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Fault Diagnosis in Electrical Machines for Traction Applications: Current Trends and Challenges

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Abstract: The widespread diffusion of electric vehicles poses new challenges in the field of fault diagnostics. Past studies have been focused mainly on machines designed for industrial applications, where the operating conditions and requirements are significantly different. This work presents a review of the most recent studies about fault diagnosis techniques in electrical machines feasible for traction applications, with a focus on the most adopted approaches of the last years and on the latest trends. Considerations about their applicability for electric vehicle purposes, along with some areas that require further research, are also provided.

Keywords: fault detection; review; electric vehicle; traction application; condition monitoring; machine learning; permanent magnet machines; induction machines; multi-phase machines

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1. Introduction

1.1. Motivation

Rotating electrical machines are extensively used across various sectors in contemporary industry. Unforeseen failures can result in significant economic losses due to production halts and the necessity to replace defective components, or in some cases, the entire machine. Consequently, numerous studies have concentrated on the condition monitoring of electrical machines to identify early-stage faults across different configurations before they evolve into severe damages [1–3]. In recent years, the deployment of electric motors in traction applications has remarkably increased. However, research focused on fault diagnosis for these machines has not progressed to the same extent. This is primarily because electric vehicle applications entail different environment, sizes, and more complex machine control strategies compared to industrial applications. These factors influence both the condition monitoring and the ability to detect incipient faults effectively.

1.2. Objective

The aim of this study is to first present a comprehensive overview of the most researched and widely implemented fault diagnosis (FD) methodologies in recent years, with a particular emphasis on electrical machines and conditions that are more fitting for traction applications. Additionally, the viability of certain FD methods for traction applications are evaluated. Future challenges and machine topologies that require further investigation are also addressed. From this perspective, the principles under which specific approaches and machines are favored over others include the following:

1. Automated faut diagnosis: the identification of incipient faults during regular machine operation is of significant importance, as it contributes to overall cost reduction, higher safety and reliability.
2. Sensors fusion: combining data from multiple sensors provides more accurate, reliable, or comprehensive information than could be achieved by using any single sensor alone. It helps FD algorithms make safer and more informed decisions.
3. Operating conditions: methodologies capable of working under non-stationary conditions should be preferred, although approaches which require steady-state conditions will also be evaluated.

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4. Machine topology: in industrial applications, induction machines (IMs) have been the most extensively studied [1,2,4–6]. Electric vehicles (EVs), on the other hand, can utilize a large variety of topologies, including IMs, permanent magnet synchronous motors (PMSMs), synchronous reluctance machines (SyRMs), and wound field synchronous machines (WFSMs). Typically, these machines feature three-phase windings and operate with radial flux. However, the interest towards the adoption of multiphase configurations as well as axial flux machines (AFMs) is gradually increasing.

2. Overview of the Key Physical Quantities in the Analysis

The condition monitoring of electrical machines is always performed through the measurement of some physical quantities, such as currents, voltages, fluxes, vibrations or temperatures. The underlying concept is that even an initial fault causes minor asymmetries and distinct behaviours from mechanical, thermal, or electromagnetic perspectives. These variations can be reflected in some of the previously mentioned key physical quantities, thereby allowing for identification. Excluding temperature, the other physical variables are also characterized by their nature as time-dependent signals, but can be seen also from a frequency domain point of view. Different manipulations in either time or frequency domains are valuable degrees of freedom to isolate specific fault characteristics. Typically, each fault generates distinct harmonics, which can be identified through appropriate transformations. In fact, these harmonics act as a signature, allowing a proper identification. Several factors influence the choice of the most appropriate quantities for FD, and these factors depend on the specific application. Below, some considerations regarding these quantities and their potential applicability to traction applications are outlined:

- *Currents*: Among the various parameters examined in extensive research, phase currents are particularly prominent, as current sensors are essential for safety and control purposes. Furthermore, their integration is relatively straightforward. Consequently, FD analysis utilizing Motor Current Signature Analysis (MCSA) remains a beneficial approach for traction applications, leveraging the existing current sensors employed for drive control [5,7–9]. However, a significant limitation of current-based FD arises in scenarios involving low loads or minor faults, where inherent measurement noise can hinder the accurate assessment of the machine's condition.
- *Voltages*: Although voltage sensors are less frequently utilized in many industrial applications, they are essential in electric vehicles (EVs), where their presence is critical not only for proper drive control [10], but also for safety reasons. Their implementation is also straightforward, making them viable candidates for FD in EVs.
- *Vibrations*: Numerous investigations have been conducted on FD for industry application through vibration measurements, particularly for identifying bearing faults [9,11–13], which constitute the largest proportion of total failure in low-voltage (LV) machines and more than one tenth in high-voltage (HV) ones, where stator insulation failure become predominant, as illustrated in Figure 1 [7]. While promising results have been obtained, several limitations are present. Specifically, the need for additional sensors and the complexities associated with their installation present challenges for accurate assessments. Furthermore, the significant mechanical noise prevalent in EV environments introduces additional obstacles.
- *Fluxes*: Some research has explored the use of flux measurements as potential indicators of faults, similar to current analysis [9,11,14,15]. However, their application is limited due to the necessity for additional sensors. Most research make use of stray flux measurement [16,17], although the available data from previous studies is currently more limited compared to that of MCSA. Another option is represented by search coils. However, in EV applications, where the air gap is typically small, their incorporation may not be practical.
- *Temperature*: In terms of temperature-based methodologies, infrared thermography has been employed for FD purposes. This technique can map the thermal distribution across machine components, facilitating the identification of faults that induce excessive or uneven losses [18,19].

While this approach is still in its nascent stages and has predominantly been tested in industrial contexts, it holds potential as a viable alternative for future applications.

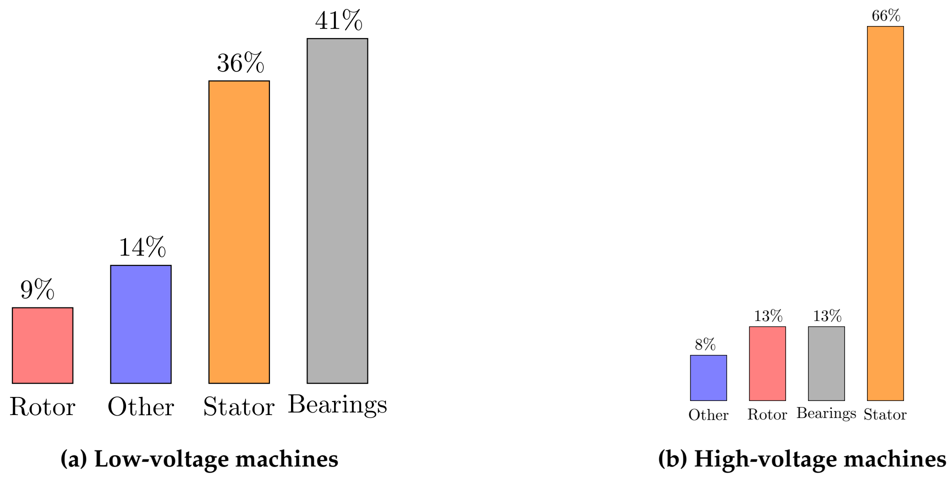

Figure 1. Electrical machines statistical fault location [7].

2.1. Signal Pre-Processing

As previously stated, the FD requires the analysis of one or more signals. Signals are often manipulated typically by applying one or more transformations, in addition to techniques such as noise reduction and various mathematical operations. Specifically, three primary possibilities exist [7,8,20]: time domain analysis, frequency domain analysis, or time-frequency domain analysis. A significant portion of the research on fault diagnosis in electrical machines predominantly relies on the latter two techniques, particularly when applied to MCSA. The most common example of a frequency-domain transformation is provided by the fast Fourier transform (FFT), which is known to be a valid tool for harmonic component isolation in stationary conditions. Another quite common method is provided instead by wavelet transforms such as discrete (DWT) or continuous wavelet transform (CWT) [21], which operate in the time-frequency domain. Figure 2 provides an overview of the most adopted transformation algorithms. Further insights into their meaning and potential applications can be found in [7]

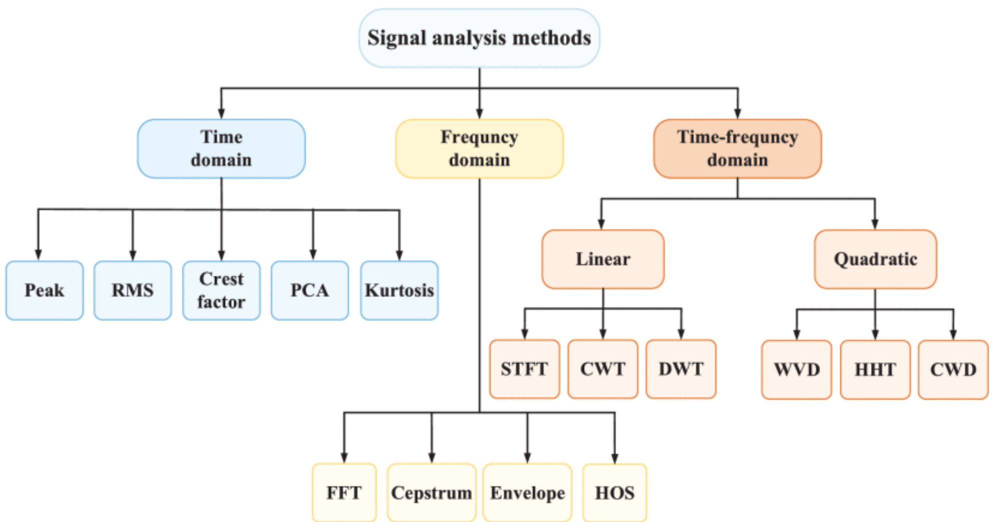

Figure 2. Signal analysis methods [7].

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3. Methods for Automatic Fault Detection

Once an appropriate FD algorithm is applied, prompt fault detection becomes essential. In automotive applications, the development of automated, real-time FD systems is crucial for both economic and safety reasons. It is important to note that FD approaches in the literature are not always clearly distinguished, as their categorization often depends on the researcher's perspective. Some processes, such as signal pre-processing, may overlap. Below, a simple distinction between two main categories is presented.

3.1. Model Based Methods

Grasping the modeling of a specific electrical machine can help for a better understanding of its behavior under varying working conditions and can allow the prediction of unknown parameter values with a certain accuracy based on available measurements. State observers are utilized to monitor specific variables of the machine, which are then used to predict others, allowing for the assessment of whether the machine is operating in a healthy state or not. This is exemplified by various types of Kalman Filters (KF) [22–25], where the estimated parameters can be compared against defined thresholds to ascertain the healthy or faulty status of the machine. KFs can provide insights into the extent of failure when the model is finely calibrated, which also constitutes its primary limitation. Nonetheless, it retains traditional challenges associated with the tuning process, which may compromise its reliability. It has be underlined that the FD based on the comparison of some measured or estimated parameters against specific selected thresholds is quite a common practice and not related only to KFs. These approaches all share the need for varying degrees of system knowledge, depending on the required accuracy of the FD method.

3.2. Artificial Intelligence Based Methods

Fostered by the availability of an increasing computational capability, last years have seen a dramatic increment of interest in automated fault detection methods based on artificial intelligence (AI) [7,8,26,27]

Once the set of FD key physical quantities has been decided and the related sensors has been placed in the system, an appropriate signal preprocessing usually returns one or more variables that have specific features associated to the presence of an incipient fault.

However, external noises and operating conditions complicate the explicit identification, making it more suited for an experienced human than for a simple 'if-then' algorithm. In automating the process, machine learning (ML) techniques can be highly effective, provided they are well trained.

Based on the learning strategy, ML algorithms can generally be categorized into two main groups:

1. *Supervised Learning*: they are by far the most adopted for electrical machine FD. Their main feature is the training based on labeled data. This means that the training dataset includes input-output pairs, where the input is the data which needs to be classified and output is the corresponding value or class. The goal of the algorithm is to learn a mapping from inputs to outputs so that it can predict the labels for new, unseen data accurately. For example, in a supervised learning task for fault classification based on current waveform measurement, the algorithm would be trained on a dataset of currents (inputs) with corresponding labels (outputs stating if the currents belongs to a healthy machine or not, or even the type of fault, if present). NNs have been widely adopted in supervised learning. Among them, deep neural networks (DNNs) have demonstrated greater potential in FD due to their enhanced flexibility and superior classification capability. Indeed, DNNs have the capacity to process both raw data and preprocessed data using various transforms [8,26]. Moreover, they exhibit great efficiency with larger datasets. NNs with a lower number of layers, called also shallow NNs (SNNs) can be also used for FD purposes. SNNs typically require extensive preprocessing of signals to emphasize features related to specific faults and are more suitable for smaller datasets [26]. Figure 3 resumes the FD methodologies utilizing neural networks. Other types of supervised learning methods which have been also

utilized are support vector machines (SVM), k-Nearest-Neighbors (k-NN), linear regression (LR) and decision tree (DT) but there may be also other examples [28].

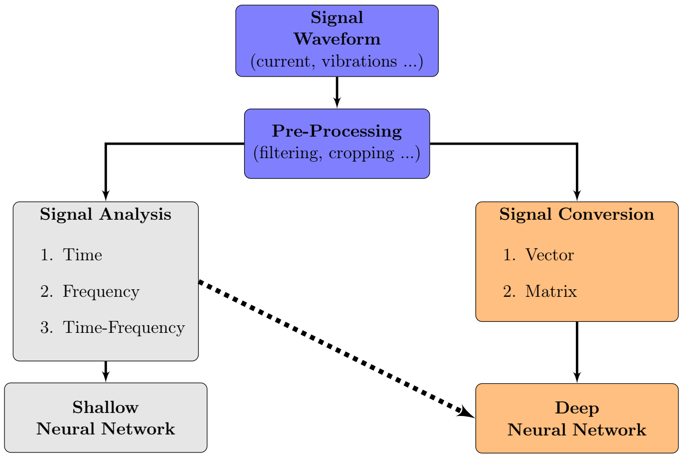

Figure 3. Neural Networks FD process.

2. *Unsupervised Learning*: it is a type of machine learning where the model is trained on data without labeled responses. The goal is to identify patterns and structures within the data. Common techniques include clustering (grouping similar data points) and dimensionality reduction (simplifying data while retaining important information). Unsupervised learning is generally less adopted for FD purposes, due to the complexity of the problem, especially if the aim is to identify incipient faults. However, some example of FD with unsupervised learning approaches are present, especially with autoencoders [29–31], which can be classified as dimensionality reduction unsupervised learning method.

The possible ML topologies have been collected in the block diagram of Figure 4

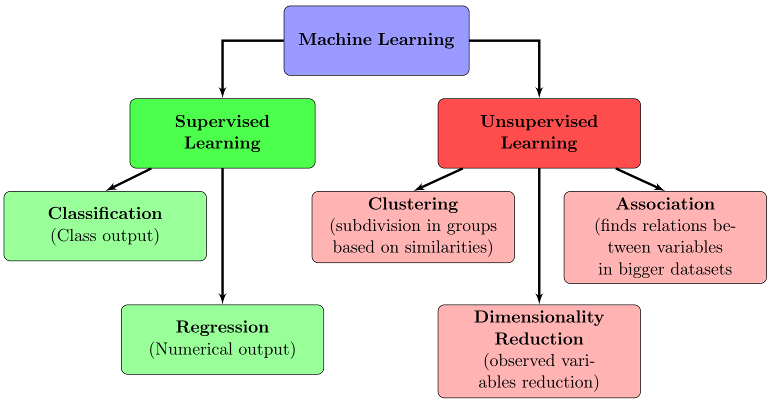

Figure 4. Machine Learning topologies

It has to be said that also hybrid approaches are possible for semi-supervised learning methods, while NNs adoption is not necessarily restricted only to supervised methods. Discussing and highlighting all the possible differences and peculiarities of ML approaches can become quite a complicated task and is not within the scope of this paper. Figure 4 is then intended to provide a brief summary of the main ML categories, each of them with its distinctive features. A useful guide for directing the search is provided by [32–34].

4. Induction Machines Faults

Induction machines (IMs) have long been, and continue to be, widely used in industrial environments, thereby attracting the majority of past research efforts. Although IMs can struggle in matching the torque and power density capabilities of PMSMs, their inherent robustness, lack of reliance on rare earth materials, and simple manufacturing procedures make them well-suited for a wide range of applications. However, it is important to note that not all insights from past research can be directly applied to EV contexts, as will be discussed later in the paper. In the following sections, a concise overview of the principal fault types affecting IMs will be presented, as well as the most adopted FD methodologies in the last years.

4.1. Broken Rotor Bar Fault

Faults in induction motors (IMs) can arise from the interplay of mechanical and thermal stresses. The presence of one or more broken rotor bars induces an asymmetry in the rotor flux, which subsequently impacts the stator currents. The primary additional harmonics generated by a broken rotor bar (BRB) are represented by (1):

$$f_{bb} = f_{se}(1 \pm 2ks), \quad k = 1, 2, \ldots \tag{1}$$

where f_{se} is the stator electrical fundamental frequency and s is the slip.

FD in IMs presents a considerable challenge due to the close proximity of the two main harmonics (for $k = 1$) to the main harmonic, particularly at low slip conditions. This issue is therefore prevalent in both low-load situations for all IMs, but even during rated load operations for high-power IMs, which are characterized by smaller the slip values. Various fault detection techniques, including frequency transformations [35–42] and time-frequency transformations such as the Continuous Wavelet Transform (CWT) or the short time Fourier transform (STFT) [42–45], have been extensively explored.

MCSA is the most adopted quantity, while some studies rely on stray fluxes [40,45] or on air gap flux [42]. However, all these methodologies have primarily been validated in specific industrial contexts that differ significantly from typical EV environments [46,47].

Most existing studies focus on steady-state operations with grid-supplied sinusoidal currents or basic Volt-Hertz control strategies. While time-frequency transformations like the CWT demonstrate high accuracy in identifying BRBs during transient conditions, they require substantial transient slip variations, which is not feasible in Field-Oriented Control (FOC) operations. Unfortunately, there remains a scarcity of data available for non-stationary low-slip operations, highlighting this as an intriguing and open area for further investigation. In addition, as highlighted in [47], research about end ring failure are rare in literature.

4.2. Bearing Faults

Bearing faults are among the most prevalent mechanical failures encountered in rotating electrical machines. Early detection of these faults can be particularly challenging due to the presence of mechanical noise. In contrast to BRB faults, the harmonics induced by bearing faults are shifted significantly towards higher frequencies relative to the fundamental harmonic, as shown in equations (2) and (3). The following equation set specifically pertains to ball bearings faults and are independent of the electrical machine type.

$$f_{bm} = kf_{fm} \pm lf_{rm} \quad k = 1, 2, 3 \ldots, \quad l = 0, 1 \tag{2}$$

$$f_{be} = f_{se} \pm kf_{fm} \quad k = 1, 2, 3 \ldots \tag{3}$$

where f_{rm} is the rotor mechanical frequency, f_{se} is the stator electrical frequency and f_{fm} is the fault-specific mechanical frequency [7], which depends on the location of the bearing defect. Table 1 provides a brief summary on the most common possible defects.

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Equation (2) is relative to the main fault harmonics at mechanical (hence physical) frequency, which can be detected, for example, by an accelerometer. Equation (3) is related instead to the electrical frequency, and can be observed through MCSA. Equations (4)-(7) allows instead the estimation of f_{fm} depending on the damage location.

Table 1

Type of fault	f_{fm}
bearing cage	f_{bc}
outer race	f_{or}
inner race	f_{ir}
rolling element	f_{re}

$$f_{bc} = \frac{1}{2} f_r \left(1 - \frac{D_b}{D_c} \cos\alpha\right) \tag{4}$$

$$f_{or} = \frac{N_{rb}}{2} f_r \left(1 - \frac{D_b}{D_c} \cos\alpha\right) \tag{5}$$

$$f_{ir} = \frac{N_{rb}}{2} f_r \left(1 + \frac{D_b}{D_c} \cos\alpha\right) \tag{6}$$

$$f_{re} = \frac{D_c}{D_b} f_r \left(1 - \left(\frac{D_b}{D_c} \cos\alpha\right)^2\right) \tag{7}$$

where N_{rb} is the number of rolling elements (balls), α is the bearing working angle ($\alpha = 0$ for rolling bearing), D_b and D_c are the rolling element diameter and pitch diameter, respectively.

Numerous studies have focused on IMs bearing FD (IMs). Recent research has increasingly employed machine learning (ML) techniques [12,13,16,48–53].

In works such as [12,13,51–53], fault diagnosis is conducted using vibration data, whereas [16,48–50] primarily utilizes electrical parameters, particularly MCSA. In all the above investigations, neural network training has been carried out on experimental data collected under steady-state conditions. Frequency and time-frequency manipulation have been intensively adopted as well. Frequency transformations have been used in [17,48,50–52], while time-frequency ones in [12,16,49]. In [13] raw signals from three different sensors are instead converted into a 2D image and then sent to a convolutional neural network (CNN), without performing any preliminary feature extraction.

4.3. Rotor Eccentricity

Eccentricity faults often arise from issues related to bearings, resulting in an uneven air gap and consequently leading to increased localized saturation. The additional harmonics generated by this fault are described by equations (8) and (9)

$$f_{IM_{ecc1}} = [(kN_{rs} \pm n_{eo})(1-s)/p \pm v] f_{se} \tag{8}$$

with $n_{eo} = 0, 1, 2 \ldots; v = 1, 3, 5 \ldots; k = 1, 2, 3 \ldots$

$$f_{IM_{ecc2}} = \left[(1-s)/p_p \pm k\right] f_{se} \tag{9}$$

where p_p is the pole pair number, N_{rs} is the rotor slot number, n_{eo} is the eccentricity order. $n_{eo} = 0$ denotes instead a static eccentricity.

In recent years, numerous studies have been conducted on faults related to eccentricity [54–58]. The research presented in [55] focuses on feature extraction based on vibration data, whereas [54,56,58] employs current measurements for the same purpose. In both instances, the analyses are conducted

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under steady-state conditions and an extensive use of frequency and time-frequency transformation is still present.

Possible online implementation is discussed in [58], which has also the peculiarity that time domain data are directly processed with TDA (topological data analysis) whose output should be used for ML training processes.

4.4. Stator Inter-Turn Short Circuit

The inter-turn short circuit (ITSC) fault is characteristic of all electrical machines and typically arises from a combination of thermal, electrical and mechanical stresses experienced by the winding [59]. The occurrence of this fault leads to a localized reduction in stator inductances, resulting in decreasing flux linkage and impedance. Consequently, this generates additional harmonics, whose frequencies are given by:

$$f_{itsc_1} = f_{se}\left(1 \pm \frac{k}{p_p}\right) \quad k = 1,2,3\ldots \tag{10}$$

The presence of ITSC can trigger also an increase of some slot harmonics at the following frequencies:

$$f_{itsc_2} = f_{se}\left(1 \pm k\frac{N_{ss}}{p_p}\right) \quad k = 1,2,3\ldots \tag{11}$$

where N_{ss} is the stator slot number and p_p the number of pole pairs.

Various investigations into ITSC FD techniques present a range of methodologies [22,57,60–64]. A key distinction in this area is the incorporation of voltage component monitoring, either alongside or as an alternative to MCSA, in some studies.

In [57], voltage reference signature analysis is utilized alongside MCSA for a six-phase IM. The results indicate that both ITSC and eccentricity faults lead to alterations in harmonic planes. However, the detection of these harmonic components within the line current may prove challenging due to their low amplitude.

According to the sensor fusion strategy, the combination of both current and voltage analysis has been used also in [22], where the FD is performed through a KF.

Other research works have considered the effects of ITSC on IMs operating under Field-Oriented Control (FOC) [63] or Direct Torque Control (DTC) [65]. In [63], spectral analysis of control signal parameters reveals an increase in the second harmonic. The use of ML approaches is here less prominent with respect to other faults and have been adopted only in [62,64].

5. Permanent Magnet Synchronous Machine Faults

Permanent magnet synchronous motors (PMSMs) are the most commonly used electrical machines in EVs. Fault detection (FD) research in PMSMs is relatively new compared to that of induction machines (IMs). Despite its recent emergence, the findings in this field are highly valuable. Moreover, PMSMs' reliance on dedicated voltage source inverters (VSIs) suggests that these results may be more directly applicable, especially for EV applications.

5.1. Demagnetization faults

Understanding the implications of demagnetization is crucial for maintaining the performance of PMSMs and other applications that rely on magnetic components. Monitoring temperature is essential to prevent irreversible losses in magnetization, which can significantly impact motor efficiency and operational reliability. This condition leads to a localized reduction in flux, which may also result in decreased saturation levels and changes in inductance values. The main harmonics generated by this fault are:

$$f_{dem} = f_{se}\left(1 \pm \frac{k}{p_p}\right) \quad k = 1,2,3,\ldots \tag{12}$$

Research on FD related to demagnetization has investigated various methodologies based on MCSA, flux, voltage analysis, but also MVSA [7]. ML techniques [66–68], the use of multiple observers for monitoring inductances [69], and the analysis of voltage effects [70,71] have been studied.

An alternative approach based on CNNs is described in [72]. The innovation lies in the training dataset for the neural network, which no longer requires a large set of faulty motors. Instead, a substantial training dataset is generated using a combination of tuned motor models and data augmentation techniques. The result is a comprehensive and effective motor condition monitoring algorithm, centered around a CNN trained on a safe and cost-effective simulation-based dataset.

Findings indicate that ITSC faults and demagnetization affect the d-q voltages in distinct ways. For example, in [71] it has been shown that, as a consequence of demagnetization, an additional back-electromotive force 5th harmonic component could be observed in double three-phase superficial PMMs.

In [67], flux leakages are transformed into 2D images through SDP transform, which are then used as input for a semi-supervised classifier. This study employs a SNN, while it should be noted that CNNs also demonstrate promising performance when applied to 2D image data.

5.2. Rotor Mechanical Faults

Recent research on both eccentricity and bearing faults in PMSM is limited, although some interesting results have been found. The estimation of additional harmonics in case of bearing faults can be done again with (2), (3). On the other hand, eccentricity additional harmonics can be computed as:

$$f_{PMecc} = f_{se}\left(1 \pm \frac{2k-1}{p_p}\right) \quad k = 1,2,3\ldots \tag{13}$$

The primary limitation in detecting eccentricity faults arises from the first harmonic (k = 1) coinciding with the frequency associated with demagnetization, complicating the differentiation between these two faults. The study presented in [73] uses a Linear Discriminant Analysis (LDA) to extract eccentricity fault features after MCSA performed through spectrum analysis. FD is then performed employing a Bayes classifier.

The voltage measurement at the midpoint of each winding phase for detecting static eccentricity is instead proposed in [74], showing that the voltage pattern in the $\alpha - \beta$ plane may be affected as well.

Another study highlighted in [75] demonstrates the potential applications of CWT and DWT on vibrations for bearing FD, although the study is not recent.

Generative Adversarial Networks (GANs) are used in a more recent research [76], showing promising results in processing collected vibration measurements for bearing FD. A quite different approach is provided instead in [77]. Here time-frequency manipulation is used to generate 2D images for Multi-Scale Structural Similarity Index computation, which does not involve any type of ML.

5.3. Stator Inter-Turn Short Circuit

PMSMs exhibit the same winding structure of IMs. As a result, the occurrence of an ITSC generates the same additional harmonics. Recently, various methods for detecting ITSC in PMSMs have been investigated. For instance, [25] utilizes a KF for fault detection, while [78] monitors both voltage and current, employing a model-based statistical approach in combination with Least Squares Method (LSM) for FD. Although the implementation specifics are not elaborated upon in [10], this study is significant for its application of wavelet transform to the q-axis reference voltage.

Voltages are used also in [79,80], where it is demonstrated the potential of high frequency voltage injection, due to the different machine response in healthy and faulty conditions. Additionally, [81] performs transient MCSA using a variant of the short-time Fourier transform to extract the fault harmonic components (FHC).

Current analysis is adopted also in [82,83]. In the first case the high frequency current ripple is taken into consideration as fault indicator, while in the latter the FD is performed by comparison between a model-based current estimation and the measured one. On the other hand, a peculiar method is illustrated in [84], with the combination of thermography and magnetic flux sensors for the end winding region. Eventually, effects on the control due to this type of fault are discussed in [85].

6. Other Electrical Machines

The availability of electrical machines for tractions applications is not restricted to IMs and PMSMs. However, as shown in the following sections, research on FD for other machine topologies is quite limited. The main studies are presented below.

6.1. Synchronous Reluctance Machines

The pressing demand for energy-efficient and environmentally friendly electric drives across is driving research towards synchronous motors that utilize reduced or minimal amounts of rare-earth permanent magnets. Anisotropic or pure synchronous reluctance machines (SynRM), which fulfill this need, offer an interesting degree of freedom in torque control for EV applications, although their nonlinear magnetic model brings along an inherent control complexity [86]. SynRMs are robust and simple machines and, due to their structure, they cannot experience BRB or demagnetization issues. Their main drawback is provided by a low power factor and poor flux weakening capabilities, restricting their adoption to lower power ratings with respect to the permanent magnet counterpart. Studies about FD for these machines are mainly restricted to ITSC [87–89]. Online implementation is discussed only in [88]. Here both voltages and currents are employed in the FD procedure and the main indicator is provided by the zero sequence voltage component, which should be close to zero in healthy conditions. Given the interest of EV manufacturers in this machine topology, it is believed that FD research will soon be accelerated.

6.2. Wound Field Synchronous Machines

Similar to SynRMs, research on alternatives to rare earth-based PMSMs has seen a surge of interest in wound field synchronous machines (WFSMs) in recent years. However, significant studies on FD for EV applications are still lacking. The main reason is that, for decades, WFSMs have primarily been used as generators due to their flexible flux regulation and ability to provide sinusoidal back electromotive force (BEMF) with low total harmonic distortion (THD). Their use in traction applications is relatively recent. Consequently, research on WFSM FD for generation applications is substantial, with few exceptions for other industrial applications, and has mainly focused on the excitation system. Some example are provided in [15,90–95].

6.3. Axial Flux Machines

Axial flux machines (AFMs) has always been important candidates in the traction field, thanks to their high torque density and limited volume, making them suitable also for direct drive applications. However, their manufacturing complexity has always limited their production, as well as the relative studies, including those related to FD.

The available research is mainly focused on demagnetization [96–98] and eccentricity [99,100]. Among them, [97,98] are based on generators. The key physical quantities are fluxes in [96,99], evaluated through search coils, while vibrations in conjuction with frequency and time frequency manipulation in [100].

Instead, currents have been used in [97] and the feature extraction has been performed with local binary pattern (LBP). FD has been performed instead with a k-NN algorithm. Both currents and voltages have been used in [98] to evaluate both the power spectrum and reconstruct the flux linkage to evaluate the machine status in a model based approach.

6.4. Multiphase Machines

Multiphase variable-speed drives (those with more than three phases) have emerged as a mainstream research area over the past decade. The primary driving forces behind this interest are specific applications related to the green agenda, including electric and hybrid electric vehicles, locomotive traction, ship propulsion, and 'more-electric' aircraft. Innovative uses of the additional degrees of freedom in multiphase machines for various non-traditional purposes are explored [101].

Multiphase machines provide a higher torque density, lower torque ripple, a better fault tolerance capability as well as the possibility to reduce the switching devices current rating when the same output power of the three-phase counterpart is fixed.

The majority of FD studies related to multiphase machines focus on open phase and open circuit fault detection, as well as fault-tolerant control under these conditions [102–113]. The primary reason for this focus is their ability to operate even when one or more phases are out of service, provided that at least three healthy phases can be controlled. In most of these studies, the importance of rapid FD is emphasized, allowing the control algorithm to adapt in real time for safer and more efficient operation. Nevertheless, the main goal remains fault-tolerant control, as detecting these fault conditions does not require the detailed modeling or tuning needed for incipient faults of other types.

There is, however, a limited fraction of studies focused on other types of faults which show also a peculiarity of these machines [57,71,113,114]. In fact, the control algorithms for multiphase machines employ specific transformations, such as space vector decomposition, which enable the observation and control of current harmonics in distinct orthogonal subspaces. These harmonics can be effectively used as additional variables to assess the operating status.

In [57] the second harmonic is used as a fault indicator to discriminate between eccentricity and ITSC in a symmetrical six-phase configuration.

In [71,114] 5th harmonic plane observation is instead adopted to detect respectively a demagnetization and an ITSC in asymmetrical double three-phase machines. Harmonic subspaces are also used in [113] both to detect open-phase conditions, but also for sensors FD. Therefore, while the previously presented FD methodologies for three-phase windings remain viable, additional methodologies can also be employed, demonstrating significant potential for future research and applications.

7. Conclusions

Most previous research on fault diagnostics has predominantly focused on three-phase IMs and PMSMs, primarily used in industrial environments. As a result, the insights gained from these studies may only be partially applicable to traction applications. A significant portion of the research has centered on machines operating under different environmental conditions and utilizing more basic control strategies. Significantly, research findings concerning SynRM, WFSMs, and AFMs are limited due to their lower prevalence and relatively recent access into the market, particularly as traction motors.

Regarding the potential integration of multiphase machines, existing FD methodologies can be adapted accordingly. Additionally, the capability to monitor specific harmonic subspaces allows for assessing how various faults affect current harmonic control, providing additional FD indicators. Although research data in this field are limited, they highlight a pressing need for further studies in the coming years.

Among the various parameters monitored for FD, complementary use of MCSA and voltage analysis is preferable. This preference arises from the availability of sensors typically used for EV drives, eliminating the need for additional instrumentation. This approach is supported by the fact that most vibration-based FD techniques perform optimally under stationary conditions, while automotive applications often experience frequent load variations, oscillations, and elevated noise levels, complicating detection efforts. Therefore, further investigation into this area is essential.

Regarding the most adopted approaches for automatic FD, the model based approach continues to be part of the recent studies, while ML methods have gained significant interest, especially with various types of supervised learning. Among these, DNNs appears to be promising candidates for processing the large amount of data expected to become available in the coming years.

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Abbreviations

The following abbreviations are used in this manuscript:

AFM	Axial Flux Machines
BEMF	Back Electromotive Force
BRB	Broken Rotor Bar
CNN	Convolutional Neural Network
DNN	Deep Neural Network
CWT	Continuous Wavelet Transform
DTC	Direct Torque Control
DWT	Discrete Wavelet Transform
EV	Electric Vehicle
FOC	Field oriented Control
FHC	Fault Harmonic Component
GAN	Generative Adversarial Network
IM	Induction Machine
ITSC	Interturn Short Circuit
KF	Kalman Filter
KLD	Kullback-Leibler Divergence
k-NN	k-Nearest Neighbor (algorithm)
LBP	Linear Binary Pattern
LSM	Least Square Method
MCSA	Motor Current Signature Analysis
ML	Machine Learning
MVSA	Motor Vibration Signature Analysis
PMSM	Permanent Magnet Synchoronous Machine
SNN	Shallow Neural Network
SynRMs	Synchronous Reluctance Machine
THD	Total harmonic distortion
WFSM	Wound Field Synchronous Machine

8.

Table 2. Summary of Main Harmonics for Different Fault and Machine

Main Harmonics	Machine Type
$f_{bb} = f_{se}(1 \pm 2ks)$	IM
$f_{IM_{ecc}} = [(kN_r \pm n_d)(1-s)/p \pm v]f_{se}$	IM
$f_{IM_{ecc2}} = [(1-s)/p \pm k]f_{se}$	IM
$f_{itsc_1} = f_{se}\left(1 \pm \frac{k}{p_p}\right)$	ALL
$f_{itsc_2} = \left(1 \pm k\frac{N_{ss}}{p_p}\right)$	ALL
$f_{bm} = kf_{fm} \pm lf_{rm}$	ALL
$f_{be} = f_{se} \pm kf_{fm}$	ALL
$f_{dem} = f_{se}\left(1 \pm \frac{k}{p_p}\right)$	PM
$f_{PMecc} = f_{se}\left(1 \pm \frac{2k-1}{p_p}\right)$	PM
$k = 1,2,3,\ldots, v = 1,3,5,\ldots, n_{eo} = 0,1,2,\ldots$	

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