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Review

A Review of Condition Monitoring of Permanent Magnet Synchronous Machines: Techniques, Challenges and Future Directions

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Abstract: This paper focuses on the latest advancements in diagnosing faults in Permanent Magnet Synchronous Machines (PMSMs), with particular attention paid to demagnetization, inter-turn short circuits (ITSCs), and eccentricity faults. As PMSMs play an important role in electric vehicles, renewable energy systems and aerospace applications, ensuring their reliability is more important than ever. This work examines widely applied methods like Motor Current Signature Analysis (MCSA) and flux monitoring, alongside more recent approaches such as time-frequency analysis, observer-based techniques and machine learning strategies. These methods are discussed in terms of strengths/weaknesses, challenges and suitability for different operating conditions. The review also highlights the importance of experimental validations to connect theoretical research with real-world applications. By exploring potential synergies between these diagnostic methods, the paper outlines ways to improve fault detection accuracy and machine reliability. It concludes by identifying future research directions, such as developing real-time diagnostics, enhancing predictive maintenance and refining sensor and computational technologies, aiming to make PMSMs more robust and fault-tolerant in demanding environments. In addition, the discussion highlights how partial demagnetization or ITSC faults may propagate if not diagnosed promptly, necessitating scalable and efficient multi-physics approaches. Finally, emphasis is placed on bridging theoretical advancements with industrial-scale implementations to ensure seamless integration into existing machine drive systems.

Keywords: condition monitoring; demagnetization; eccentricity; electrical machines; fault diagnosis; permanent magnet machines; renewables; stator faults

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1. Introduction

Permanent Magnet Synchronous Machines (PMSMs) are used across various industries due to their high efficiency and power density. The superior performance characteristics of PMSMs place them as the preferred choice over traditional induction motors in applications demanding high efficiency, precise control, high power and torque density and reliability [1,2]. Also, induction machines (IMs) rely on a rotor current induced by the stator field and thus always operate at a slip, which inherently reduces both their power factor and their overall efficiency. In contrast, permanent magnet synchronous machines (PMSMs) run at synchronous speed without slip, delivering higher efficiency and power factor by virtue of their permanent magnet excitation. Furthermore, PMSMs achieve superior torque density in smaller machine sizes, making them ideal where compact, high-performance drives are required. These attributes explain the growing focus on PMSMs in many industrial and servo applications, despite the enduring popularity of induction motors [3,4]. In aerospace [5], they are applied for propulsion

systems and electric aircraft initiatives. Automotive applications including electric power steering (EPS) [6], electric vehicles (EVs), and hybrid powertrains also use these types of machines. PMSMs are particularly useful in renewable energy systems, particularly in wind turbines and especially for offshore installations. In the field of energy harvesting, PMSMs are employed in wave energy converters, tidal stream generators, and small-scale hydroelectric systems. The excellent performance and high power density of PMSMs make them an ideal choice for these high-performance electromechanical systems. However, PMSMs are vulnerable to several types of faults that, if not mitigated, may seriously impair their reliability and operation. These include demagnetization faults, which can reduce the machine's efficiency and power output; inter-turn short circuit (ITSC) faults, which can lead to localized heating and further damage; and eccentricity faults, which can cause unbalanced magnetic pull and increased vibration, leading to eventual catastrophic failures. Each type of fault produces a different characteristic frequency in the stator current spectra, as summarized in Table 1.

Table 1. Current frequency harmonics under the different faults.

Fault Type	Current Frequency Harmonics
Bearing ball defect [7]	$f_s \cdot \left(1 \pm k\frac{D_p}{D_b} \times \frac{1}{p}\left(1 - \left(\frac{D_b cos\theta}{D_p}\right)^2\right)\right)$
Bearing inner race defect [7]	$f_s \cdot \left(1 \pm \mathrm{k}N_b \times \frac{1}{2p}\left(1 + \frac{D_b cos\theta}{D_p}\right)\right)$
Bearing outer race defect [7]	$f_s \cdot \left(1 \pm \mathrm{k}N_b \times \frac{1}{2p}\left(1 - \frac{D_b cos\theta}{D_p}\right)\right)$
Demagnetization [7]	$\left[1 \pm \frac{k}{p}\right] \cdot f_s$
Inter Turn Short Circuit [8]	$3 \cdot k \cdot f_s$
Dynamic Eccentricity [9]	$\left[1 \pm \frac{2k-1}{p}\right] \cdot f_s$
Static Eccentricity [9]	$\left[1 + \frac{2k}{p}\right] \cdot f_s$
Mixed Eccentricity [10]	$\left[1 \pm \frac{k}{p}\right] \cdot f_s$

k: positive integer, f_s : electrical frequency, p: number of pole pairs, D_b: bearing ball diameter, θ: bearing ball contact angle, D_p: pitch diameter of bearing and N_b: number of rolling elements.

This reviewing article summarizes the latest research on fault diagnostics and mitigation strategies for Permanent Magnet Synchronous Machines (PMSMs), focusing on the three aforementioned fault types. The study examines diverse approaches from aerospace, automotive, industrial, and energy harvesting applications to identify critical design trade-offs and emerging trends. The review covers both traditional and advanced condition monitoring techniques. Conventional methods, such as signal analysis, parameter estimation, and model-based approaches, are discussed and compared with emerging trends. The comparison highlights the strengths and limitations of each approach, providing insights into their applicability in different scenarios. Additionally, the paper explores the synergies between various fault detection methods and examines how integrated approaches, combining traditional and advanced techniques, can enhance overall system reliability and fault diagnosis accuracy. By analyzing the current state-of-the-art techniques, this review aims to highlight gaps in existing research and propose future directions for improving the fault tolerance, reliability, and performance of PMSMs across various applications.

2. Demagnetization Faults

The demagnetization fault describes the condition where one or more of the machine's permanent magnets have lost their initial magnetic properties. Demagnetization can be either

uniform or not depending on the spatial distribution of the asymmetry on the magnets' population. Furthermore, demagnetization is triggered by thermal stresses, short-circuit faults, external magnetic fields and mechanical loads. For instance, aerospace applications have shown that Neodymium-Iron-Boron (NdFeB) magnets, although widely used for their magnetic properties, show varying thermal and electrical stress resistance with respect to their grades. To address these problems advanced diagnostic and mitigation strategies are proposed and presented in Table 2. Simulation of fault scenarios with finite element analysis (FEA) has revealed flux distribution, back EMF variations, and torque stability under partial and uniform demagnetization conditions [11,12]. Experiment validations have shown that robust fault detection and thermal management systems are needed for the resilience of PMSMs in diverse applications [13,14]. The latest research on demagnetization diagnostics and mitigation strategies for PMSMs is explored in the paper, which examines several different approaches from aerospace, automotive, and industrial applications to identify critical design trade-offs and future directions of research on the fault tolerance and reliability of PMSMs.

Irreversible demagnetization (ID) in Permanent Magnet (PM) machines refers to a loss in the magnet's remanent flux density (B_r) or the machine's electromotive force (EMF) [15]. This degradation leads to a decline in the machine's performance and overall efficiency. Under normal operating conditions PMs maintain a specific remanent flux density and the open-circuit voltage (E_{oc}) at the machine's terminals is stable and predictable. However, when permanent magnets are under extreme temperatures or strong external demagnetizing fields, ID can occur changing permanently the magnet's properties. As a result, the E_{oc} decreases significantly impairing the machine's performance.

ID depends on the PM's operating point and its position on the demagnetization curve, which is typically located in the second quadrant of the B-H [16]. The B-H curve shows the relationship between the magnetic flux density (B) and the magnetic field intensity (H) considering both the external field and the PM's contribution. During ID, the PM operates on a minor loop of the B-H curve, which is approximated by a recoil line derived from the major or minor B-H curve. This behavior is often shown in diagrams like Figure 1, where the recoil line highlights the PM's altered magnetic properties.

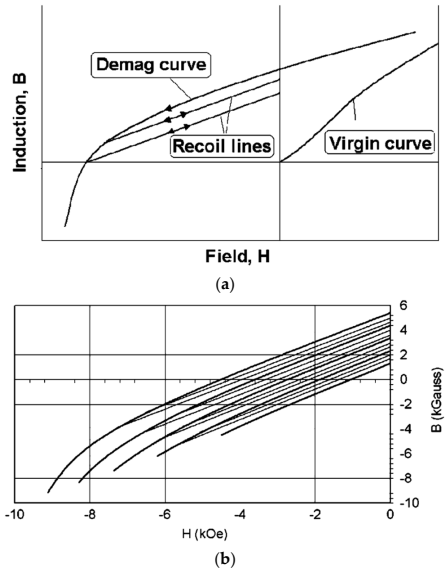


Figure 1. (**a**) Demagnetization Curve and Recoil Lines of Permanent Magnet and (**b**) Major and Minor B−H curve [16].

2.1. Time-Frequency Analysis Techniques

Time-frequency domain methods allow for fault detection in nonstationary conditions of Permanent Magnet Synchronous Machines (PMSMs). Transient signals and fault-induced harmonics can be captured by these methods and are therefore considered mandatory for high reliability applications. Yet their adoption generates debates regarding computational complexity, diagnostic sensitivity and practical implementation challenges.

A new Hilbert-Huang Transform (HHT) addresses the weakness of classical Fourier-based methods which often fail under nonstationary conditions. Decomposition of stator current signals into intrinsic mode functions (IMFs) with detailed energy-frequency-time distributions distinguishes demagnetization from eccentricity faults is performed by HHT [17]. However, its dependence on empirical mode decomposition (EMD), which introduces errors in noise-dominated signals and thus limits its industrial robustness. Additionally, high computational demands on HHT remain a barrier to real-time applications—particularly for embedded systems.

Motor Current Signature Analysis is widely used but has been criticized for being inadequate in diagnosing non-uniform demagnetization faults. For instance, the harmonic cancelation effect in some rotor topologies leads to false negatives when faults are grouped across non-adjacent magnets [18]. Against this background, complementary methods like airgap flux monitoring have been proposed to get closer to the magnetic asymmetries. Such methods usually involve more hardware and increase system complexity and cost.

Wavelet transform techniques are popular for localizing fault-induced harmonics across several frequency bands. Discrete Wavelet Transform (DWT) for example has shown reliability in the early-stage demagnetization detection by analyzing specific frequency components of stator currents [19]. But wavelet-based methods are sensitive to wavelet function choice and require expert knowledge for optimal implementation. Empirical Wavelet Transform (EWT) permits signal refinement based on the spectral content, but the computational demands remain a problem in real-time applications [20].

A robust method for fault diagnosis under nonstationary conditions has emerged through position-frequency analysis. Transforming current signals into the position domain via this method leads to fractional harmonic detection via FFT [21]. While accurate in detecting demagnetization under load and speed variations, it is susceptible to errors in practice and raises doubts about its robustness in various operating conditions.

Various rotor displacement signal analysis techniques have been applied to improve diagnostic accuracy, such as Variational Mode Decomposition (VMD) and Teager energy spectrum analysis to isolate fault-specific features [22]. While such methods are very sensitive, advanced signal preprocessing steps may hinder their integration in standard monitoring systems. Furthermore, such approaches have difficulty with handling several fault types at once.

Time-frequency methods are also used to diagnose coupled faults, such as static eccentricity and partial demagnetization. Studies using combined Motor Current Signature Analysis (MCSA) and Wavelet Packet Transform (WPT) have revealed unique diagnostic features even in complex fault scenarios [23]. But the problem of managing overlapping fault signatures and ensuring scalability over different machine configurations remains. Clearly defined diagnostic thresholds for such coupled faults need further work.

New advanced analytical methods combining time-frequency analysis and finite element simulations are promising to quantify the operational impacts of demagnetization faults. For example, electromotive force spectrum analysis has been applied to identify fractional harmonics and their correlation with torque ripples and efficiency losses [24]. Though such methods yield deep insights, they are expensive computationally and thus

not applicable to on-line diagnostics, so better algorithms are needed while maintaining diagnostic accuracy.

Techniques such as the Shift-Invariant Dictionary of Dynamic Time Warping (SID-DTW) allow for sparse representations of fault signals and robust demagnetization level characterization [25]. But even those innovations have challenges: complex dictionary construction and dynamic time warping computations may prevent real-time deployment on systems with limited computational resources.

While time-frequency domain methods have significantly advanced PMSM fault diagnostics, some questions remain. How to make these methods robust to noise and operational variations? Are their computational demands justified for industrial applications? Solving these will require balancing methodological precision and practical applicability. Further efforts need to focus on scalable, low-cost solutions which provide high diagnostic accuracy without compromising real world deployment constraints.

Hence, time-frequency domain methods constitute an extremely important step towards PMSM fault diagnostics. But their wide acceptance rests on overcoming their present shortcomings regarding computational efficiency, robustness and ease of integration in existing systems. Considering these areas may continue to improve the reliability and performance of modern electromechanical systems using these methods.

2.2. Observer-Based Approaches

Observer-based techniques have been successfully applied to diagnose demagnetization faults of Permanent Magnet Synchronous Machines (PMSMs) utilizing advanced control algorithms for fault detection and system resilience. These methods, however, are not without difficulties: questions regarding robustness under different operational conditions and exact parameter estimations remain pending.

A robust fault-tolerant predictive control algorithm based on sliding mode and Luenberger observers is proposed to suppress the demagnetization effect on rotor flux linkage [26]. This approach allows for precise current control even at high loads and high temperatures. Although useful, the method depends on complex observer design and raises doubts about scalability in industrial applications. Also, the sensitivity of the control algorithm to parameter variations indicates that adaptive mechanisms are needed for handling machine-specific uncertainties.

Designed Sliding Mode Rotor Flux Observers (SM-RFOs) are applicable for uniform demagnetization fault diagnosis in high-reliability domains such as aviation. Such observers employ Lyapunov-based stability analysis for robust flux estimation under inductance variations [27]. But noise sensitivity of SM-RFOs may compromise their diagnostic accuracy in real-world scenarios. Their broad adoption requires improvements in noise filtering and robustness to parameter fluctuations.

To eliminate chattering effects during PM flux linkage reconstruction and demagnetization-induced deviation detection, super-twisting algorithm-based sliding mode observers (STA-SMOs) have been built. Such ways highlight the importance of dynamic torque precision in fault conditions [28]. The computational demands of super-twisting algorithms may, however, limit their use in real time. Exploring simplified algorithms with comparable performances is still a research area.

Combined with Equivalent Input Disturbance (EID) approaches, improved Sliding Mode Observers (ISMOs) decouple motor speed from state error reconstruction to improve diagnostic precision. Integrating EID estimation into ISMOs allows for fault-tolerant control and stability under varied operation conditions [29]. Their dependence on accurate disturbance modeling, however, limits their robustness in highly dynamic systems. Adaptive disturbance estimation techniques may fill this gap.

Modern diagnostic frameworks employing super-twisting sliding mode observers (STSMOs) address coupled fault scenarios, including demagnetization and speed sensor faults. Such frameworks accurately estimate counter-electromotive force (CEMF) components to obtain accurate characterizations of fault types and severities [30]. The added complexity of managing coupled faults, however, introduces a computational overhead and questions their applicability in resource constrained applications.

As regards ultra-high-speed PMSMs, observer-based approaches combining STA-SMOs and EID methods are promising to compensate for flux linkage variation due to demagnetization. These methods increase the system's stability and torque accuracy in extreme conditions [31]. But their flexibility for lower-speed applications and their dependence on machine-specific parameters. Optimized simplified observer designs balancing performance and complexity are needed to extend their application range.

Tracking harmonic flux components using flux observer-based techniques has been applied to reveal uniform and localized demagnetization faults. They introduce magnetization indices based on flux waveform distortions for fault classification [32]. These are precise but sensitive to variations in stator winding configurations, requiring calibration and adaptive solutions for robustness.

The temperature estimation models embedded into observer-based frameworks have dealt with demagnetization in electric vehicle applications. Adapting motor operating conditions dynamically prevents catastrophic failures of permanent magnets [33]. But their predictive capabilities are constrained by the accuracy of the thermal network models employed. Real-time thermal feedback may be added to such frameworks.

Sequential Sliding Mode Observers are novel fault diagnosis devices that estimate flux linkage and inductance variations. Such methods allow for better fault detection accuracy under steady-state conditions compared to observer-based techniques [34], but their transient performance remains to be investigated. Techniques for transient responses are needed without sacrificing steady-state results. Notwithstanding these developments, observer-based methods continue to face difficulties in meeting computational complexity requirements while preserving high real-time performance. There are still issues with their adaptability to various PMSM configurations and resilience to loud and extremely dynamic environments. Optimal computational efficiency should be a future research target: simplifying observer design, improving noise resilience. In addition, trade-offs between diagnostic precision and practical implementation costs must be critically assessed for wider adoption. In conclusion, observer-based methods represent a significant step forward in PMSM fault diagnostics and provide powerful tools for real-time monitoring and control. Addressing current limitations and refining these approaches may improve the reliability and performance of electromechanical systems in various applications.

2.3. Machine Learning Methods

Machine Learning (ML) approaches have become novel diagnostic tools for demagnetization faults in PMSMs. Using sophisticated algorithms these methods improve fault detection accuracy, scalability and adaptability to diverse operation conditions. Still, critical issues like model interpretability, data dependency and computational efficiency remain debated.

A notable ML technique is the analysis of acoustic noise signals for uniform demagnetization fault diagnosis. Using back-propagation neural networks (BPNNs), these methods process psychoacoustic and objective indicators such as Hilbert-Huang Transform and power spectrum density to distinguish faulty machines [35]. While this approach is an alternative to the invasive methods, the consistent noise pattern used in this approach leads to some doubts about robustness in noisy industrial environments. However, noise-based

diagnostics may not be able to differentiate overlapping fault types effectively limiting their standalone applicability.

Another approach is to combine Motor Current Signature Analysis (MCSA) and wavelet packet transforms (WPT) to demagnetization-specific features to be classified by convolutional neural networks (CNNs). This method showed good diagnostic accuracy under noisy conditions [36]. But its dependence on large, labeled datasets for training which are not always available for all fault scenarios limits its adaptability. Additionally, because CNNs are computationally intensive, it has been questionable whether they are suitable for real-time diagnostics under resource constrained conditions.

Current and torque signal features mapped to fault severity using Support Vector Regression have been quantified for demagnetization levels. This method requires less physical experimentation and provides low-cost monitoring solutions [37]. But nonlinearities in PMSM behavior under extreme operating conditions may compromise its performance. Such nonlinearities may require hybrid approaches involving physical models in learning.

Hybrid approaches such as fuzzy logic—Extreme Learning Machines (ELMs) have also been explored for diagnostic accuracy. Combining wavelet packet decomposition for feature extraction and fuzzy membership functions for classification allows for fault detection under non-stationary conditions [38]. The advantages aside, the complexity of hybrid models can prevent real-time implementation. Furthermore, their dependence on tuning parameters often requires expert intervention, reducing their practical appeal.

Attention-based Convolutional Neural Networks (AM-CNNs) have been proposed to diagnose demagnetization faults of traction motors. AM-CNNs extract fault-related features with more than 93% diagnostic accuracy by converting back-EMF signals to grayscale images [39]. Questions about generalizability of image-based methods to different machine configurations remain, however, unresolved. Moreover, image processing computational demands may prevent their adoption in embedded systems.

Transfer learning methods with pre-trained deep learning models like VGG-16 have demonstrated robust detection of irreversible demagnetization faults (IDFs). Such models classify faults accurately in noisy conditions combining vibration and stator current signals [40]. The high computational requirements of such methods may not prevent their application in real-time scenarios however, especially in latency constrained industries.

Combined machine learning and physical model provide a novel approach to fault diagnosis. For example, similarity-based models (SBMs) estimate remaining magnetic flux to proactively handle demagnetization faults and extend system life via adaptive control strategies [41]. However, such methods generally involve more detailed machine-specific parameters that are sometimes not universally available. In addition to this, model complexity–interpretability trade-off is an ongoing topic for future exploration.

Advanced techniques like one-class support vector machines (OC-SVMs) use inverter-based phase current data up to 99% of the time for anomaly detection and partial demagnetization fault detection [42]. This eliminates additional sensors but its application to different machine types is limited to precise inverter data. Additionally, questions regarding its robustness to different inverter configurations and noise conditions raise improvement opportunities.

Though potentially useful for ML-based methods, interpretability and reliance on quality training data remain critical roadblocks to wide adoption. Equally, overfitting and generalization concerns regarding unseen fault conditions require rigorous model validation. Future research should balance model complexity with real-time applicability to make these advanced techniques compatible with industrial practical demands.

In short, machine learning approaches have contributed to PMSM fault diagnostics detection and quantification techniques. Knowing their limits and enhancing implemen-

tation of these methods might rethink predictive maintenance and improve reliability of electromechanical systems.

2.4. Sensor-Based Diagnostic Techniques

Sensor-based techniques are currently indispensable tools for the diagnosis of demagnetization faults in Permanent Magnet Synchronous Machines (PMSMs). These methods employ various sensor inputs for fault detection and localization under various operating conditions. These approaches have their benefits however, and conflicting perspectives remain.

An alternative is rotor partitioning with toroidal yoke coils for measuring residual voltage signals. Because the rotor is segmented, faults are localized based on voltage differences between healthy and affected regions. Such a method demonstrated accuracy even for minor faults like 10% demagnetization, reducing sensor requirements and installation complexity [43]. Yet its dependency on configurations leads to questions of scalability for motors of non-uniform designs and further validation in different setups.

The other one involves electromagnetic signature analysis using stator mounted search coils. Focusing only on basic frequency components, this approach can find faults in nonstationary conditions and demonstrate demagnetization apart from static eccentricity [44]. But the problem remains that omitting harmonic components restricts the method's diagnostic range for more complex fault scenarios and cite the utility of hybrid approaches including higher-order harmonics.

Toroidal yoke-type search coils are used for fault localization, which involves three strategically placed coils with low invasiveness and high diagnostic accuracy for complex demagnetization patterns [45]. In addition, in marine propulsion systems, search coils embedded in stator slots have provided faulty localization under various severity conditions [46]. However, environmental factors like temperature and vibration may affect the reliability of this approach and additional robustness testing is needed for harsh environment application.

The symmetry challenges presented by this fault type make airgap flux measurements superior to traditional techniques for detection of trailing edge demagnetization [47]. This is promising, but it begs the question: What is promising? Can airgap flux-based methods be used as standard diagnostic tools or are they constrained to specific use cases because they require specialized equipment?

A model-based approach using rotor reference frame voltage errors is proposed to differentiate between uniform demagnetization and static position sensor offset errors (SPSOE). This method enables reliable fault differentiation by analyzing proportional changes in quadrature-axis voltage errors. But this dependency on exact modeling parameters can lead to error under real conditions in machines under variable load and environmental stress.

Other prognostic methods use the remaining magnetic flux density margin to predict irreversible demagnetization faults (IDFs). Those methods combine real-time flux monitoring with finite element simulations enabling actionable insight for preventive maintenance [48]. The computational intensity of such simulations may limit their application to resource constrained systems, however, and call for simplified but effective prognostic models.

Wavelet transforms and Bayesian networks are combined with acoustic noise and torque data to perform multi-sensor fusion techniques. This approach demonstrated higher detection accuracy than single-sensor methods under dynamic operation [49]. But its dependency on sensor integration and data fusion complexity leads to implementation challenges in legacy systems, where retrofitting additional sensors is expensive or impractical.

Besides, Hall-effect field sensors have been applied to detect rotor eccentricity and demagnetization faults in Interior PMSMs. This low-cost method uses existing motor sensors and provides real-time diagnostic capability with minimal hardware modifications [50]. But

questions regarding their sensitivity to overlapping fault types and noise-induced distortions remain unresolved and require further study on sensor signal preprocessing techniques.

Real-time demagnetization assessment evolved, combining finite element analysis (FEA) and physics-based thermal models to estimate flux density variations due to armature reactions and temperature changes. This dynamic approach increases reliability and efficiency of PMSM drives [51]. But the difficulty of coupling thermal with electromagnetic models may prevent its commercial use in cost sensitive industries.

Another possibility is using stator tooth flux measurements processed with deep learning algorithms to diagnose several faults such as demagnetization, inter-turn short circuits, and eccentricity. Its experimental validations show it can distinguish fault types well [52]. Yet, questions regarding the interpretability of deep learning models in critical applications remain and efforts to improve model transparency and trustworthiness are needed.

Several challenges regarding the diagnosis of demagnetization faults in permanent magnet generators (PMGs) have been solved by motor current signature analysis (MCSA) and airgap flux monitoring. Such techniques stress early fault detection to avoid efficiency losses and circulating currents due to uneven electromotive forces [18]. Yet the shortcomings of MCSA for detection of non-uniform demagnetization suggest the need for other complementary methods for holistic fault condition analysis.

The flux density and inductance variations investigated in structural analysis methods further contribute to fault localization accuracy, especially in dynamic operating environments [53]. Such methods, however, require large computational resources and precise input parameters, and their implementation is often complicated. A key problem is reconciling computational demands with diagnostic accuracy.

A recent development among these techniques is the Recursive Least Squares algorithm for partial demagnetization fault detection under stationary and nonstationary conditions. The RLS algorithm extracts fault-related harmonics in real time using harmonic magnitudes as fault indicators. Like classical signal processing methods such as Fourier Transform and Wavelet Transform, the RLS approach needs fewer computational resources and can be easily integrated in embedded devices. Experimental validation confirmed the method's robustness at various operating speeds and eccentricity values [54]. Despite its advantages, some questions regarding the performance of the algorithm under high-noise conditions remain open for further scrutiny and call for improved noise mitigation strategies.

Analytical models are refined for flux estimation and demagnetization prediction. Nonlinear models including harmonic and saturation effects can realistically simulate high-stress conditions with high prediction accuracy and low computation time [55]. But such models are limited to detailed material properties and operating conditions and thus require adaptive modeling techniques.

Also, Extended Kalman Filters (EKF) performed well for real-time flux linkage monitoring and were resistant to parameter variations and fault detection [56]. However, EKFs performance under extreme transient conditions remains to be investigated.

Alongside these electromagnetic and flux-based sensor solutions, vibration analysis is another sensor-driven approach widely used for fault diagnosis in permanent magnet synchronous machines (PMSMs), including magnet demagnetization. Unlike many diagnostic methods which rely on electrical signals, vibration measurements can give unique hints about the mechanical consequences of demagnetization and show specific patterns in the stator's dynamic response. Recently, it has been shown that by measuring the motor vibration and using techniques like Fast Fourier Transform (FFT) or power spectral density analysis, new harmonics or significant amplitude changes are identified due to weaker magnetic fields. Such partial demagnetization can, for example, introduce low-order vibra-

tion modes or sidebands at the mechanical frequency of the rotor that were not present in a healthy machine [57,58].

In advanced coupled electromagnetic–mechanical models, demagnetization-induced asymmetries alter the deformation shape of the stator. In coupled electromagnetic-mechanical models, partial demagnetization usually introduces additional spatial harmonics in the air gap, which excite specific low-order stator modes [58,59]. Monitored development of these modes indicates strong demagnetization. In addition to the spectrum itself, some authors have proposed time-domain metrics such as peak-to-peak, RMS, kurtosis, crest factor to quantify demagnetization severity, although such approaches generally require stable load and speed conditions to avoid mismatch with other mechanical perturbations [59]. A further challenge is when vibration harmonics from demagnetization overlap with those from other faults like rotor eccentricity or bearing defects [60]. To cope with this, advanced vibration-based frameworks combine hybrid signal processing methods such as wavelet transforms with classification algorithms capable of separating demagnetization-specific patterns more reliably [36]. Further validation by finite element analyses and laboratory experiments is also being conducted. As shown in [47], even a single partially demagnetized pole induces significant changes in the vibration spectrum, including the excitation of low-order modes that reveal the demagnetization condition. Accordingly, vibration-based analysis can be used as an external and nonintrusive route to detect demagnetization faults when traditional current-based diagnostics fail to detect the fault due to uniform or trailing-edge magnet weakening.

Generally speaking, sensor-based techniques combine advanced signal processing, machine learning and multi-physics models for fault diagnosis in PMSMs. These innovations make substantial improvements, but scalability, computational requirements and real-world robustness of these methods are critical for wider adoption. All these discussions show how critical evaluation is required for PMSM fault diagnostics.

2.5. Emerging and Hybrid Fault Detection Strategies

Innovative diagnostic methods for permanent magnet synchronization machines—PMSMs—are developed for detecting demagnetization faults in varying operational conditions. Such methods are alternatives to conventional ones which involve advanced modeling/signal processing and adaptive control strategies. But challenges like computational complexity, adaptability and robustness remain and need critical evaluation.

A new inverter-embedded technique for automatic detection and classification of rotor faults, including demagnetization and eccentricity, was proposed by [61]. Such an approach uses d-axis differential inductance monitoring by injecting combined direct-current and alternating-current signals while the motor is stationary. While the method was sensitive and robust, its dependence on motor stationary conditions limits its applicability in active operations. Moreover, inverter hardware compatibility dependency raises scalability issues between machine types.

The Cubature Kalman Filter (CKF)-based diagnostic approach is a robust solution for local demagnetization detection. This method, combining volumetric Kalman filtering and mathematical modeling, identifies specific harmonic components in air-gap flux density as indicators of fault severity [62]. However, the computational demands of CKF algorithms might prevent their integration in real-time systems, especially in dynamic operational situations. A research question on how to simplify such algorithms without compromising diagnostic accuracy remains open.

Alternatives to demagnetization fault detection methods are field reconstruction techniques (FRM). FRMs perform fault identification faster than finite element methods by calculating phase flux linkages and using FFT analysis [63]. Even with all these advantages,

the model sensitivity of the method to modeling inaccuracies, especially in highly dynamic systems, warrants further investigation. Increasing the robustness of FRM via hybrid modeling techniques may extend its application domain.

Real-time adaptive strategies have been demonstrated to be useful in integrating flux- weakening control mechanisms for demagnetization management. Such approaches mitigate irreversible magnetic losses during flux weakening by dynamically estimating magnet flux operating points and applying current limiters [64]. Such methods are effective but often require very specific machine parameters which make generalization difficult for different machine geometries. Developing parameter-agnostic control strategies needs further efforts to extend their utility.

The Sum of Squares of Stator Currents (SSC) method has been successfully applied to diagnose partial and uniform demagnetization faults by filtering fundamental frequency components and enhancing fault-related harmonics [65]. SSC provides a sensitive and reliable diagnostic tool but lacks experimental validation. To close this gap, it is necessary for its adoption in practice under real-world noise and variability.

Most recently, the least-square estimation and error-bound analysis have been proposed for EV parameter variations such as d-q axis inductance changes and stator resistance [66]. These methods allow for reliable diagnosis in rapidly changing operational conditions, but their large computational requirements raise scalability issues for resource constrained platforms.

Magnetic saturation effects and structural characteristics were used as analytical approaches to improve faulty flux linkage estimations. Inductance calculation models for example have been validated by finite element analysis (FEA) for interior PMSM diagnostics [67]. Their dependence on detailed material properties and load conditions, however, can restrict their application to particular machine configurations.

Develop diagnostic algorithms for multiphase PMSMs that exploit additional degrees of freedom for better resistance to local demagnetization faults. These methods analyze harmonic components of back EMF to estimate fault severity and optimize post-fault torque [68]. Experimental validations confirm their usefulness, but challenges remain in scaling these techniques to higher phase counts and more complex systems.

New diagnostic frameworks also incorporate correlation-based approaches to fault localization like Pearson coefficient analysis of residual stator branch currents. These methods can identify partial and uniform demagnetization faults in motors with complex slot-pole ratios [69]. Their precision notwithstanding, accurate baseline data for healthy conditions may limit their adaptability to systems with differing operational histories.

Conclusion: these advanced diagnostic methods are indeed much better than traditional ones but computational demands, machine adaptability and robustness in noisy environments are still critical issues. Future work should target their scalability and resilience to meet the real-world demands of industrial and automotive applications.

Table 2. Comparison of Existing Demagnetization Diagnostic Methods in PMSMs.

Fault Signature/ Approaches	Merits	Demerits	Comments	Applicable Range	Quantitative Analysis
2.1 Time-Frequency Analysis (HHT, DWT, EWT, Position-Frequency, Wavelet Packet) [17–25]	- Robust for non-stationary conditions - Can isolate fault-induced harmonics in stator currents - Useful for early detection of partial demagnetization	- High computational cost (e.g., HHT) - Noise sensitivity (especially EMD-based methods) - Requires expert knowledge to tune transforms	Methods like Hilbert–Huang or advanced wavelets detect fractional harmonics or transient features. Combining them with finite element simulation yields deep insights but may not be real-time friendly for embedded systems.	- Situations with varying load/speed - Transient conditions (start-up, speed ramp) - Aerospace, EVs, other high-reliability domains	Some works report clear harmonic markers for partial demagnetization. Actual detection rates or accuracies vary; no universal benchmark is consistently cited. Most labs rely on offline or semi-real-time evaluations.

Table 2. *Cont.*

Fault Signature/ Approaches	Merits	Demerits	Comments	Applicable Range	Quantitative Analysis
2.2 Observer-Based Approaches (Sliding Mode, Flux Observers, Luenberger, EID) [26–34]	- Real-time feasible if well optimized - Good synergy with advanced drive control - Allows for fault-tolerant operation	- Parameter sensitivity (machine constants, temperature) - Complex design (e.g., super-twisting, EID) - Noise can degrade observer accuracy	Provide direct flux or EMF estimation for online fault detection. Sliding-mode approaches are robust but can suffer chattering. EID-based methods decouple speed from error, improving fault tolerance at the cost of higher modeling complexity.	- High-speed or aerospace systems needing fast detection - EV traction drives with thermal constraints - Systems embedding observer-based controllers	Some studies show precise flux tracking (<1% error) in controlled rigs. Real-world performance under large load changes or sensor noise is less reported..
2.3 Machine Learning (ML) Methods (CNN, SVM, Fuzzy-ELM, Transfer Learning) [35–42]	- Potentially high accuracy and adaptability - Can fuse multiple signals (current, torque, acoustic) - Handles nonlinear behaviors	- Data-intensive (large labeled sets) - Black-box interpretability issues - High computational burden for real-time edge deployment	Often combines stator current signatures, torque, or acoustic signals in neural nets or SVM. Useful for partial demagnetization classification but requires large training sets. Data labeling and domain expertise remain key challenges.	- Research labs or industries with robust data-logging - Environments supporting ML-based analytics (digital twins, big data)	Some references claim >90% detection accuracy. Transfer learning (e.g., VGG-16) handles demagnetization under noise. Generalization to new machines or harsh conditions is uncertain. CPU/GPU overhead complicates real-time adoption.
2.4 Sensor-Based Techniques (Rotor Partitioning, Search Coils, Hall-Effect, Flux, Vibration [43–60]	- Direct measurement of flux/vibration - Potentially high-resolution detection - Real-time feasible with integrated hardware	- Often invasive (extra coils, rotor modifications) - Environmental factors (temp, vibration) can degrade reliability - Cost and geometry constraints can hamper scaling	Includes rotor partitioning with toroidal coils, flux measurement with search coils, Hall sensors, and vibration-based diagnostics. Vibration analysis can reveal mechanical responses (e.g., low-order modes) caused by magnet weakening. These can complement electrical signals for more robust detection.	- Applications needing localized fault detection - Large or specialized machines (marine, aerospace) - Systems open to extra sensor hardware	Some sensor-based methods detect ~10% magnet loss. Vibration references emphasize new sidebands or altered mode shapes. Results are often lab-based or machine-specific. There is no universal performance metric used across all studies.
2.5 Emerging/Hybrid Strategies (Inverter-Embedded, FRM, Flux-Weakening) [61–69]	- Combine multiple detection logics (MCSA + flux + advanced analytics) - Potentially more holistic or faster detection - Can exploit existing inverter hardware	- Largely under research; limited real-world validation - Some approaches require motor standstill or specialized inverters - Model/hardware complexity can be high (CKF, sum-of-squares, etc.)	Blends hardware modifications (e.g., specialized signal injection) with advanced Kalman filtering (CKF, RLS) or flux-weakening control. Promising synergy but minimal industrial track records. Computational intensity can be significant without optimization.	- High-end systems or R&D testbeds needing integrated solutions - Potential next-gen industrial/EV drives if overhead is managed	Some prototypes show faster detection or improved robustness. Typical claims focus on partial demagnetization detection. Numerical gains (e.g., fewer false positives, shortened detection time) remain in small-scale demos rather than mass industry use.

2.6. Open Challenges and Future Directions

Some open research directions are needed for robust and efficient demagnetization fault diagnosis in PMSMs. Robust detection under non-uniform or partial demagnetization is one of the important topics. Existing methods typically capture overall rotor flux reduction but fail to localize magnetically weakened regions on the rotor surface. Small spatially distributed losses of remanence often produce weak fault signatures masked by normal operation noise. New approaches should emphasize fine-grained magnetic field reconstruction or multiple Hall sensors for mapping localized demagnetized areas. Such signal processing algorithms like Empirical Wavelet Transform, Variational Mode Decomposition or high-resolution spectral analysis require better optimization to run in real time without excessive computational cost.

The other potential field is integrated thermal-magnetic modeling. Finite element analysis remains the de facto standard for simulation but is often too slow for real-time applications. Rather simple approaches would use thermal and magnetic field computations in unified

multi-physical models. Such modeling must account for nonlinear material behavior in magnets along with variable cooling and load conditions. With temperature estimates from embedded sensors and real-time magnet flux linkage measurements, the algorithm can update the magnet's health state continuously and predict irreversible demagnetization before it worsens. An associated problem is the need for better magnet selection and grading: Each magnet type reacts differently to heat and stray fields, thus careful selection of magnet materials and their positioning may limit demagnetization risks.

Other observer-based control approaches need further research especially for high-performance applications where dynamic conditions are demanding. Whether sliding-mode or Kalman-based observers can estimate flux linkage but lose accuracy when machine parameters drift due to saturation or heating. Such adaptive and fault-tolerant observer architectures should be investigated together with real-time magnet temperature feedback to obtain reliable flux estimates during demagnetization events. Such observers may also allow for online flux-weakening control or post-fault derating strategies to stop the machine in regions of high magnet decay rate.

Also promising are machine learning and data-centric techniques. Hence, pure data-driven methods often fail because there are few labeled datasets for inclement magnetization, and because real-world faults differ from lab scenarios. A better path is to combine physics-based magnet models with machine learning: The magnetic model supplies physically consistent constraints and features while the ML framework deals with noisy conditions and partial observations. Carefully curated open datasets with different magnet types, load profiles, and demagnetization severities would accelerate this direction. Transfer learning may also be needed for adapting an ML model trained on one machine type to another configuration without losing accuracy.

Sensing and hardware costs should be addressed in future work. Several advanced diagnostics assume air-gap flux probes, rotor search coils, or distributed Hall-effect sensors that are too expensive or invasive for mass production. Studies of miniature, integrable sensors embedded in motors at manufacturing may reduce installation barriers. Meanwhile, special signal-processing hardware in the form of FPGAs or digital signal processors can accelerate computationally heavy tasks such as wavelet transformations or advanced observer algorithms. High diagnostic accuracy is required while practicality in terms of cost and complexity must be achieved for wider commercial acceptance.

And thirdly, uniform testing and benchmarking protocols would standardize the field. Today different studies use custom test rigs or proprietary procedures to compare algorithmic performance. A unified methodology for introducing controlled demagnetization faults, detection latency characterization, and performance quantification in terms of harmonic signal-to-noise ratio would be beneficial to academia and industry. Just as important is industry collaboration for the validation of new methods on large, high-power prototypes under real operating stresses. Such partnerships would validate whether proposed methods can detect partial demagnetization early enough to initiate corrective actions such as scheduled downtime or torque derating.

3. ITSC in PMSMs

Inter Turn Short Circuit (ITSC) occurs when the turn insulation between two or more turns of the shame face degrades and fails. The shorted coil perceives the magnetic field of the air gap, inducing a voltage across the shorted turns according to Faraday's law. This voltage will generate a circulating current, that runs through the shorted coil, this current may be several times greater than the nominal current of the phase [70]. Although the ITSC does not cause an immediate breakdown of the machine, the current in the shorted coil generates localized heating, which increases the temperature in the affected

area. Additionally, the fault can lead to an increase in vibrations, these two factors further deteriorate the insulation, increasing the severity of the fault. Over time, it will evolve into more catastrophic faults such as phase-to-phase or phase-to-ground short circuits. In PMSMs, the magnetic field generated by the current in the shorted coil opposes the magnetic field of the permanent magnets. This opposing field, combined with the elevated temperature in the affected area, can lead to the demagnetization of the permanent magnets, compromising the machine's performance and efficiency. Furthermore, the inductances change during ITSC [71]. Therefore, vector control-based techniques are utilizing the inductance difference to diagnose the ITSC [72,73]. Additionally, the coil configuration needs to be considered, as seen in [70]. Finally, the PWM ripple of the drive system cannot be underestimated, as it can reach an amplitude of 25–50% of the fundamental [74,75].

3.1. Modeling of PMSMs Under ITSC

The first step in diagnosing an (ITSC) is the modeling of the fault. Numerous methods are used to analyze ITSCs, with the most common being analytical modeling. FEA simulations and the equivalent circuit are very helpful with the understanding of the fault behavior. The equivalent Circuit is very helpful to study the effects of the ITSC on the PMSM. The coil configuration of a PMSM can be series-connected, parallel-connected, or a combination of both. Figures 2 and 3. shows the equivalent circuit of series-connected and parallel-connected coils respectively. Series-connected coils are studied in [8,71,72,75–83], parallel-connected coils are studied in [74,84,85], and multiphase PMSM in [86,87]. Due to the influence of mutual inductances between the coils and the shorted coil, series and parallel connections will be studied separately.

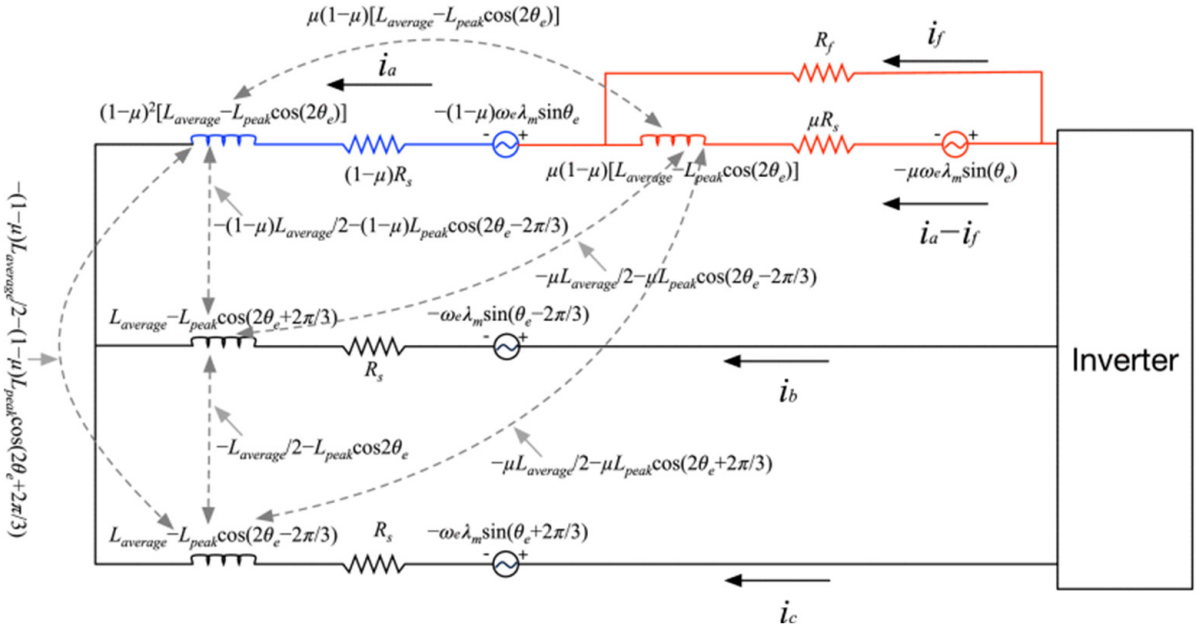


Figure 2. Equivalent circuit of series connected PMSM under ITSC [71].

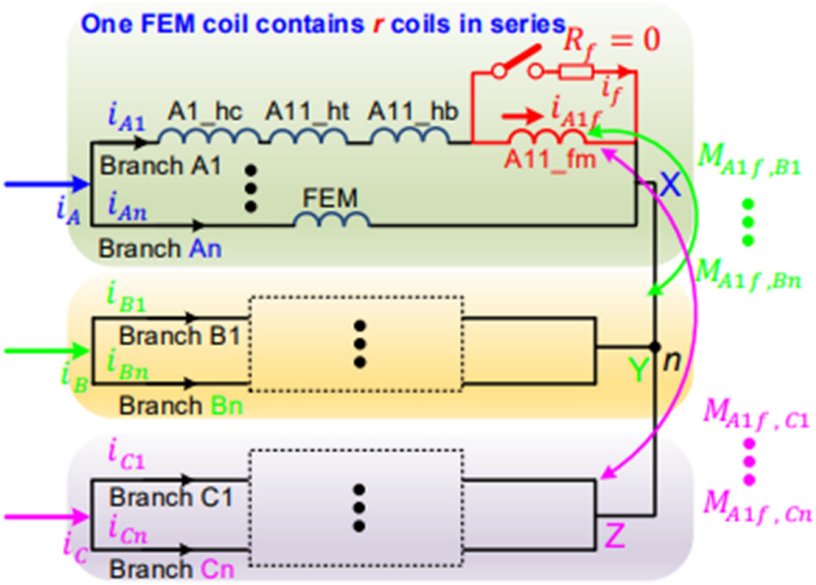


Figure 3. Equivalent circuit of parallel connected PMSM under ITSC [84].

3.1.1. ITSC in Series Connected of PMSM

Studies have shown that the shorted current is proportional to the inductance of the shorted coil. As the coil impedance is proportional to the rotor speed, at low speed the effects of the inductance are low and the shorted current is proportional to the coil resistance, on the other hand in case the rotational speed is high, then the coil resistance can be neglected, and the shorted current is proportional to the inductance.

Due to PMSM driver requirements, the most common way for analysis is the Park Transformation into d and q axes. This transformation has taken place in [8,70–72,78,79,81]. The mutual inductance between the shorted coil and the rest of the coils will generate an asymmetry in the three phases of the machine. A study in [71] has shown that a second harmonic in the current will be generated and can be calculated. This harmonic is generated by the interaction of the healthy current and the faulty current, as both share the same frequency. As the shorted current is higher in high rotational speeds and the impedance asymmetry is also higher, high rotational speed machines are more critical and easier to diagnose [71]. Ref. [75] has shown that the Pulse Width Modulation (PWM) of the driver has effects on the machine under ITSC. This study showed that the dominant current harmonic of PWM can reach the value of 25% of the fundamental harmonic, and this will lead to an increase in losses and thermal stresses. The contact resistance also affects the amplitude of the shorted current, Ref. [8] has stated that in perfect short circuit the shorted current is expected to be the highest. On the other hand, Ref. [71] showed that with the effect of the contact resistance, the shorted current is larger when the contact resistance is small, it also showed that the effect of the contact resistance is decreasing as the number of shorted turns increases.

3.1.2. ITSC in Parallel Connected of PMSM

The shorted coil will also affect the mutual inductance of the rest of the coils, Ref. [8] showed that detecting ITSC in parallel configuration is harder due to lower local leakage flux in shorted coils under equal fault conditions. The parallel connection of the coils also reduces the generated EMF. As with series connection, the most common analysis is the Park's Transformation. A study in [74], stated that the PWM of the drive will generate a harmonic with the value of 50% of the fundamental, which is higher than series, and therefore the effects of the PWM cannot be neglected. The same research also proved

that with simulations and experimental results, the previous claim to be correct, as the faulty current ripples, are much larger in parallel connection than in series. One more interesting phenomenon has been observed in [84], as the coils that are in parallel connected branches showed in Figure 3, after the ITSC is taken place, the amplitude of the current of these branches increases. The result can be observed in Figure 4. As the ITSC begins, the inductance of each branch changes, the branch that the ITSC is taking place, will have reduced coil self-inductance, coil resistance and EMF. Therefore, a circulating current between the branches will be generated and will increase the amplitude of the parallel branches. This gives the potential of sensor-based diagnostic methods. Due to the change in the mutual inductances between the coils, as can be seen in Figure 5, there is a small fluctuation in phase C.

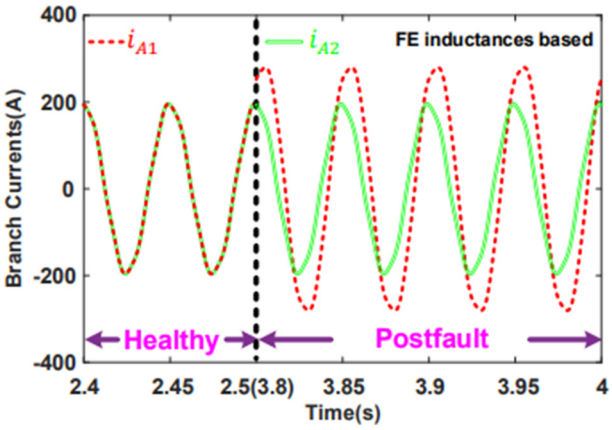


Figure 4. Phase A current of the parallel branches under ITSC [84].

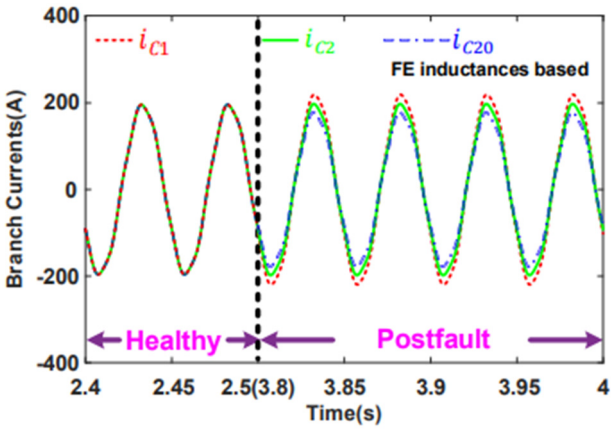


Figure 5. Phase C current of the parallel branches under ITSC [84].

3.2. Diagnostic Methods for ITSC in PMSMs

After the ITSC is modeled, the next step is the diagnosis of this fault. Since PMSMs are using drive systems, the most common diagnostic method is by using the current and voltage-based methods, and applying methods such as FFT, Wavelet transformation (WT) [88], Park and Clarke transformation [71] and vector control [74,75]. Other methods are based in Torque analysis have also been studied [89] and finally some magnetic flux sensors techniques have been tested in [90,91]. Each diagnostic method will be studied separately below and will be presented in Table 3.

3.2.1. Vector Control-Based Models

Starting with [71], the Park and Clarke transformation is applied, by using the Kalman filter, to monitor the 2nd order harmonic. Furthermore, Kalman filter has been studied

in [78], this research is using both Extended Kalman Filter Algorithm (EKF) and Unscented Kalman Filter Algorithm (UKF). EKF has the advantage of implementation simplicity, lower computation cost and memory efficiency. On the other hand, UKF has better accuracy in the fault estimation. The block diagram of PMSG diagnosis can be observed in Figure 6. Refs [74,75] are vector control-based studies in parallel and series connected coils respectively. Ref. [75] is modeling the effects of the drive and can predict the PWM harmonic. In [74] by calculating the faulty current, Laplace transformation is applied in order to extract the effect of the PWM on the fundamental component of fault current.

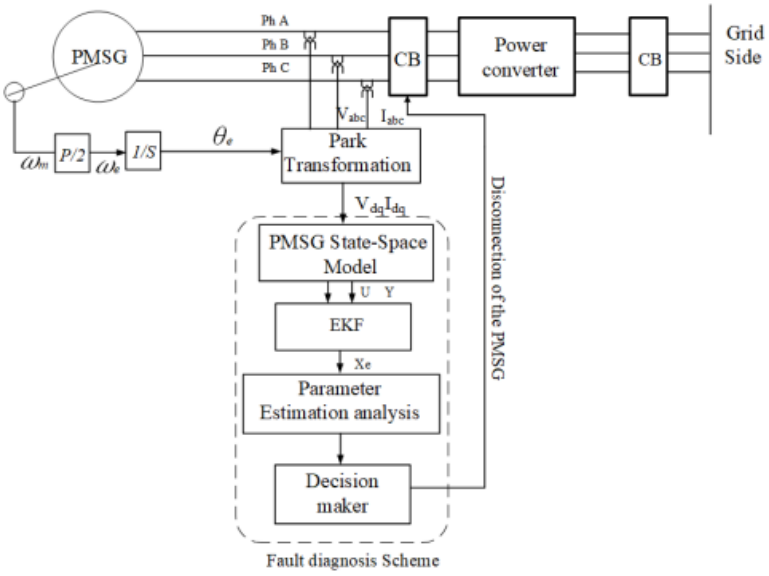


Figure 6. Block diagram of PMSG monitoring by using Kalman Filter [78].

3.2.2. Torque and Current Wavelet Methods

Firstly, Ref. [89] showcases many diagnostic techniques. Torque analysis is presented, then current analysis takes place and finally a sensor-based method is applied and will be discussed later. Although directly measuring torque is impractical in real applications, similar signatures can be observed by monitoring vibrations [92]. By applying FFT in the torque, under healthy conditions the 6th order harmonic is the most noticeable after the fundamental, as the EMF consists only the 1st, 5th, 7th, 11th order harmonics. When the fault appears, the 2nd order harmonic is expected to drastically increase in amplitude. In the same study, an asymmetric load and an asymmetric source have been considered, and when that happens the torque signatures are very similar with the fault symptoms. Furthermore, when the 3-phase asymmetry is co-existing and interacting with the ITSC, it can also cancel-out the 2nd order harmonic leading to misdiagnosis. Then, by studying current signatures, the negative current and the DWT analysis has been applied. In this study, by monitoring the 3rd order harmonic of the negative sequence current, there is a potential in tracking the fault, but more measurements need to be conducted. On the other hand, the DWT analysis is also giving some potential, as the decomposed components peak values of DWT are increasing with the fault severity. Also, the asymmetry has similar results, making this method unreliable at this moment. Moreover, in [88], FFT and DWT has been studied under load and speed variations. The FFT could not detect the fault feature in different states. In [93], EWT has also been studied, showcasing that as the ITSC severity increases, the peak values of decomposed components of EWT are also increasing.

3.2.3. Search Coil Techniques

Starting with [89], where a search coil is wound at the tooth tip to capture the main flux that passes through each stator tooth. The induced voltages of all the search coils are placed in a polar diagram. This technique was able to identify the ITSC from unbalance conditions, but on the other hand this technique requires access in the stator tooth, making this method difficult to implement. In [91] a search coil has been placed in the stator tooth where the ITSC is taking place. The simulation begins under healthy conditions and then the ITSC is activated. The Discrete Fourier Transform (DFT) is applied to analyze the steady-state operation of the machine, while the Short Time Fourier Transform (STFT) is used for the transient state. These techniques have been employed to examine the induced voltage under varying fundamental and PWM frequencies. This research showed that this method has reliable results only when the PWM frequency is an even natural number multiple of the fundamental frequency. Furthermore, since the exact location of the inter-turn short circuit (ITSC) is unknown in real applications, a search coil must be placed in every stator tooth.

Additionally, the search coil requires access to the machine's air gap, significantly increasing computational demands and making this method challenging to implement. In [90] two search coils have been implemented; the first one is placed on the stator and the second on the rotor. Both coils cover the maximum symmetrical area of the machine. Under healthy conditions, symmetry ensures that no voltage is induced in either coil. When the machine operates under ITSC, magnetic asymmetry in the airgap induces voltage in the rotor search coil, following the law of Faraday. The rotor search coil is short-circuited; therefore, a current will be generated, and this current will create a magnetic field. This magnetic field will induce voltage in the stator search coil. While this method requires only two search coils, it still requires access to the air gap. Furthermore, two more factors must be considered. Firstly, the magnetic flux that is generated by the rotor search coil may affect the current of the phase. And lastly, this magnetic flux, along with the heat produced by the ohmic losses in the rotor search coil, can potentially cause demagnetization in the permanent magnets. Although search coil techniques offer high accuracy in diagnosing ITSC, their implementation presents significant challenges and requires further study.

3.2.4. Impedance Monitoring

Impedance monitoring is a well-established and reliable method for diagnosing ITSC in Induction Machines (IM). In [94], various techniques for measuring the impedance of IM are presented. Additionally, studies in [95,96] have demonstrated that impedance monitoring can effectively diagnose ITSC. This method has been expanded to PMSMs as in [97] with the use of simulations. In this study, the authors designed a fault diagnosis indicator based on the high-frequency current response, successfully addressing the effects of mutual inductance. Although this method is promising, two important factors must be considered. The first is the effect of contact resistance, which plays a crucial role when an electrical machine experiences ITSC, as it directly influences the current in the shorted coil. In real applications, the contact resistance will not be zero, meaning that the ITSC will not be ideally maximum. Assuming zero contact resistance implies that the current in the shorted coil will be severe, which may not accurately reflect real-world conditions. The second factor to consider is that the same analysis must be conducted for cases where the number of shorted turns is low, and the results must be validated through experimentation. In general, when PMSM applications are critical or the machine is not easily accessible, it is of high interest to ensure that the machine can continue operating despite the presence of ITSCs.

Table 3. Comparison of Existing Inter-Turn Short Circuit Diagnostic Methods in PMSMs.

Fault Signature/ Approaches	Merits	Demerits	Comments	Applicable Range	Quantitative Analysis
3.1 Current-Based Methods (Vector control, Wavelet transformation and current sequence) [84,89]	- Online diagnosis - Fault estimation - Easy to implement - Low computational cost	- Diagnosis in low-speed machines - Similar signatures as coils asymmetries	Estimation of the fault severity but they are vulnerable to coil asymmetries. The effects of the PWM drive should be considered.	- Situations with varying load - Transient conditions - High speed machines as EV or aerospace - Low and high-cost machines	Some works report clear fault indicators, but the experiments are usually with high fault severity and the contact resistance is neglected.
3.2 Sensor-based methods [89,91]	- High detection accuracy - Able to distinguish the ITSC by coil asymmetries	- High computational cost - Difficult to implement, requires air gap accessibility	It was the most effective method, as the magnetic flux is proportional to EMF. This method requires accessibility to the machine air gap, making it very difficult to implement.	- High and low speed machines - Transient conditions - Situations with varying load - High cost and critical applications	The fault indicator is clear and visible even when the fault severity is low. This method is difficult to implement, and it is suggested when the application is critical.
3.3 Torque and vibration analysis [89,92]	- Low computational cost - Generally high accuracy	- Difficult to implement - The position of the ITSC cannot be determined - Load and current asymmetries will generate similar signatures	Torque and vibration analysis is able to detect the ITSC, although experiments and load asymmetries need to be considered as they can lead to miss-diagnosis.	- High and low speed machines - Transient conditions - Low cost or non-critical applications	Some references presented the effects of the load and current asymmetries and proven a critical aspect.
3.4 Impedance monitoring [97]	- Effective in high frequencies - Potentially able to distinguish the ITSC by coil asymmetries	- High computational cost - Difficult to implement - Low-severity faults present challenges in detection	Although in IM the impedance monitoring is considered reliable, in PMSMs extensive analysis and experimental results are required to verify its efficiency.	- High and low speed machines - High cost and critical applications	The studies showed that the effects of mutual induction that can lead to misdiagnosis can be addressed. In the same studies on the other hand, the fault severity was significant, and studies with low severity faults are required.

3.3. Future Work

For current-based methods, strategies aiming to distinguish the ITSC from other three-phase asymmetries such as: coil asymmetries, supply imbalances, high resistance connections and others, are required. For sensor-based methods, extensive experimentation is required to evaluate the effectiveness and reliability of the studies. Moreover, existing methods require access to the machine's air gap, many sensors, and high computational costs. Therefore, it is crucial to explore methods that utilize sensors placed outside of the machine. Additionally, minimizing the number of required sensors will help towards the computational costs' reduction. For torque and vibration analysis, experimental results are necessary, as load and phase asymmetries can affect the torque in a similar manner to ITSC. Finally, for impedance monitoring, simulations are required that consider the effects of contact resistance, especially in cases of low fault severity. Once these simulations are conducted, the results should be validated through experimental testing.

4. Eccentricity Faults in PMSMs

Eccentricity faults are common malfunctions in PMSMs that can severely degrade performance and reliability by inducing unbalanced magnetic fluxes, mechanical stress and excessive vibration [98,99]. These faults typically manifest as static eccentricity (SE), dynamic eccentricity (DE), or a mixture of both (ME), with the latter case often complicating diagnosis because of overlapping fault signatures [100]. Early and accurate detection of eccentricities is crucial to prevent secondary failures, such as rotor rubbing, bearing damage and demagnetization [101]. The discussed types of eccentricity faults can be effectively illustrated using 2D models as shown in Figure 7, which clearly depict the relationships between the stator center, rotor center, and, in the case of mixed eccentricity, the rotational center [98]. This approach serves as a principal theoretical example that explains the rotation of machines under eccentricity. In the case of axial 3D models, the same principle can be applied in the axial direction, following the same theoretical framework.

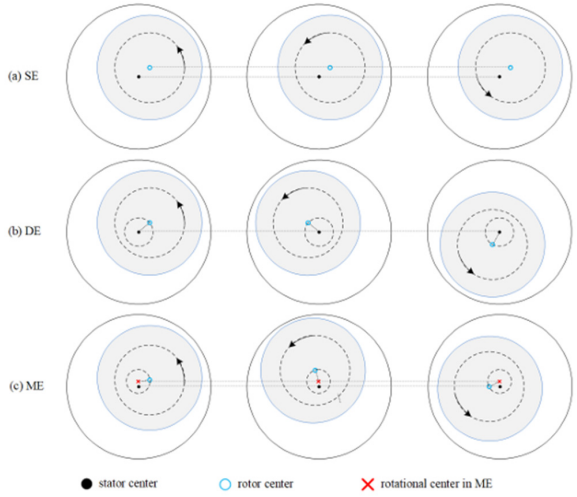


Figure 7. Diagram of Eccentricity Faults (**a**) SE, (**b**) DE and (**c**) ME [98].

Over the years, researchers have proposed a variety of diagnostic approaches, ranging from motor current signature analysis (MCSA) to external magnetic flux sensing [98], incremental inductance measurement [99], back-EMF analysis [101] and advanced signal processing techniques in both time and frequency domains.

Further enhancements in the detection process have been achieved using artificial intelligence algorithms such as convolutional neural networks and autoencoders that help in processing non-stationary signals and extracting relevant features [102].

Aside from electrical-based methods, vibration analysis and sensors embedded in the air gap or stator slots (e.g., Hall sensors or search coils) also provide robust monitoring capabilities under adverse operating conditions. Nevertheless, each technique must contend with confounding factors such as load fluctuations, noise from magnetic saturation and the presence of other mechanical or electrical faults. Consequently, developing a low-cost, noninvasive and reliable detection strategy that can reliably distinguish eccentricity from other anomalies remains a key research challenge. These methods are presented in Table 4.

4.1. Eccentricity-Aiming Diagnostic Methods

4.1.1. Stator Current Analysis

Different diagnostic methods have emerged so far, but one of the most widely used techniques for eccentricity fault diagnosis is Motor Current Signature Analysis (MCSA). The authors proposed a method to diagnose static, dynamic and mixed eccentricity faults in PMSMs using MCSA [103]. Specific frequency components were identified in the stator current spectrum

that correspond to different types of eccentricity faults. The index shown is based on the amplitude of the sideband components in the stator current spectrum at frequencies:

$$f_{ecc} = \left[1 \pm \frac{(2k-1)}{P}\right] \cdot f_s$$

where k is an integer, P is the number of pole pairs and f_s is the supply frequency.

Key advantages of the MCSA include the non-invasive nature of this method, the ability to detect multiple fault types and the fact that it is applicable to online condition monitoring, which is a distinct advantage especially for PMSGs that are less accessible (offshore wind turbines, wave energy harvesters et. al). However, this method's effectiveness can be limited by factors such as machine design and operating conditions. Additionally, other static faults can amplify the same signatures in the MCSA spectrum and in this case no reliable results can be extracted [98].

By extending the MCSA method, broken bearings can be detected with greater detection ability, indirectly, via the use of eccentricity harmonics. The proposed method extends the application of MCSA beyond conventional stator phase currents to include zero-sequence (i_0) and q-axis (i_q) currents in the dq_0 reference frame. This technique offers particular advantages, including advanced detection of rotor eccentricities through analysis of i_0 current harmonics, particularly the third harmonic of rotor frequency, improved fault detection across a wide speed range and the ability to identify even minor eccentricity faults. In addition, the method features specific fault frequencies associated with bearing damage. However, the approach does have drawbacks, such as the requirement for additional signal processing work to obtain dq_0 currents, potential challenges in distinguishing between different fault types based only on harmonic analysis and the need for baseline healthy motor data for comparison. Despite the constraints, the proposed technique is a satisfying approach for early fault detection in PMSMs [104].

4.1.2. External Magnetic Sensing

Another approach for eccentricity faults in PMSGs is the external magnetic sensing which was proposed in 2022. A magnetic equivalent circuit is used to analyze the effects of SE and DE faults on external leakage flux density. Two indicators are proposed: one for SE detection and location and another for DE detection. The SE indicator is calculated using measurements from three external magnetic sensors, while the DE indicator can be obtained from a single sensor. Key advantages include non-invasiveness, fast detection speed due to light computation, applicability to PMSGs with different slot/pole combinations and robustness to load and speed variations. The method can detect both fault types and severity. Disadvantages of this method include the need for precision in sensor placement, possible interference from external magnetic fields and not great effectiveness for machines with significant pre-existing asymmetries or harmonics from power electronics. Additionally, this method may require recalibration if the machine's magnetic properties change over time [105].

4.1.3. Stator Voltage Analysis

The use of stator voltage signature analysis has also been proposed. This approach is used for detecting all types of eccentricity in PMSGs using an index based on the amplitude of sideband components that are extracted from the stator voltage spectrum. Advantages of this method include the ability to detect faults in both load and no-load conditions while also diagnosing eccentricity faults in no-load status before further damage occurs. The authors employ the time-stepping finite element method to model the PMSG under eccentricity and calculate the stator voltage, in order to achieve high precision in the

signal computation. However, the study has some limitations. It relies exclusively on simulation results without presenting experimental validation, which would be necessary to confirm the method's practical applicability. Additionally, the paper does not discuss the method's performance under varying operating conditions or its sensitivity to different fault severities. Overall, the approach presents a valuable contribution to the field of fault detection in PMSGs, by offering an early and non-invasive diagnostic technique [106].

The utilization of the voltage signal is also followed in a novel approach using the neutral voltage difference signal for investigating eccentricity faults in Axial Flux PMSGs. This method can distinguish between demagnetization and static eccentricity faults using spectral analysis of the neutral voltage difference signal [107]. The V_{NO} signal is defined as the voltage between the common star point of the stator and the common star point of the load. A 3D finite element model is used to simulate the generator under healthy and faulty conditions. The V_{NO} signal is calculated as:

$$V_{NO} = \frac{V_{EMF_A} + V_{EMF_B} + V_{EMF_C}}{3} - \frac{R_A I_A + R_B I_B + R_C I_C}{3}$$

where $V_{EMF_A}, V_{EMF_B}, V_{EMF_C}$ are the EMF voltages and I_A, I_B, I_C are the phase currents.

Fast Fourier Transform is applied to analyze the frequency components of the V_{NO} signal. Key advantages include the ability to detect both eccentricity and demagnetization faults and distinguish between them based on characteristic harmonic components, $1.5f_s$ for demagnetization, where f_s is the fundamental frequency. This method is non-invasive and can detect faults when EMF or current signals alone are insufficient. However, there is a need for precise measurement of the neutral point voltages and additional sensitivity is prone to other asymmetries or harmonics in the system.

4.1.4. Back EMF Analysis

While MCSA, external magnetic sensing and stator voltage analysis have shown effectiveness in detecting eccentricity faults, Back electro-motive force (Back-EMF) analysis is another good technique with some distinct advantages. Back-EMF is the voltage induced in the stator windings due to the rotating magnetic field of the rotor. This parameter is particularly sensitive to changes in the air gap caused by eccentricity faults. Based on the Back-EMF analysis, a new dynamic eccentricity diagnosis method for PMSGs was recently proposed [108]. This method introduces a new DE index called Normalized Envelope Mean (NEM) of the Back-EMF, which can be extracted without using FFT, making it suitable for variable-speed conditions. It is reported to be more effective than stator current methods as it is not affected by load disturbances while it can accurately diagnose DE under both constant speed and variable-speed conditions, addressing a major limitation of existing techniques. The equation used for the calculation of the NEM is as follows:

$$F_{di} = \frac{\sum_{j=1}^{n_j} \mathrm{v}F_{d_{ij}}}{n_j}$$

where F_{di} is the NEM, F_{dij} are envelope amplitudes, n_j are the total envelope points, e_{An} is the normalized EMF, IRS is the instantaneous speed and IRS_R is the rated speed.

The speed normalization is done based on the rated speed after dividing the original test back EMF point-to-point by the rated speed IRS(t) and then multiplying by the rated speed IRS_R.

$$e_{An}(t) = \frac{e_A(t)}{IRS(t)} \times IRS_R$$

Several recent methods for eccentricity fault detection in permanent magnet machines rely on different types of external sensors to capture and analyze magnetic asymmetries.

Search-coil-based approaches mount coils around the stator teeth or in the air gap, measuring induced voltages that reveal fault signatures during both steady-state and transient conditions [109]. The first method uses only two search coils placed on opposite sides of the rotor, reducing sensor count while detecting eccentricity and demagnetization faults in PMSGs under varying speeds [50]. The other approach uses three search coils uniformly distributed around the air gap in axial flux machines, enabling real-time monitoring of static eccentricity by examining the envelope of induced voltages [110]. Hall-effect field sensors, strategically installed to measure magnetic field variations around the rotor, also enable online detection of rotor eccentricity and demagnetization, benefiting from the sensors' non-invasive nature and immunity to temperature fluctuations. Finally, a method using an additional winding wound around specific stator teeth offers real-time dynamic eccentricity detection in PM motors by analyzing the back-EMF signal, avoiding heavy post-processing [111]. While these sensor-based techniques generally can be classified as accurate fault detection solutions and can operate in real-time, they may require hardware modifications (e.g., adding coils or windings) and can have specific design constraints, such as an even number of stator teeth. Despite these limitations, they are promising solutions for reliable eccentricity fault detection across different motor topologies.

4.1.5. Mechanical Signal Extraction

Based on the mechanical properties of the PMSMs, a recent study proposed a method for extracting features from vibration signals to detect eccentricity faults. The authors use a multi-physical model of the PMSM to generate vibration displacement signals under different operating conditions, including rotor eccentricity faults. They then apply time-domain and frequency-domain signal processing techniques to extract features from these vibration signals. The evolution of these features with respect to fault severity is analyzed to select proper criteria for fault detection. Key advantages of this approach include the ability to model and analyze both static and dynamic eccentricity faults and the extraction of multiple time and frequency domain indicators that can potentially improve fault detection accuracy. Potential disadvantages could be the complexity of creating the multi-physical model, which requires detailed machine parameters. In addition, the approach may be less effective for machines with pre-existing harmonics or for those driven by inverters, the production of interfering high-frequency harmonics [59].

Vibrations Analysis (VA) has emerged as a robust diagnostic tool for detecting rotor eccentricity faults in PMSMs. A study demonstrated that VA effectively identifies static eccentricity by monitoring electromagnetic force-induced vibrations in both frequency and time-frequency domains. This work reveals that SE reforms the airgap permeance, amplifying specific vibration harmonics, particularly the component associated with the lowest mode of the magnetic force determined by the pole-slot combination [112]. This harmonic's amplitude is increasing as the SE fault severity increases. The merits of this approach include the VA's superiority over MCSA in diagnosing mechanical faults, as MCSA struggles with the detection of noise from inherent current harmonics in fractional slot concentrated windings. In addition, VA is robust enough in both steady-state and transient operations, making it suitable for real-time monitoring [113]. However, the method relies heavily on expensive vibration sensors and extensive signal processing, compared to MCSA, which utilizes existing current sensors. Furthermore, the analysis has been conducted to a specific AFPM topology, which does not guarantee that other configurations could show the same behavior [50].

4.1.6. D-Axis Inductance Methods

The measurement of the d-axis inductance has also been proposed. The technique involves using an inverter to inject a small AC signal in the d-axis direction when the motor is at standstill, measuring the resulting d-axis inductance. Key strengths of this method include the ability to detect eccentricity faults offline without requiring additional sensors and its independence from variations in load or speed. The proposed fault detection algorithm shows a particular strength in distinguishing between different types of eccentricity faults. The study relies primarily on finite element analysis and experimental validation on a single 10-hp PMSM, which may limit its generalizability to other motor designs. Additionally, the method requires the motor to be at standstill for testing, which could be inconvenient in some applications. Finally, the approach presents a valuable contribution to the field of eccentricity fault detection in PMSMs, offering a potentially sensitive and reliable diagnostic technique that is not affected by load variations or oscillations [114].

Building on the theme of offline eccentricity detection, another innovative approach is the incremental inductance method for detecting static eccentricity in PMSMs. While the previously discussed D-axis inductance-based method relies on injecting an AC signal along the D-axis during standstill operation, the incremental inductance approach focuses on analyzing two specific features of the incremental inductance curve: the D-axis saturation current and the height of the hump. These are extracted automatically from the DC values of the Q-axis voltage using computer algorithms [115]. This technique offers unique strengths, including independence from controller bandwidth and high-resolution signal requirements, while enabling fault separation and achieving robust performance against temperature changes and minor rotor misalignments. Hardware constraints are present that require the development of a controller that eliminates the need for external rotation systems during testing. However, like the D-axis inductance method, the incremental inductance approach is constrained to offline conditions, making it less ideal for real-time monitoring. Additionally, the modified approach demonstrated slightly lower classification accuracy, highlighting sensitivity to implementation details. Together, these inductance-based methods represent a noticeable advancement in offline eccentricity fault diagnosis, trading real-time usability for precision and simplicity.

4.1.7. Time-Frequency Analysis

While traditional techniques are effective in diagnosing specific faults under steady-state conditions, less basic techniques are reliable under transient operating conditions. For this reason, time-frequency analysis is used being a signal processing technique that decomposes a signal into both time and frequency domains. Common methods include Short-Time Fourier Transform (STFT), Wigner-Ville Distribution (WVD) [116] and Gabor Spectrograms [117,118]. Each of these techniques allows for the detection of harmonic components that vary over time.

A fault detection method based on time-frequency analysis is proposed by researchers to identify mechanical faults like bearing damage in PMSMs under non-constant working conditions [119]. This method uses the Gabor Spectrogram, selected for its combined time and frequency resolution compared to STFT and WVD. By analyzing the stator current of the motor as its speed decreases from 3000 rpm to 2000 rpm under nominal load, the Gabor Spectrogram identifies fault-related harmonics shifting in frequency. Despite its effectiveness, the method focuses only on bearing faults and requires further development to extend its capabilities to eccentricity and other fault types.

A well-known time-frequency analysis method is the Wavelet Transform [120]. A study presented a method for eccentricity detection through Wavelet Transform and the FFT of the stator current signal [121]. The main advantage of this approach is the ability to provide a time-varying frequency spectrum, which enables fault detection by revealing transient behaviors

and harmonics that traditional methods often cannot detect. This could be beneficial for identifying both static and dynamic eccentricities, as well as bearing damage, by analyzing the resulting changes in current signatures under various operational conditions. However, the method can be computationally intensive and may require careful selection of wavelet parameters to optimize sensitivity. Additionally, while WT can denoise signals and focus on specific frequency bands, the interpretation of results can be complex, requiring the user to have a thorough understanding of the machine dynamics and fault characteristics to avoid misdiagnosis. Overall, the time-frequency analysis method offers good diagnostic capabilities for PMSMs but it also presents challenges for accurate fault identification.

4.1.8. Innovative Approaches in Eccentricity Fault Detection

The ongoing advancements in eccentricity fault detection for Permanent Magnet Synchronous Machines (PMSMs) have expanded beyond traditional techniques, employing novel algorithms, deep learning and sophisticated signal analysis methods. For example, innovative modeling forms the basis of one proposed algorithm that uses a Fault Signature Block Binary Array (FSBBA) to predict harmonic fault signatures caused by dynamic eccentricity [122]. This approach, validated through 3D Finite Element Analysis (FEA), ensures accurate fault detection for any slot-pole combination and strengthens the reliability of Motor Current Signature Analysis (MCSA). However, its implementation complexity and sensitivity to inverter harmonics highlight practical limitations.

Leveraging machine learning, a convolutional autoencoder (CAE) was recently developed for anomaly detection in offshore wind generators [102]. By extracting spectral features and employing Principal Component Analysis (PCA) alongside Mahalanobis distance metrics [123], this unsupervised method demonstrated robustness under varying operating conditions. Nevertheless, its reliance on multiple sensors and inability to classify fault severity pose challenges.

Similarly, the static eccentricity detection method based on coherence analysis exploits spectral correlations between mechanical and electrical signals, such as current, voltage and torque [124]. This technique provides crucial insights into joint signal properties, although its testing under limited load conditions restricts its applicability.

Deep learning approaches are also demonstrating significant potential in sophisticated fault diagnosis. One-dimensional convolutional neural networks (1D CNNs) have emerged for fault classification by automatically extracting multiscale features from torque and current signals [125]. These methods, while achieving high accuracy, are complex to implement and require extensive parameterization.

Building on this, transfer learning with VGG-16 convolutional neural networks has successfully combined vibration and current signal data to classify bearing faults, showcasing the growing importance of hybrid approaches [40]. However, the computational intensity and the need to convert raw signals into 2D images limit its ease of application.

Each of the above proposed methods for eccentricity detection provide their unique insights into condition monitoring. For real-time monitoring in applications like wind turbines or electric vehicles, MCSA, external magnetic sensing, or back-EMF analysis (possibly enhanced by advanced signal processing) can be a strong choice when sensor access is limited, and direct machine modifications are undesirable. If the drive system allows for offline testing or standstill conditions, incremental inductance or d-axis inductance checks offer high sensitivity, making early stages of SE or DE faults easier to spot. Meanwhile, search coil methods are particularly useful when accurate flux profiles are available or for axial flux machines, but they require custom sensor placements. Finally, AI-based methods can unify multiple sensor signals—current, voltage, vibration—into a single classification pipeline that excels at distinguishing eccentricity from demagnetization and other similar faults, provided training covers representative operating conditions.

In general, a hybrid or multi-sensor approach that combines MCSA (or voltage monitoring) with advanced time-frequency analysis and possibly data-driven classification yields the best coverage for various load speeds and fault severities. When relevant machine parameters, such as rotor geometry and magnet design, are available, finite-element-based modeling and time-varying inductances can further strengthen fault isolation. Ultimately, the optimal strategy typically depends on practical constraints like sensor availability, permissible offline testing, and the required speed of fault detection.

Table 4. Comparison of Different Eccentricity Detection Approaches.

Methods	Merits	Demerits	Comments	Applicable Range	Quantitative Analysis
4.1.1 Stator Current Analysis [103,104]	- Non-invasive, - Multiple fault detection - Online monitoring	- Limited effectiveness - Fault distinguishing	- Widely used technique for eccentricity fault diagnosis in PMSMs, identifying specific frequency components in the stator current spectrum. - Can be enhanced by extending it beyond conventional stator phase currents to include zero-sequence and q-axis currents.	- PMSMs in challenging environments	- Fault frequencies are determined by the given formula.
4.1.2 External Magnetic Sensing [105]	- Non-invasive - Fast detection speeds - Applicability on PMSGs with different slot/pole combinations	- Precise sensor placement - External Interference - Limited Effectiveness for machines with significant pre-existing asymmetries of harmonics - Recalibration requirement	- This approach analyzes the effects of SE and DE faults on external leakage flux density using a magnetic equivalent circuit. - Two indicators are used for SE and DE detection	- PMSMs	- SE indicator is calculated using measurements from three external magnetic sensors. - DE indicator is obtained from one sensor. - The method uses a magnetic equivalent circuit to quantify the relationship between eccentricity faults and external leakage flux.
4.1.3 Stator Voltage Analysis [106,107]	- Early fault detection - Non-invasive - Multiple fault detection	- Lack of experimental validation - Limited Discussion - Measurement Precision	- This approach uses an index based on the amplitude of sideband components extracted from the stator voltage spectrum. - A novel approach utilizing the neutral voltage difference signal is used for axial-flux PMSGs.	- PMSMs (specifically Axial Flux PMSMs) - In load and no-load conditions	- The neutral voltage difference is calculated using the aforementioned formula. - FFT is applied to analyze the frequency components of the V_NO signal.
4.1.4 Back EMF Analysis [50,108–111]	- Effective detection - Non-invasive - Variable Speed applicability - Load disturbance immunity - Accurate DE diagnosis - Real-time DE detection	- Sensor limitations - Design constraints	- Back EMF analysis is sensitive to changes in the air gap caused by eccentricity faults. - A new dynamic eccentricity diagnosis method for PMSGs has been proposed based on Back-EMF analysis. This method introduces a new DE index called Normalized Envelope Mean (NEM) of the Back-EMF. - Several recent methods for eccentricity fault detection in permanent magnet machines rely on different types of external sensors to capture and analyze magnetic asymmetries.	- PMSMs in constant and variable speed conditions.	- The NEM of the Back-EMF is calculated based on the aforementioned equation. - Speed normalization is done based on the rated speed.

Table 4. *Cont.*

Methods	Merits	Demerits	Comments	Applicable Range	Quantitative Analysis
4.1.5 Mechanical Signal Extraction [59,112]	- Effective SE identification - Robustness for both steady-state and transient conditions	- Costly measurement equipment - Topology limitation as the analysis has been conducted on a specific AFPM. - Complexity - Limited effectiveness for machines with pre-existing asymmetries.	- SE reforms the airgap permeance, amplifying specific vibration harmonics, particularly the component associated with the lowest magnetic force mode determined by the pole-slot combination - The harmonic's amplitude increases as the SE fault severity increases, making it a reliable fault indicator.	- AFPMs with concentrated windings - Suitable for both steady-state and transient operations.	- The amplitude of a specific harmonic component associated with the lowest magnetic force mode increases with SE fault severity.
4.1.6 D-axis inductance methods [114,115]	- No Additional Sensors - Load and Speed Independence - Fault Type Differentiation - Independence from Controller Bandwidth and high-resolution signal requirements.	- Constrained to offline monitoring - Standstill requirement - Limited Applicability - Hardware constraints	- Small AC signal injection in the d-axis direction - This method analyses the D-axis saturation current and the height of the hump in the incremental inductance curve. - The inductance-based methods trade real-time usability for increased precision and simplicity in offline eccentricity fault diagnosis.	- PMSMs	- The incremental inductance method analyzes the D-axis saturation current and the height of the hump in the incremental inductance curve.
4.1.7 Time-Frequency Analysis [116–121]	- Transient behavior detection - Multiple fault detection - Improved resolution by the Gabor Spectrogram.	- Computational intensity - Careful parameter selection - Complex Interpretation - Limited Eccentricity focus (Gabor spectrogram).	- Time-frequency analysis decomposes a signal into both time and frequency domains, allowing for the detection of harmonic components that vary over time. - Common methods include Short-Time Fourier Transform (STFT), Wigner-Ville Distribution (WVD), Gabor Spectrogram, and Wavelet Transform. - Wavelet Transform (WT) combined with FFT offers a time-varying frequency spectrum for fault detection.	- PMSMs under non-constant working conditions and variable speeds.	- The method utilizes the analysis of the stator current signals and extracting time-varying frequency spectrums, which implies quantitative analysis of frequency components and their changes over time.
4.1.8a FSBBA [122]	- Accurate fault detection - Strengthens the reliability of MCSA.	- Implementation complexity - Sensitivity to inverter harmonics.	- Novel algorithm that works for any slot-pole combination.	- PMSMs	- Predicts harmonic fault signatures caused by DE.
4.1.8b Machine Learning (CAE) [101,123]	- High accuracy in fault classification.	- Complexity - Extensive parameterization	- Employs the Mahalanobis distance metrics.	- PMSGs for offshore wind generators.	- Uses Principal Component Analysis (PCA) to extract spectral features.
4.1.8c Hybrid or Multisensor Approach [40]	- Covers various loads and fault severities.	- Complexity	- Combines MCSA (or voltage monitoring) with advanced time-frequency analysis and potentially data-driven classification. Finite-element-based modeling and time-varying inductances can further strengthen fault isolation.	- PMSMs	- Relies on relevant machine parameters like rotor geometry, magnet design, and time-varying inductances.

4.1.9. Future Directions in Eccentricity Fault Detection

Recent advancements in eccentricity fault detection for PMSMs show significant progress in condition monitoring but challenges in reliability, adaptability, and practical implementation are always present. This should drive future research efforts not only to refine the existing methods but also integrate novel diagnostic techniques that holistically target the root causes of eccentricity. For instance, hybrid approaches combining physics-based models with data-driven algorithms could enhance detection sensitivity under different operating conditions.

Eccentricity faults arise from diverse mechanical, electromagnetic, or manufacturing origins, such as bearing degradation, rotor misalignment, unbalanced magnetic pull and improper assembly. Physics-based models that simulate these structural degradation mechanisms are critical for mapping the progression of airgap asymmetry. For dynamic eccentricity, which fluctuates with speed and load, integrating vibration or acoustic sensors with motor current signature analysis (MCSA) could correlate mechanical degradation (such as ball-pass frequencies) with current harmonics, offering earlier fault warnings. Similarly, static eccentricity could benefit from digital twin frameworks that compare real-time performance with idealized models to identify deviations. Closed-loop systems using predictive control strategies, such as injecting compensation currents, might further mitigate electromagnetic imbalances induced by static faults.

Advancements in signal processing are equally vital. Existing stator current and voltage analysis methods rely on spectral resolution, which deteriorates under transient conditions. The enhancement of time-frequency techniques such as wavelet transforms, empirical mode decomposition (EMD), and variational mode decomposition (VMD) could improve fault signature resolution in non-stationary operation. Real-time adaptive filtering algorithms may reduce computational complexity, while advanced harmonic decomposition methods could isolate eccentricity-related frequencies from overlapping noise caused by unrelated faults or load variations. For dynamic eccentricity, self-tuning algorithms that normalize fault indices against operational parameters, such as speed-adaptive envelope analysis of back-EMF or d-axis inductance, could suppress false alarms from load-induced harmonics. Extending methods like the Normalized Envelope Mean (NEM) to mixed eccentricity scenarios, with adaptive threshold recalibration, would further enhance robustness.

Despite these innovations, hardware-dependent approaches (such as search coils and Hall sensors) remain limited by ways of intrusiveness and scalability. Virtual sensing techniques that use inverter data or observer-based models to estimate airgap flux could reduce the need for physical sensors, while incremental inductance methods optimized for online monitoring might minimize offline testing. However, generalizing diagnostic criteria across PMSM designs remains challenging due to the machine variations in slot-pole combinations, winding types, and magnet configurations. To overcome these challenges, parametric studies and open-access benchmarking platforms are needed in order to establish universal standards.

Finally, implementing real-time smart algorithms demands minimizing latency and power consumption without sacrificing accuracy. This is a critical requirement for remote applications like offshore wind turbines. Integrating edge computing with adaptive signal processing and predictive control could enable autonomous diagnostics in resource-constrained environments. By unifying advanced analytics, adaptive control, and distributed sensor networks, future systems could extend the operational lifespan of PMSMs in increasingly demanding industrial settings.

5. Conclusions and Future Work

This review shows the challenges and advancements in diagnosing faults in PMSMs, particularly focusing on demagnetization, inter-turn short circuits (ITSCs) and eccentricity faults. These faults will impact the performance and reliability of PMSMs.

Demagnetization often results from high temperatures, electrical faults and mechanical faults, which will reduce the magnetic properties of magnets. ITSC faults, caused by degradation of the turn insulation, worsen these problems by increasing the temperature in the area and by generating a magnetic field opposing the magnets. On the other hand, eccentricity faults arise from misalignment between the rotor and stator, disturbing the airgap flux and creating additional stress on the system. These faults often interact with one another, and thus it is of great interest that diagnostic methods can detect and differentiate each one of them.

Techniques that are presented in Table 5. like time-frequency analysis, observer-based methods and finite element analysis have shown promise in detecting these faults by identifying unique patterns such as harmonic distortions or torque irregularities. However, in real applications, there are some factors to be considered. These include the need for low computational costs, low sensitivity to noise, and finally, the fact that these methods need to be scaled for different machines.

Looking ahead, the use of machine learning with traditional physics-based approaches offers a way to improve fault detection accuracy while overcoming data limitations. Hybrid diagnostic systems use the advantages of both methods to adapt to dynamic operating conditions. Real-time adaptive algorithms will also play an important role in managing complex faults across various applications.

From a design perspective, innovations like hybrid magnet configurations and advanced winding techniques can help reduce fault vulnerability. Improved cooling systems, especially for applications that suffer from high temperatures or transient stresses, are equally important in mitigating cascading failures.

Finally, adopting predictive maintenance frameworks that combine sensor data with simulation models can transform how PMSMs are monitored and maintained. These systems can identify emerging faults early, reducing downtime and extending machine lifespans. By integrating advanced diagnostics, robust designs and proactive maintenance strategies, the performance and reliability of PMSMs can be significantly enhanced to meet the demands of modern energy and industrial applications.

Table 5. Comparison of Different Fault Detection Approaches.

Fault Signature/ Approaches	Non-Intrusive	Computational Capability/Memory	Real-Time Diagnostics	Type of Fault
Time-Frequency Methods	Yes	High	Conditional	Demagnetization, ITSC, Rotor Eccentricity
Observer-Based Methods	Yes	Moderate	Yes	Demagnetization, ITSC
Machine Learning (ML) Methods	Yes	High	Conditional	Demagnetization, Rotor Eccentricity
Sensor-Based Methods	No	High	Yes	Demagnetization, ITSC, Rotor Eccentricity
Other Methods	Conditional	Moderate	Conditional	Demagnetization, Rotor

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