu, P. Enjeti, H. Li, J. Hawke, and H. Krishnamoorthy, “Survey on fault-tolerant techniques for power electronic converters,” *IEEE Trans. Power Electron.*, vol. 29, no. 12, pp. 6319–6331, Dec. 2014.

[309] S. Yantao and W. Bingsen, “Analysis and experimental verification of a fault-tolerant HEV power train,” *IEEE Trans. Power Electron*., vol. 28, no. 12, pp. 5854–5864, Dec. 2013

[310] U. Choi, F. Blaabjerg, and K. Lee, “Reliability improvement of a T-Type three-level inverter with fault-tolerant control strategy,” *IEEE Trans. Power Electron*., vol. 30, no. 5, pp. 2660–2673, May. 2015.

[311] B. C. Mecrow, A. G. Jack, J. A. Haylock, and J. Coles, “Fault-tolerant permanent magnet machine drives,” *Proc. Inst. Elect. Eng.-Electr. Power Appl*., vol. 143, no. 6, pp. 437-442, Nov. 1996

[312] A.M. El-Refaie, “Fault-tolerant permanent magnet machines: A review,” *IET Electr. Power Appl*., vol. 5, no. 1, pp. 59-74, Jan. 2011

[313] W. Zhao, L. Xu, and G. Liu, “Overview of permanent-magnet fault tolerant machines: topology and design, ”*CES Trans. Electrical Machines and Systems*, vol. 2, no. 1, pp. 51-64, Mar. 2018

[314] O. Dieterle, T. Greiner, and P. Heidrich, ‘‘Control of a PMSM with quadruple three-phase star-connected windings under inverter short-circuit fault,’’ *IEEE Trans. Ind. Electron*., vol. 66, no. 1, pp. 685–695, Jan. 2019.

[315] F. Baudart B. Dehez, E. Matagne, D. Telteu-Nedelcu, P. Alexandre and F. Labrique, “Torque control strategy of polyphase permanent-magnet synchronous machines with minimal controller reconfiguration under open-circuit fault of one phase,” *IEEE Trans. Ind. Electron*., vol. 59, no. 6, pp. 2632–2644, Jun. 2012.

[316] F.-J. Lin, Y.-C. Hung, and M.-T. Tsai, ‘‘Fault-tolerant control for six-phase PMSM drive system via intelligent complementary sliding-mode control using TSKFNN-AMF,’’ *IEEE Trans. Ind. Electron.,* vol. 60, no. 12, pp. 5747–5762, Dec. 2013

[317] H. Guzman, M.J. Duran, F. Barrero, B. Bogado, and S. Toral, “Speed control of five-phase induction motors with integrated open-phase fault operation using model-based predictive current control techniques,” *IEEE Trans. Ind. Electron*., vol. 61, no. 9, pp. 4474–4484, Sep. 2014.

[318] H. Wang, W. Zhao, H. Tang, T. Tao, and S. Saeed, “Improved fault tolerant model predictive torque control of five-phase PMSM by using deadbeat solution,” *IEEE Trans. Energy Convers.*, vol. 37, no. 1, pp. 210-219, March 2022.

[319] D. Zeng, Z. Jibin, and Y. Xu, “An indirect testing method for the torque ripple of multi-unit permanent magnet synchronous machines,” *IEEE Trans. Ind. Electron*., vol. 67, no. 4, pp. 2734-2743, April 2020,

[320] Y. Luo and C. Liu, “Pre- and post-fault tolerant operation of a six-phase PMSM motor using FCS-MPC without controller reconfiguration,” *IEEE Trans. Veh. Technol*., vol. 68, no. 1, pp. 254-263, Jan. 2019.

[321] A. Gaeta, G. Scelba, and A. Consoli, “Modeling and control of three phase PMSMs under open-phase fault,” *IEEE Tran. Ind. Appl.,* vol. 49, no. 1, pp. 74-83, Jan./Feb. 2013.

[322] A. Kontarcek, P. Bajec, M. Nemec, and V. Ambrozic, and D. Nedeljkovic, “Cost-effective three-phase PMSM drive tolerant to open phase fault,” *IEEE Trans. Ind. Electron*., vol. 62, no. 11, pp. 6708-6718, Nov. 2015.

[323] A. Kiselev, G. R. Catuogno, A. Kuznietsov, and R. Leidhold, “Finite-Control-Set MPC for Open-Phase Fault-Tolerant Control of PM Synchronous Motor Drives,” *IEEE Trans. Ind. Electron.,* vol. 67, no. 6, pp. 4444-4452, June 2020.

[324] I. Jeong, B. J. Hyon, and K. Nam, “Dynamic modeling and control for SPMSMs with internal turn short fault,” IEEE *Trans. Power Electron.,* vol. 28, no. 7, pp. 3495-3508, Jul. 2013.

[325] J. Zhang, W. Zhan and M. Ehsani, “Fault-tolerant control of PMSM with inter-turn short-circuit fault,” *IEEE Trans. Energy Convers.,* vol. 34, no. 4, pp. 2267-2275, Dec. 2019.

[326] S. Im and B. Gu, “Interturn fault tolerant drive method by limiting copper loss of interior permanent magnet synchronous motor,” *IEEE Trans. Ind. Electron.,* vol. 67, no. 9, pp. 7973-7981, Sept. 2020.

[327] B. Wang, J. Wang, A. Griffo and L. Huang, “A turn fault mitigation strategy based on current injection technique for a triple three-phase PMA SynRM,” *IEEE Trans. Ind. Electron.,* vol. 67, no. 4, pp. 2511-2522, Apr. 2020

[328] Y. Jiang, Z. Zhang, W. Jiang, W. Geng and J. Huang, “Three-phase current injection method for mitigating turn-to-turn short-circuit fault in concentrated-winding permanent magnet aircraft starter generator” *IET Electric Power Appl.,* vol. 12, no. 4, pp. 566-574, Jan. 2018.

[329] J. G. Cintron-Rivera, S. N. Foster and E. G. Strangas, “Mitigation of turn-to-turn faults in fault tolerant permanent magnet synchronous motors,” *IEEE Trans. Energy Convers.,* vol. 30, no. 2, pp. 465-475, Jun. 2015.

[330] J. Holtz, “Acquisition of position error and magnet polarity for sensorless control of PM synchronous machines,” *IEEE Trans. Ind. Appl.,* vol. 44, no. 4, pp. 1172–1180, Jul./Apr. 2008.

[331] X.Wu, S. Huang, X. Liu, K. Lu, J. Gao, and J. Zheng, “Design of Position Estimation Strategy of Sensorless Interior PMSM at Standstill Using Minimum Voltage Vector Injection Method,” *IEEE Transactions on Magnetics*, vol. 53, no. 11, Art. 8110804, Nov. 2017.

[332] Shuang Wang, Kang Yang, and Kang Chen, “An Improved Position-Sensorless Control Method at Low Speed for PMSM Based on High-Frequency Signal Injection into a Rotating Reference Frame,” *IEEE Access*, vol. 7, pp. 86510–86521, 2019.

[333] F. Mwasilu, and J. W. Jung, “Enhanced fault-tolerant control of interior PMSMs based on an adaptive EKF for EV traction applications,” *IEEE Transactions on Power Electronics*, vol. 31, no. 8, pp. 5746–5758, 2016.

[334] T. Szalai, G. Berger, and J. Petzoldt, ``Stabilizing sensorless control down to zero speed by using the high-frequency current amplitude," *IEEE Trans. Power Electron.*, vol. 29, no. 7, pp. 3646-3656, Jul. 2014.

[335] G. Xie, K. Lu, S. K. Dwivedi, J. R. Rosholm, and F. Blaabjerg, ”Minimum voltage vector injection method for sensorless control of PMSM for low-speed operations,” *IEEE Trans. Power Electron.*, vol. 31, no. 2, pp. 1785_1794, Feb. 2016.

[336] A. Akrad, M. Hilairet and D. Diallo, “Design of a fault-tolerant controller based on observers for a PMSM drive”, *IEEE Trans. Ind. Electron.*, vol. 58, no. 4, pp. 1416-1427, Apr. 2011.

[337] G. Zhang, G. Wang, H. Zhou, C. Li, G. Wang and D. Xu, "Current Sensor Fault Diagnosis and Fault-Tolerant Control for Encoderless PMSM Drives Based on Dual Sliding-Mode Observers," *2019 IEEE Applied Power Electronics Conference and Exposition (APEC)*, 2019, pp. 2549-2553

[338] Y. Bensalem, A. Kouzou, R. Abbassi, H.Jerbi, R. Kennel, M. Abdelrahem, “Sliding-Mode-Based Current and Speed Sensors Fault Diagnosis for Five-Phase PMSM.” *Energies*, vol. 15, Art. 71, 2022.

TERESA ORLOWSKA-KOWALSKA (M’93–SM’05) received the Ph.D. and D.Sc. degrees in electrical engineering from Wroclaw University of Technology (WUT), Wroclaw, Poland, in 1976 and 1990, respectively. Since 1993, she has been a Professor of electrical engineering (since 2004 – Full Professor) and the Head of the Electrical Drives Control Chair at the Faculty of Electrical Engineering, WUT. In the period 2002-2019 she has been the Director of the Institute of Electrical Machines, Drives, and Measurements, WUT. She is the author of over 400 journal papers and Conf. proceedings, two textbooks, two books, and fifty chapters in monographs. Her research interests include controlled electrical drives, applications of the observer theory and artificial intelligence methods in sensorless control of AC drives, control methods of the drive systems with elastic couplings, diagnostics and fault-tolerant control methods for AC drives. Prof. Orlowska-Kowalska is a member of the Electrical Engineering Committee of the Polish Academy of Science (since 1996), the Council of Provosts of IV Division of the Polish Academy of Science (2011-2018), and International Steering Committees of a few well-known conferences. In the period 2004-2014 she has been an Associate Editor for the IEEE Transactions on Industrial Electronics. She is a member of Editorial Boards of a few international journals and Editor-in-Chief of Power Electronics and Drives journal. She serves as a reviewer of many IEEE, IET, Elsevier, Springer, Taylor & Francis, MDPI, SAGE and other journals.

MARCIN WOLKIEWICZ received the M.Sc., Ph.D. and D.Sc. degrees from Wroclaw University of Science and Technology, Wroclaw, Poland, in 2007, 2012, and 2020, respectively. Since 2020 he has been an Associated Professor in Electrical Engineering Faculty of Wroclaw University of Technology, the Department of Electrical Machines, Drives and Measurements. He is the author and co-author of more than 55 journal papers and conference proceedings. His main fields of interest are fault monitoring and diagnosis of electrical drives using signal analysis including advanced methods and transforms, and neural networks.

PRZEMYSLAW PIETRZAK received the M.Sc. degree from the Faculty of Electrical Engineering, Wroclaw University of Science and Technology, Wroclaw, Poland, in 2020. Since 2020, he has been a Ph.D. student in the Department of Electrical Machines, Drives and Measurements of Wroclaw University of Science and Technology. His main fields of interest are condition monitoring and fault diagnosis of electrical drives.

MACIEJ SKOWRON received the M.Sc. and Ph.D. degrees from the Faculty of Electrical Engineering, Wroclaw University of Science and Technology, Poland, in 2018 and 2021, respectively. Since 2021, he is an Assistant Professor in the Department of Electrical Machines, Drives. His main fields of interest are diagnostics of AC motor drives, signal processing methods, artificial intelligence, digital implementation of control and diagnostic systems.

PAWEL EWERT received the M.Sc. and Ph.D. degree from the Faculty of Electrical Engineering, Wroclaw University of Science and Technology, Poland, in 2007 and 2012, respectively. Since 2013, he has been an Assistant Professor in the Department of Electrical Machines, Drives and Measurements at his home University. He is the author or co-author of 27 journal articles, 12 conference papers and one handbook. His main area of interest is diagnostics of electrical machines and drives using advanced signal processing methods and artificial neural networks.

GRZEGORZ TARCHALA received the M.Sc., Ph.D. and D.Sc. degrees from Wroclaw University of Science and Technology, Wroclaw, Poland, in 2009, 2013 and 2020, respectively. Since 2020, he has been an Associated Professor in the Department of Electrical Machines, Drives and Measurement of Wroclaw University of Science and Technology. He is an author and co-author of more than 60 journal and conference papers. His main research interests are: modern control structures for induction motors, sliding mode control, state variables estimation, power electronics, monitoring and diagnosis. He serves as a reviewer of many IEEE Transactions and other scientific journals.

MATEUSZ KRZYSZTOFIAK received his M.Sc. degree in automation and robotics from Wroclaw University of Science and Technology in 2019. Since 2019, he has been a Ph.D. student in the Department of Electrical Machines, Drives and Measurements. His research interests include monitoring and fault diagnosis of electrical machines, in particular PMSM analysis based on mathematical models and the possibility to detect faults in a closed control structure.

CZESLAW T. KOWALSKI, received the Ph.D. and D.Sc. degrees from Wroclaw University of Technology, Wroclaw, Poland, in 1983 and 2006, respectively. He has the Full Professor position at Electrical Engineering Faculty of Wroclaw University of Technology, in the Department of Electrical Machines, Drives and Measurements. He is author and co-author of more than 170 journal papers and Conf. proceedings, two textbooks, one book. His field of interest is mathematical modeling and control of electrical drives, fault monitoring and diagnosis of the electrical drives using state observers and neural networks. Prof. Kowalski is a member of the Polish Society of Theoretical and Applied Electrical Engineering and Int. steering committees of a few well-known conferences. He serves as a reviewer of many IEEE, IET, MDPI and other journals.