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REVIEW

Condition monitoring of permanent magnet AC machines for all-electric transportation systems: State of the art

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Abstract

The current state of the art on emerging and efficient techniques for condition monitoring of permanent magnet (PM) alternating-current (AC) machines deployed in electric vehicle (EV) applications is presented. The discussion includes the most common and specific types of faults in PM motors, such as rotor demagnetisation and stator inter-turn faults, respectively. Fault indicators, such as voltage (v_s) and current (i_s) signals and machine signatures based on motor back electromotive force (EMF) (E_B) and magnetic flux (ϕ), are taken into account as a measuring quantity in diagnosing motor faults. Other signatures, including thermal analysis, acoustic noise, and vibrations, are also illustrated as some of the emerging techniques in estimating the performance of EV motors while under operations. In addition, various fault modelling methods, condition monitoring techniques, and comprehensive approaches applied in diagnosing the effect of machine faults during its incipient stages are illustrated. Since most of the fault diagnostic techniques discussed here include only machine-based quantities as fault indices/indicators, the provided solutions are therefore found to be more reliable and accurate for diagnosing the motor faults. This comprehensive review study is inclusive of the existing fault diagnostic techniques, which are currently employed in industrial and commercial practices, in addition to the new methodologies proposed by the authors. All the given condition monitoring schemes therefore seem significantly vital in estimating the state of health of PM AC machines while under operation in all-electric transportation systems.

KEYWORDS

electric vehicles, fault diagnosis, permanent magnet motors

1 | INTRODUCTION

Permanent magnet (PM)-based electric machines are widely adopted in high-reliability industrial and commercial applications like electric vehicles (EVs). Because these motors have significant characteristics like high torque density, maximum power-to-weight ratio, high dynamic performance, and better efficiency, they are therefore also finding wide employment in marine and all-electric aircraft applications [1–3]. However, during practical operations of these motors under unfavourable conditions, they are subjected to environmental, physical, and thermal stresses that trigger *faults* [2, 3]. Faults can manifest into electrical quantities like voltage (v_s) and current (i_s); magnetic quantities like flux (ϕ) and magnetomotive force; mechanical quantities like acoustic noise and vibrations; and thermal characteristics like change in surface temperatures (Δt) of the machine [1, 2, 4–6]. Faults in PM machines employed in EV applications can therefore result in serious fatigues and failures, risking both passenger life and property. However, if the state of health (SOH) for a motor drive system is continuously monitored, it can alert for any unusual condition in advance and subsequently prevent system failure, adding safety to life [2, 4–6]. For safe and reliable operation of an electric traction drive system, condition monitoring of electrical machines—including fault detection and diagnosis—is vital for healthy motor operations. Fault tolerance mechanisms are an indispensable solution not only for the reliability of the electric-drive system, but also for the proper operation of the vehicle following fault conditions [2, 6–8]. A typical PM motor-based electric drive system is illustrated in Figure 1, while the closed-loop operational drive with a control block diagram is shown in Figure 2 [9].

There are numerous studies [1–4, 6] on fault diagnosis in EV components, among which the *electric powertrain* is a vital and significant part of the integrated EV drive system. Electric vehicle powertrains comprise power operating units like battery packs [7, 8], power semiconductor devices/switches [7–9], power electronic converters/inverters, and the mechanical unit, which includes the electric motor and drive systems [3, 4, 6–9], as shown in Figure 3.

Most of the literature incline toward the diagnosis of induction motor drives employed in EVs, which mostly focus on the faults in lithium-ion battery units [7, 8] and three-phase inverters [1, 3, 10]. On the motor side, faults related to stator windings, broken rotor bars, and mechanical bearing faults are more commonly investigated [1, 3, 9–11]. However, with the emergence of PM AC machines, the research focus has widened on the diagnosis of rotor PM demagnetisation, physical defects of rotor magnets, and rotor eccentricities, apart from the conventional stator winding-related faults [9, 12]. Thus, with the rapid expansion of PM AC machines in EV applications, there are vigorous and productive efforts formulated in condition monitoring and fault diagnosis of PM motor-based electric drive systems [1, 2, 4, 9, 12, 13].

This paper presents the comprehensive state of the art on fault diagnosis and condition monitoring techniques of PM AC machines employed in EVs and all-electric transportation systems. It takes into account past research relevant to these subjects and brings out significant inferences out of those studies. In addition, this paper illustrates various fault modelling techniques, fault detection tools, and comprehensive approaches applied in diagnosing the effect of faults in these machines during their incipient stages. Fault indicators, such as v_s and i_s signals [4, 6, 8–10] and signatures based on motor back electromotive force (EMF) (E_B) and magnetic flux (ϕ) [9, 12, 13], are considered as a measuring quantity in diagnosing motor faults. Other signatures, including thermal analysis [14], acoustic noise, and vibrations [15], are also illustrated as some of the emerging techniques in estimating the performance of the EV motor.

The 1D analytical simulations are done using MATLAB®/SIMULINK® tools, while the numerical solutions are obtained using the 2D Finite Element Method Magnetics (FEMM) solver. Both the simulations are carried out on a 64-bit operating system x64-based processor; Intel® Core ™ i7-4970 CPU at 3.60 Hz. Number of cores = 4, while core speed was 798.10 MHz.

2 | SOURCES AND TYPES OF FAULTS IN PM AC MOTORS

Under abnormalities and adverse conditions, electric motors can suffer several types of faults depending upon the source and anomalous operating conditions [1, 2, 9, 13]. However, depending on the fault location in the machine [1–3], they can be classified as stator-related or rotor-related faults. Focusing the discussion on PM AC machines as shown in Figure 4, they comprise a stator with three-phase electrical windings, a rotor with permanent magnets, and a shaft to carry mechanical load. Depending upon the physical geometry of the PM AC machines, faults in these motors can therefore be classified into (1) *electrical*, (2) *magnetic*, or (3) *mechanical* faults. Classification of faults is given in Figure 5.

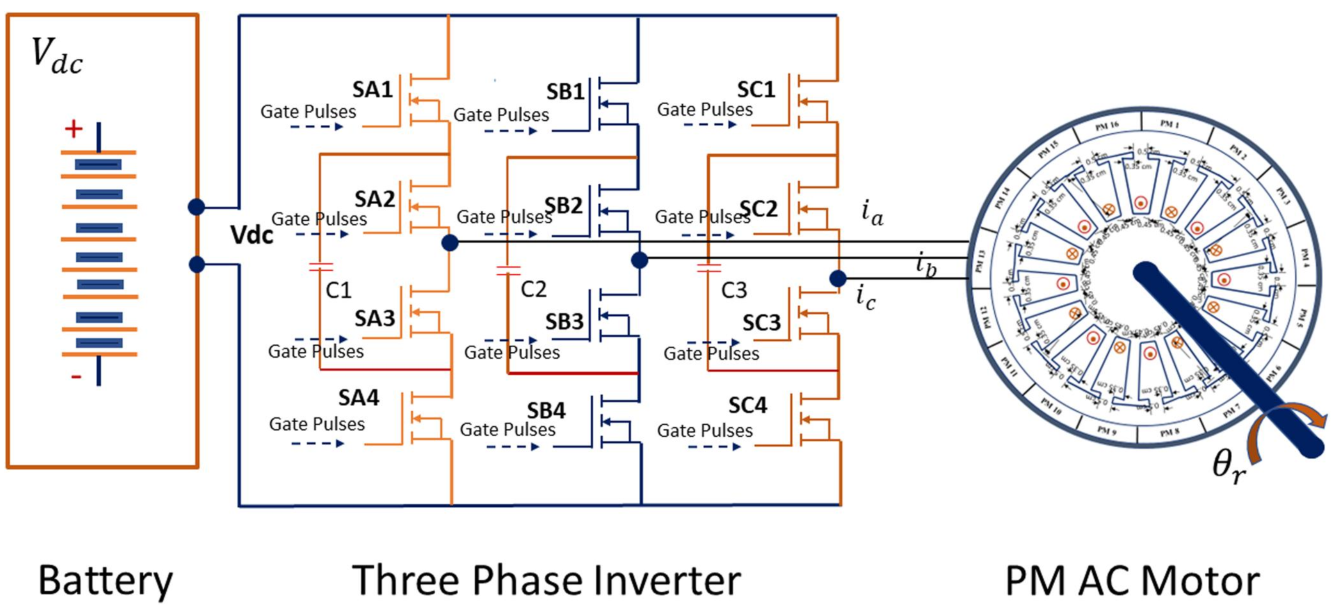

FIGURE 1 Permanent magnet alternating-current motor-based electric drive system.

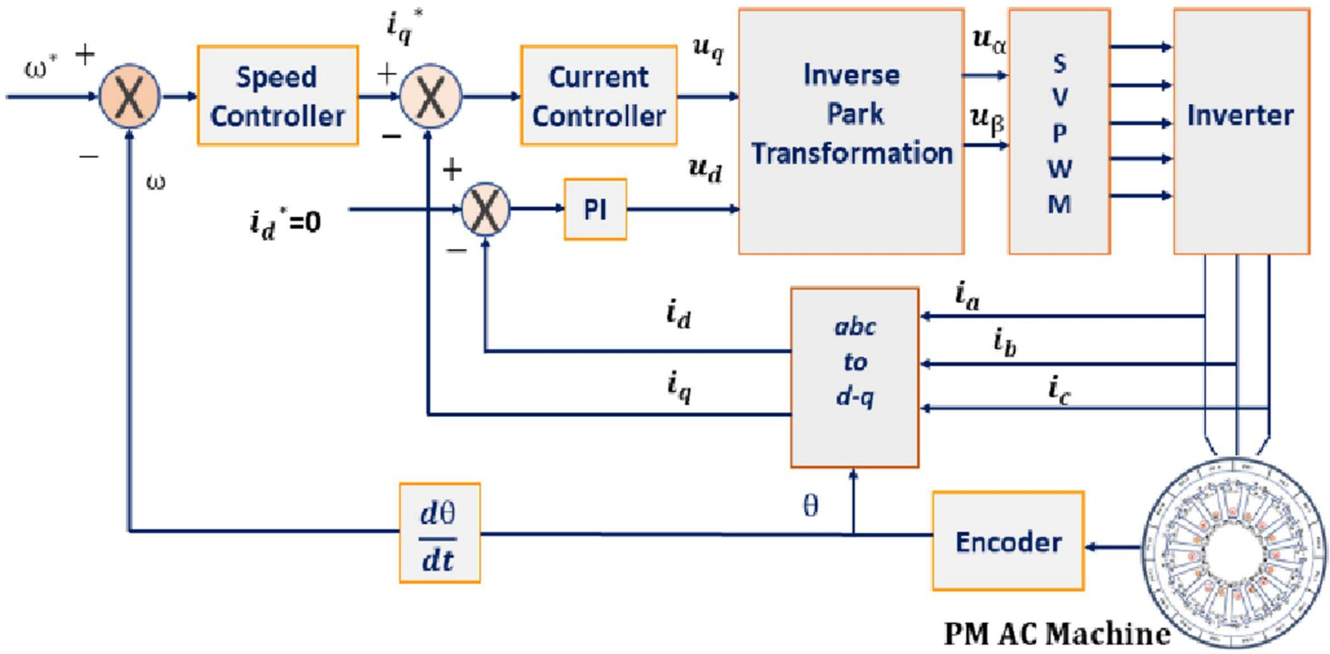

FIGURE 2 Closed-loop control block diagram of a permanent magnet AC motor drive system [6].

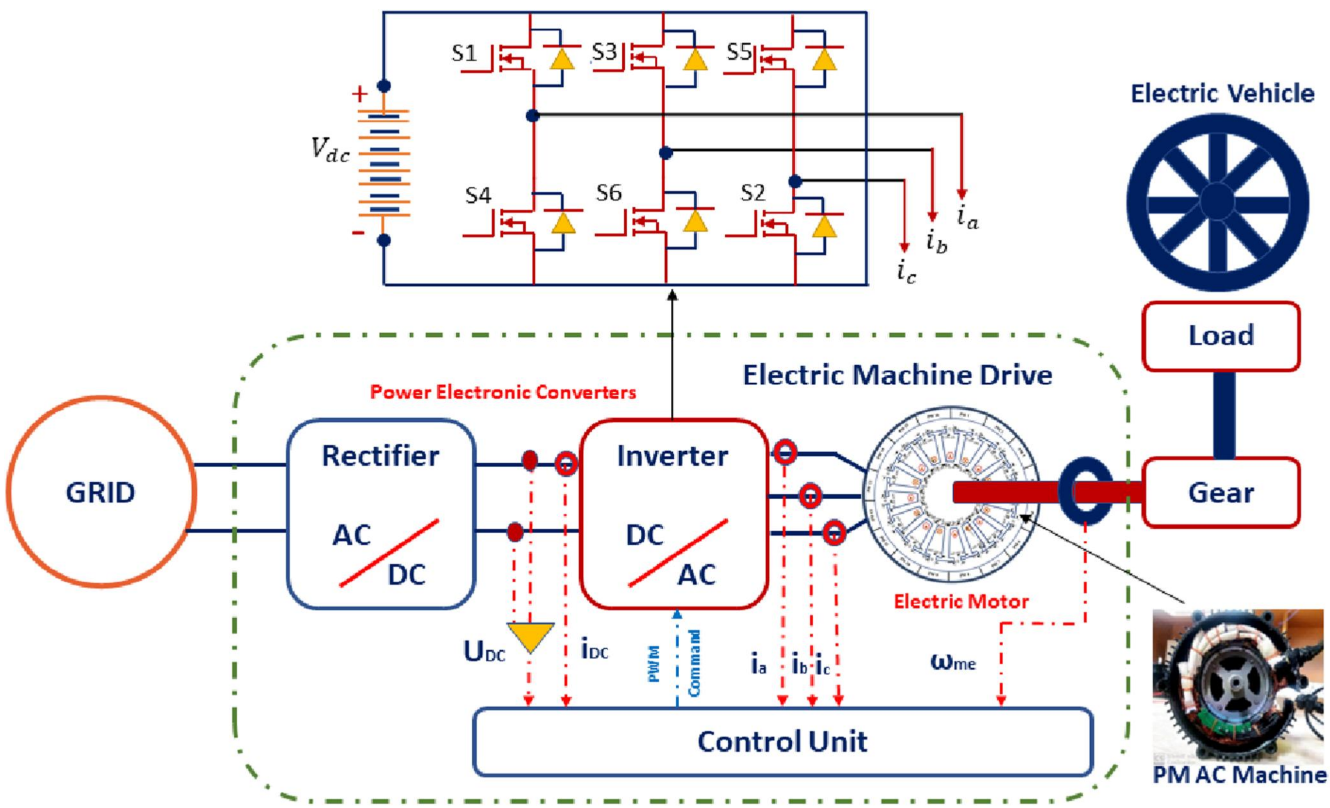

FIGURE 3 Integrated structure of a permanent magnet AC motor-based electric-drive system employed in electric transportation systems [1, 3, 4].

2.1 | Electrical faults

Most of the electrical faults in PM AC machines are associated with three-phase windings of the stator. Stator winding faults are caused by the breakdown of winding insulation, which leads to the heavy flow of inrush currents, thereby damaging the stator windings. The adverse effects of stator winding faults are cumulative and consecutive in terms of high current spreading in adjacent windings, burning them, and eventually causing the system to completely shut down. The factors

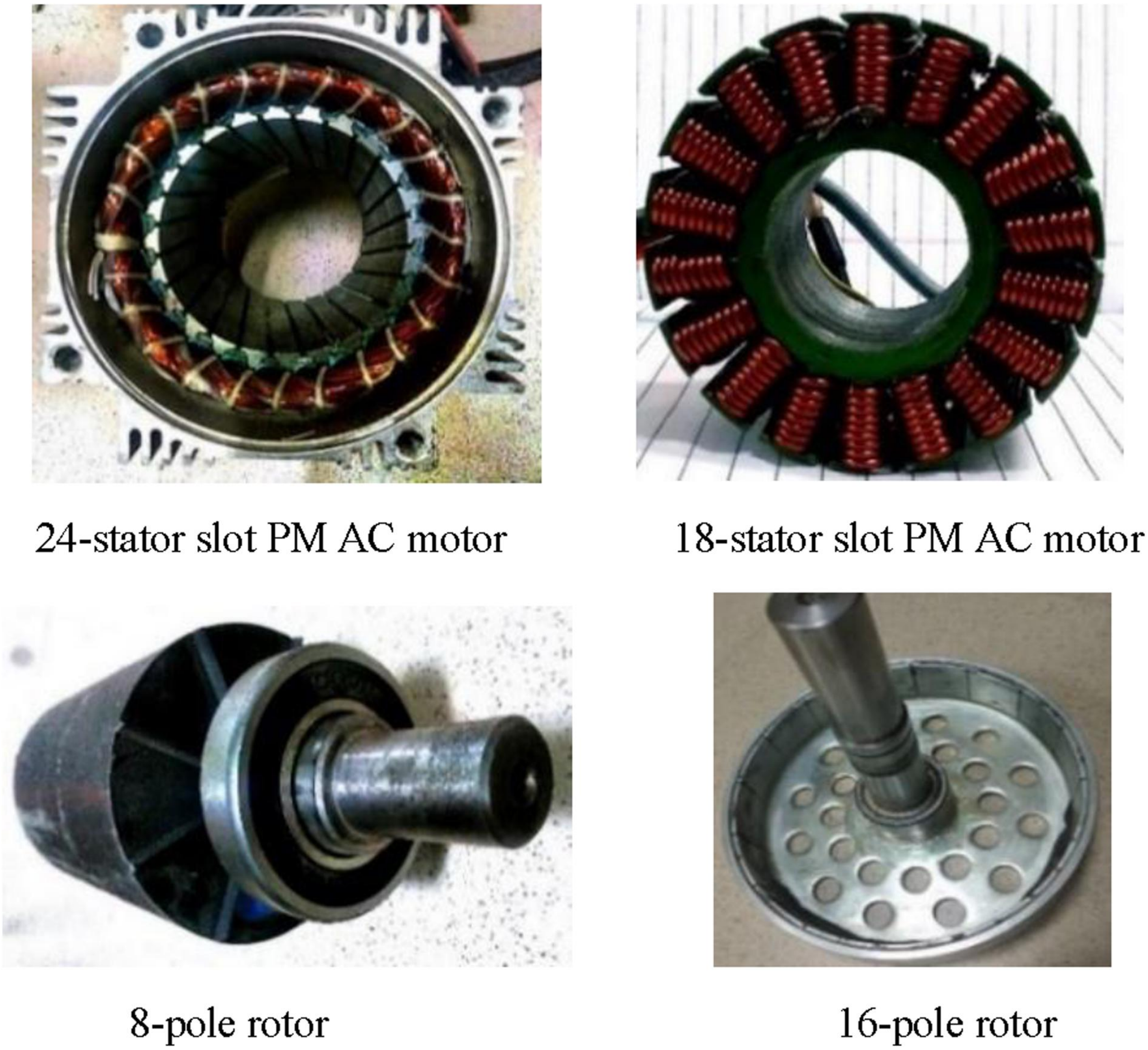

FIGURE 4 Permanent magnet AC motor illustrating stator with windings and rotor with permanent magnets (motor pictures are taken at the Special Electrical Machine Laboratory, Indian Institute of Technology Mandi, India).

leading to insulation breakdown are reported as mechanical stress, humidity, and inverse currents [14–17]. Among many other motor faults and failures, stator inter-turn short-circuit faults are reported to account for the highest percentage ranging from about 25% to 40% [16–20]. Consequently, a tremendous amount of research has been done to diagnose stator winding faults in PM AC machines at its incipient stage to avoid hazardous conditions and maintain transportation safety [16–24].

A stator winding of a PM AC machine comprises a *coil*, and the coil is made of a significant number of *turns*. Thus, depending upon the fault location within the winding, stator winding faults are further classified into four types: (1) *stator inter-turn fault* (SITF), (2) *coil-to-coil fault*, (3) *phase-to-phase fault*, and (4) *open-circuit winding fault*.

1. *SITF*: The fault that occurs when there is a short circuit between two or more stator winding turns of the same coil within the same winding phase. Such faults are caused in the machine due to insulation failure between windings [16–19, 24–26].
2. *Coil-to-coil fault*: The short circuit between two coils of the same winding phase [17–19, 24–26].
3. *Phase-to-phase fault*: Occurs between any two phases of a winding. Two inter-phase coils or turns are shorted under such types of faults [16–19].
4. *Open-circuit winding fault*: Occurs when any of the winding phases is open circuited [19, 20]. Contrary to the other three types of stator winding faults, which occur due to insulation failure, open-circuit winding faults happen due to mechanical vibrations and sometimes due to material breakdown of the winding [19, 20, 27, 28], [23–26, 29].

Since all these faults occur in the windings of the stator, they directly impact the winding phase currents (i_s) of the machine and hence are classified as *electrical faults*. The

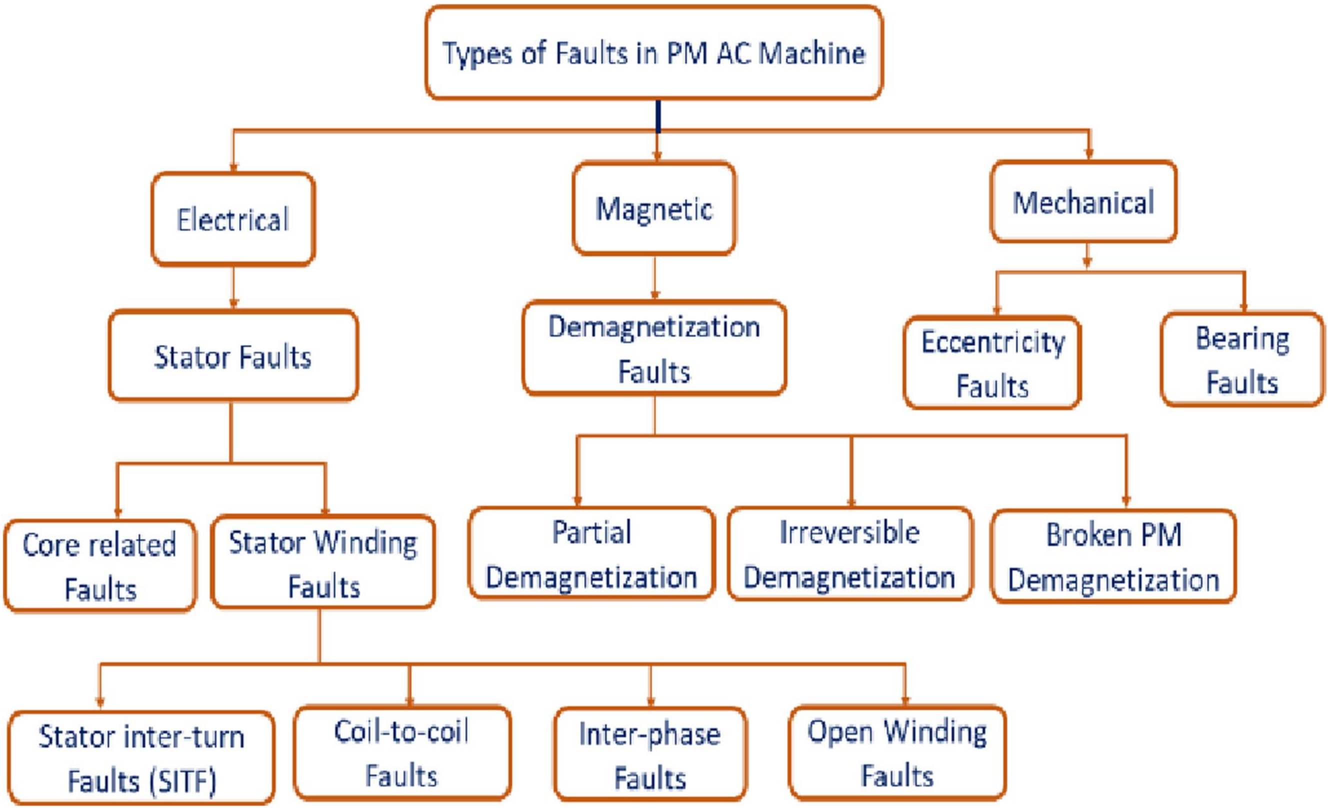

FIGURE 5 Classification of faults in permanent magnet AC machines.

general equivalent SITF model of a winding, along with different types of stator winding faults, is illustrated in Figure 6, [16, 19]. Here, i_f signifies the *fault current* flowing across the windings during insulation breakdown.

Since stator inter-turn-induced voltages persist considerably longer in PM AC machines, SITFs require early or incipient stage detection and diagnosis [15–19, 21–24, 29–33]. This requires effective fault signatures or indicators and sophisticated fault diagnostic techniques, which are discussed in Section III.

2.2 | Magnetic faults

As illustrated earlier (Figure 4), PM AC machines contain permanent magnets made of rare-earth materials like neodymium-iron-boron *(NdFeB)* mounted on the rotor of the machine [33, 34]. Depending upon the placement of PMs on the rotor, PM AC machines can be classified as (1) *surface-mounted PM-type* or (2) *interior PM-type* AC motors [33–35]. However, PMs are among the most critical components in the electric machines, which get damaged due to various adverse conditions. Primarily, machine rotors are directly exposed to the motor airgap and stator teeth, which make the PMs more susceptible to physical and thermal variations of the machine during operating conditions [33–36]. Second, inverse magnetic fields, machine operating temperature increases, operating stress, motor armature reactions, electrical faults (stator short-circuit faults), unbalanced loads, rotor mechanical eccentricity, and increased vibrations further lead to defects in magnets, causing *irreversible demagnetisation* in the machine [33–35, 37–39]. In addition, magnet ageing is another significant factor causing *rotor demagnetisation* in PM AC machines [33, 34, 38]. The consequent effects of rotor PM demagnetisation are that it alters and leads to reduction in motor E_B [33, 36–39] and ϕ quantities of the machine [33–39], thereby adversely affecting the efficiency and reliability of a machine drive system, which ultimately affects the performance of an EV drivetrain. Magnetic faults in PM AC machines are eventually manifested through thermal and magnetic phenomena [12, 14, 33, 34, 36–39]. A typical demagnetisation characteristic of an NdFeB magnet material at various temperatures is given in Figure 7 (i) [12, 13, 33–35, 37].

A residual flux density (*Br*) and linear variation with a relative permeability over the second quadrant are illustrated through the given *BH characteristics* curves. As long as the operating points are within the limits of the recoil line, the demagnetisation is temporary, which does not reach the saturation point (*Neumann boundary conditions*) [12, 39]. Such types of demagnetisation faults are referred to as *partial demagnetisation faults* [33, 34, 39]. However, in the linear region, it is seen that the recoil line coincides very closely with the demagnetisation line, and therefore, the operation of the magnet tending towards the third quadrant into the curved portion produces a permanent demagnetisation effect also known as an *irreversible demagnetisation fault* [12, 33, 36, 38,

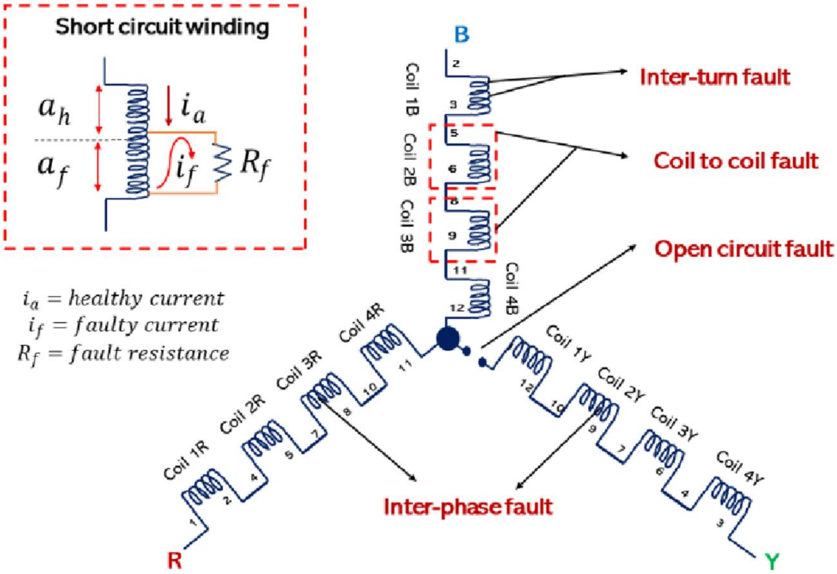

FIGURE 6 Three-phase stator windings of a permanent magnet AC motor illustrating all types of electrical faults, viz [16, 17, 27].

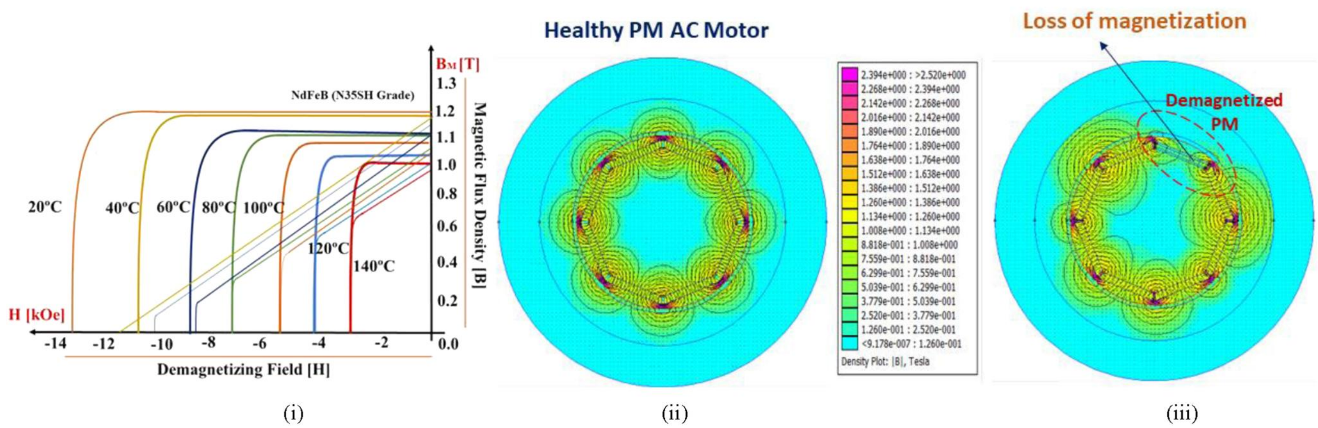

FIGURE 7 (i) BH characteristic curves of an *NdFeB* magnet (grade N35SH) [12, 13, 33–38]. 2D FE analysis of a permanent magnet (PM) AC motor under (ii) healthy and (iii) demagnetisation fault operating conditions. The demagnetised motor illustrates the loss of magnetization for the corresponding demagnetised PM.

39]. Thus, during the motor system design, PM operation requiring high-temperature operation should not be allowed under the given conditions [13, 14, 34, 36, 38]. Irreversible demagnetisation leads to physical cracks and mechanical, thermal, and electrical stresses, including corrosion [12–14], which further lead to another demagnetisation effect known as *broken PM faults* [33, 34, 38, 39]. It can thus be concluded from the literature that demagnetisation faults can be classified as (1) *partial demagnetisation*, (2) *irreversible demagnetisation*, and (3) *broken PM* faults. It is observed that for all the types of demagnetisation fault, there is a significant change in magnetic flux (ϕ) quantities.

Therefore, studying the flux characteristic of electric motor individually for each type of demagnetisation condition can give appropriate classification to the faults as reported in [12, 13, 33–38]. The detrimental effects in terms of loss of magnetization/magnetic flux (ϕ) quantities during demagnetisation fault are illustrated through the motor flux model carried out using the 2D *Finite Element Method Magnetics (FEMM)* tool as shown in Figure 7 (ii)-(iii). Here, the magnetic coercivity value, H_c, for all healthy PMs is 890,000 A/m, while for the corresponding demagnetised PM, the H_c value is reduced at the edges. It is observed that for a healthy motor, the magnetic flux/field lines are found to be uniform (Figure 7 ii); while for a motor under demagnetised condition, there is a loss of magnetic flux/field lines for the corresponding PM as shown in (Figure 7 ii). The loss of magnetization is not uniform across the corresponding demagnetised PM as can be observed in Figure 7 ii, and thus, it can be concluded from the 2D flux analysis that it is a case of *partial demagnetisation fault*, which eventually could lead to *irreversible demagnetisation* depending upon the severity of the adverse conditions.

2.3 | Mechanical faults

Like any other electric motor, PM AC machines also have an airgap between the stator and rotor. In a healthy machine, it is expected that the rotor centre is centrally aligned with the stator core and the rotor's centre of rotation is the same as the centre of the stator core [13]. However, when the centre of the rotor does not coincide with the centre of the stator core, it leads to an unequal or non-uniform airgap, causing mechanical misalignment or *eccentricity* [40–44]. With the wide employment of PM AC machines in electric transportation systems, such as electric trains, hybrid vehicles, and aircraft, eccentricity and its intrinsic acoustic noise and vibrations during operating conditions [45, 46] have become a critical challenge for all-electric transportation systems. These adverse effects continuously degrade the performance of the complete integrated drive system.

Eccentricity faults can be classified as (1) *static*, (2) *dynamic*, or (3) *mixed* as illustrated through a spatial geometry of a rotor and stator assembly shown in Figure 8 [43]. When the axis (centre) of rotation of the rotor and stator does not coincide, while the rotor rotates around its own centre, it is called *static eccentricity*. When the centres of the stator and rotor are aligned but the rotor does not rotate around its own axis, it is referred to as a *dynamic eccentricity*. This means that minimum airgap revolves with the rotor. Lastly, mixed eccentricity occurs in the presence of both static and dynamic eccentricities simultaneously [13, 41–43]. When the eccentricity becomes significant, the resulting unbalanced radial forces result in *unbalanced magnetic pull*, which is another type of consequent fault caused due to rotor eccentricities. This type of fault can cause a stator-to-rotor rub causing vibrations and noise [42–44], which subsequently results in damage to the stator and the rotor assemblies [43–46].

Considering all the past comprehensive literature, the above discussion covered all the major types of faults in PM AC machines. Among all the various faults, the two types widely reported in literature [1–3, 13, 27, 28, 31] are SITFs and rotor demagnetisation faults existing on the stator and rotor side of the PM AC machine, respectively. Section 3 discusses the modelling methods for these types of faults.

3 | FAULT MODELLING METHODS AND DETECTION TECHNIQUES IN PM AC MACHINES

Condition monitoring is a process of diagnosing faults by discerning, identifying, and ultimately distinguishing the type and extent of fault to estimate the SOH of the system [1–3, 13, 27, 28, 31]. Fault diagnosis typically involves continuous and comprehensive monitoring and investigation of machine data and quantities to alert for abnormalities (if any) causing mismatch of reference/or expected quantities, tending towards the conditions of *faults*. Fault modelling is one of the most significant and vital steps for the fault diagnosis in machines [1, 2]. This section is therefore concerned with an elaborate study on different *fault modelling methods* employed for PM AC machines. Based on the comprehensive literature study in preceding sections, fault modelling methods can be mainly classified [2, 19, 33, 37, 39] as (1) *electrical equivalent circuit (EEC)*-based methods, (2) *magnetic equivalent circuit (MEC)*-based methods, and (3) *numerical method (NM) (NM)*-based approaches. These three approaches cover all the broad areas of modelling PM AC machine faults as discussed in the following subsections.

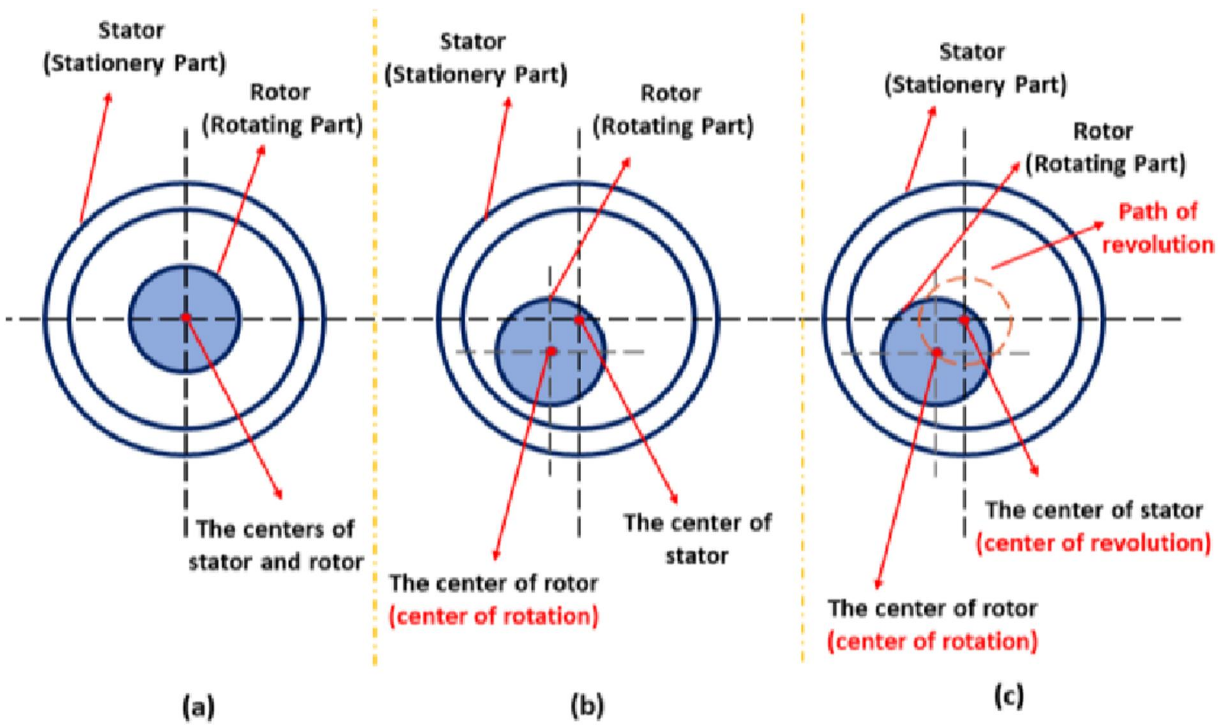

FIGURE 8 A PMSM motor (a) without eccentricity, (b) with static eccentricity, and (c) with dynamic eccentricity faults [43].

3.1 | EEC-based approach

EEC-based fault modelling methods are mostly used for modelling *electrical faults*, which involve stator short-circuit or inter-turn faults. During short-circuit faults, the *inductance* (L_s) of the winding changes, leading and accelerating the faults through high inrush of stator phase currents. EEC-based approaches are therefore found to be most suitable in determining the inductance of the windings to model the faults. EEC-based approaches include all the winding-related theories, such as winding function theory (WFT), modified winding function theory (MWFT) [47, 48], and multiple coupled circuit modelling [49] approaches. All these subclassification methods involve physical geometry of the PM AC machine – which includes motor architecture and dimensions comprising stator phase winding arrangements, slot dimensions, and airgap length – to establish mathematical expression in terms of winding currents (i_s), voltages (v_s), resistance (r_s), and magnetomotive force to determine the fault inductances ($L_{s\text{-}f}$). Several reports [2, 16–19, 47–49] have been presented advocating for the advantages and merits of these methods for the effective diagnosis of stator winding faults. Figure 9 [47] shows the equivalent winding arrangement of a stator phase windings under healthy and short circuit fault conditions. Winding function theory and MWFT are used to derive *turns function* $n_C(\phi)$ and *winding functions* $N(\phi)$ to calculate inductances of the winding under fault conditions.

The WFT is mathematically implemented in Equations (1)–(3) [37], [47–49] to arrive at the calculation of the *winding inductances* using turn function $n_C(\phi)$ and winding function, $N(\phi)$, to model the fault.

Turn function, $n_C(\phi)$, for stator winding [37]:

$$n_C(\phi) = \frac{\text{Total number of turns in the winding}}{\text{Number of Slots per Phase}} = \frac{N}{6} \quad (1)$$

Winding function, $N(\phi)$, for a stator winding:

$$N(\phi) = \frac{n_C(\phi)}{2} = \frac{N}{12} \quad (2)$$

The mutual inductance, $L_{AB}(\theta_m)$, between winding A and B is given as follows:

$$L_{AB}(\theta_m) = \frac{\mu_0 . r . l}{g_a} \int_0^{2\pi} N_A(\phi) \, . \, N_B(\phi) d\phi \quad (3)$$

where μ_0 is permeability of free space, r is the radius of the rotor, l is the rotor length and the air gap length is given by g_a. $N_A(\phi)$ and $N_B(\phi)$ are the winding functions of phases A and B, respectively. The winding inductance changes under fault conditions, thereby diagnosing the electrical faults in PM AC machines.

Along with several advantages, the EEC-based method also has some disadvantages [2, 16–19, 47–49], accuracy being one of the major aspects of demerit, as EEC techniques incorporate many assumptions. However, such demerits are overcome by the time-stepping finite element-based approaches, which can also be referred to as NMs [2, 13, 16–19, 22–26]. NM-based techniques have shown the ability to address the spatial harmonics, tooth slot pattern, tooth tip saturation, and non-linearities in PM AC machines [50]. Electrical or SITFs are usually diagnosed through physics-based back-EMF estimation techniques, motor current signature analysis (MCSA), and Kalman filtering as reported in the literature [2, 16, 19, 33, 37, 39, 51].

3.2 | MEC-based approach

MEC-based fault modelling methods are mostly used for modelling *magnetic faults*, which involve rotor PM demagnetisation in PM AC machines. Any fault related to the rotor

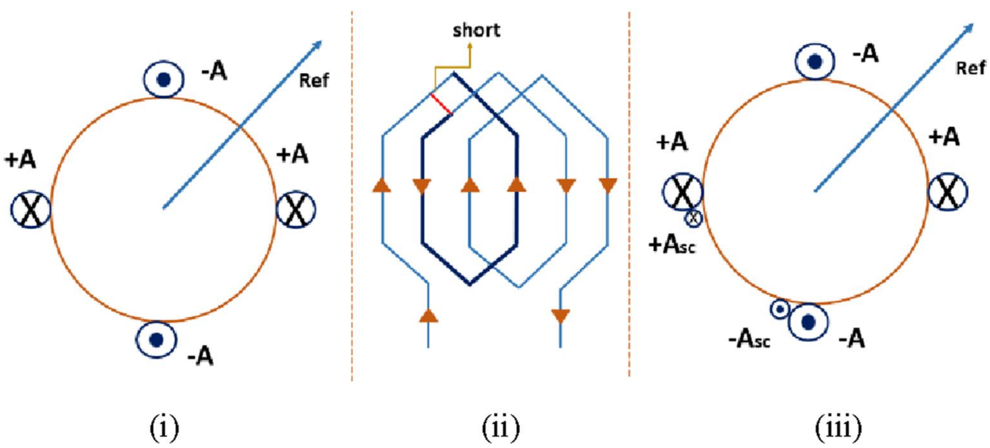

FIGURE 9 (i) Equivalent winding arrangement for Phase A, (ii) winding configuration of turn-to-turn fault and (iii) winding placement of Phase A and short circuit [47].

of a PM machine will primarily alter the *magnetic flux density* (B_M) of the motor. Consequently, other machine quantities will be adversely affected, thereby degrading the performance of the machine. MEC-based approaches use an equivalent magnetic circuit model in terms of lumped model [52], permeance network (PN) [53], and field reconstruction method [54] to eventually model the machine [2, 33, 37, 39, 52–54]. Flux density distribution is directly modelled using these methods, and therefore, magnetic faults are easily diagnosed using such approaches. Figure 10 [53] shows the MEC of a PM AC machine along with its PN model to model the faults.

The mathematical expressions for the estimation of airgap magnetic fields and flux linkages are given through Equations (4)–(6) [33], [37], [52–54]. These are used for estimating and diagnosing demagnetisation faults in PM machines.

3.2.1 | Calculation of airgap magnetic fields (B_g)

The radial component of the magnetic flux density can be derived from [1, 3, 12, 33, 37] and given as Equation (4):

$$B_g = \frac{B_r}{1 + \frac{g}{h_m}} \tag{4}$$

where B_g is an airgap flux density, B_r is residual flux density of PMs, g is an airgap length, and h_m is the magnet thickness.

3.2.2 | Calculation of flux linkages λ_S by PM

When the stator windings are opened, the stator currents are zero ($i_s = 0$), and the flux linkage (λ_S) due to PM under healthy and fault conditions can be derived from [1, 3, 33, 37] and given through Equations (5) and (6):

$$\lambda_{PM,s} = \int v_s dt \tag{5}$$

$$\mathrm{e_a} = \frac{\mathrm{d}\lambda_{PM,s}}{\mathrm{d_t}} = \frac{\mathrm{d}\theta_\mathrm{r}}{\mathrm{d_t}}\frac{\mathrm{d}\lambda_{PM,s}}{\mathrm{d}\theta_\mathrm{r}} = \omega_\mathrm{m}\frac{\mathrm{d}\lambda_{PM,s}}{\mathrm{d}\theta_\mathrm{r}} \tag{6}$$

where v_s is the motor supply phase voltage, e_a is the motor back EMF, θ_r is the angular displacement or rotor position, and ω_m is the mechanical speed.

In addition, several advanced techniques for demagnetisation fault diagnosis are listed in the literature. The use of B_M as the fault indicator to detect and diagnose rotor demagnetisation fault is presented in [12, 33, 38, 39], while the motor E_B estimation techniques are used in [33–36] for rotor fault diagnosis. The demagnetisation characteristic curve (Figure 7 i) is used for estimating the health of a magnet with thermal variations, thereby evaluating the performance of the machine with respect to the flux profile shown in Figure 7 (ii)-(iii).

3.2.3 | Eccentricity faults

As discussed in Section II, regarding the effect of rotor *eccentricity* under the classification of mechanical faults, eccentricity results in an uneven *airgap permeance* and further induce certain frequency components in the *stator current spectrum* [40–44]. Since the airgap permeance is affected under this type of fault, eccentricity faults can thus be modelled using *MEC*- or *PN* method-based fault modelling approaches [52–54]. In [55], static and dynamic eccentricity has been calculated with the help of a magnetic lumped parameters [52] model that considers the permeance function [53] in the airgap and non-linear properties of motor material, thereby diagnosing the faults more effectively.

In addition, the existence of frequency components in the motor current spectrum enables the detection of eccentricity

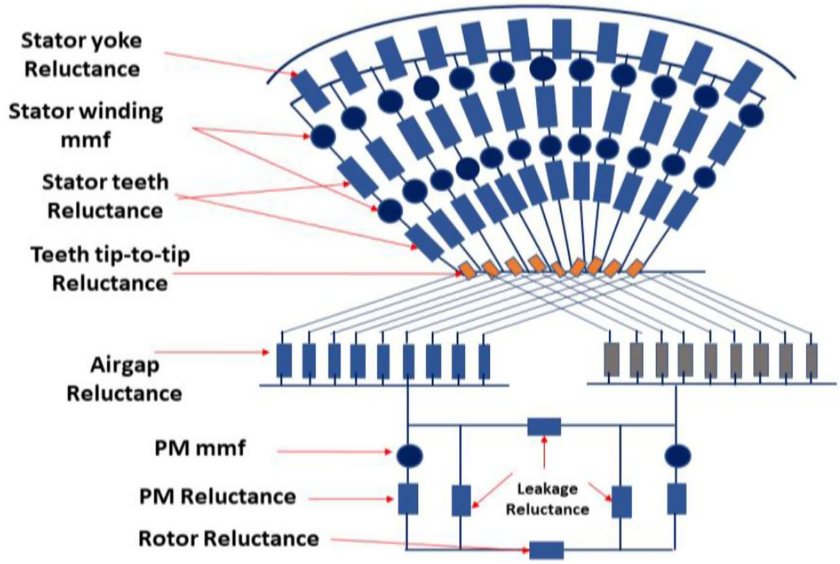

FIGURE 10 Magnetic equivalent circuit model of a permanent magnet AC machine using permeance network equivalence [53].

faults more conveniently using MCSA-based techniques discussed under EEC-based fault modelling methods. Other methods involved in modelling and diagnosing eccentricity faults can be found in [13, 40–44, 55].

3.3 | NM-Based Approach

In the NM-based fault modelling approach, a physical machine is modelled and solved numerically [2]. Among various available NM methods, such as method of lines, finite volume method, finite difference method, finite element method (FEM), and spectral method [2, 11, 19, 27, 28], FEM is found to be the most accurate approach for modelling PM AC machines [33, 37, 39]. Numerical method or FEM techniques are considered to be more accurate and are therefore widely used for parameter estimation and identification under different fault conditions [11–13]. They are also preferred since they consider spatial harmonics and non-linearities and carry out effective field and loss evaluation in PM AC machines [1–3, 13], thereby diagnosing the performance of electrical machine in terms of flux models, also shown earlier in Figure 6. The significant advantage of FEM techniques is that they can model any type of machine faults, including electrical, magnetic, and mechanical faults. Evidently, FE tools are more commonly used for validating EEC and MEC-based fault modelling approaches. Figure 11 [12, 33, 39] shows the rotor demagnetised flux profile (magnetic faults) obtained through FEM (NM)-based approaches. The reduction in the airgap magnetic flux density (*Bg*) for the corresponding half-cycle signifies the % equivalent change in magnetic coercivity of the PM, deducing the rotor demagnetisation fault.

To improve the accuracy of the system and reduce the computational time of diagnosing faults, new fault modelling techniques are also reported in the literature [9, 33, 37, 39]. Here, the authors have combined two conventional fault modelling approaches to develop a new and efficient *hybrid analytical-numerical (EEC-NM) method-based fault diagnostic technique* [33]. Such techniques have proven to be faster in terms of computational time and better in terms of accuracy, giving higher precision to fault diagnosis.

From the carried-out literature study, fault modelling methods can thus be given a classification as shown in Figure 12. [1–3, 9, 33]. These methods are found to be mostly used while performing fault diagnosis in PM AC machines.

4 | FAULT INDICES AND DIAGNOSTIC TOOLS

Considering the discussion in Sections 2 and 3, it can be inferred that for the different types of faults and fault modelling methods, a particular index is used as a reference to detect and diagnose machine faults. For instance, the short-circuit electrical faults use frequency components of stator phase current (i_s) (using MCSA as a fault index [16–19], while the magnetic faults use motor-back-EMF, (E_B) [33–36] and magnetic flux (ϕ) [12, 33, 37, 39]-based signatures as fault indices.

4.1 | MCSA

Motor current signature analysis (MCSA) is widely reported in the literature for diagnosing stator short-circuit faults [1–3, 16–19]. Most of the conventional approaches involve the negative sequence components of the stator impedances and currents, magnetic field drooping oscillations, fluctuations in instantaneous power, and developed electromagnetic torque [47–49]. The frequency component of the MCSA can be analysed through Equation (7), derived from [16–19, 37, 39, 47–49]:

$$f_q = \left(\frac{z}{P/2}\right) f_s = z f_r, z=1, 2, 3\ldots.. \quad (7)$$

where f_q is the frequency of the zth component in the spectrum, f_s is the supply (electrical) frequency, f_r is the rotational frequency, and P is the number of poles. The additional

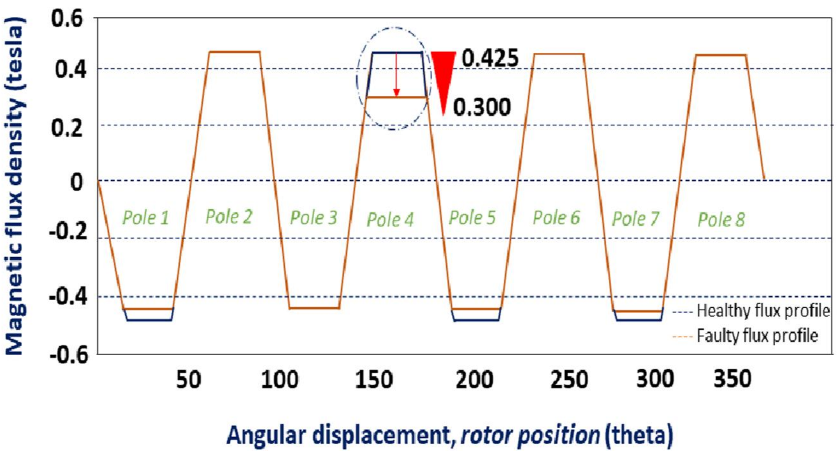

FIGURE 11 FE-based results for reduction in magnetic flux density due to rotor permanent magnet (PM) demagnetisation faults in a PM AC machine [12, 33, 39].

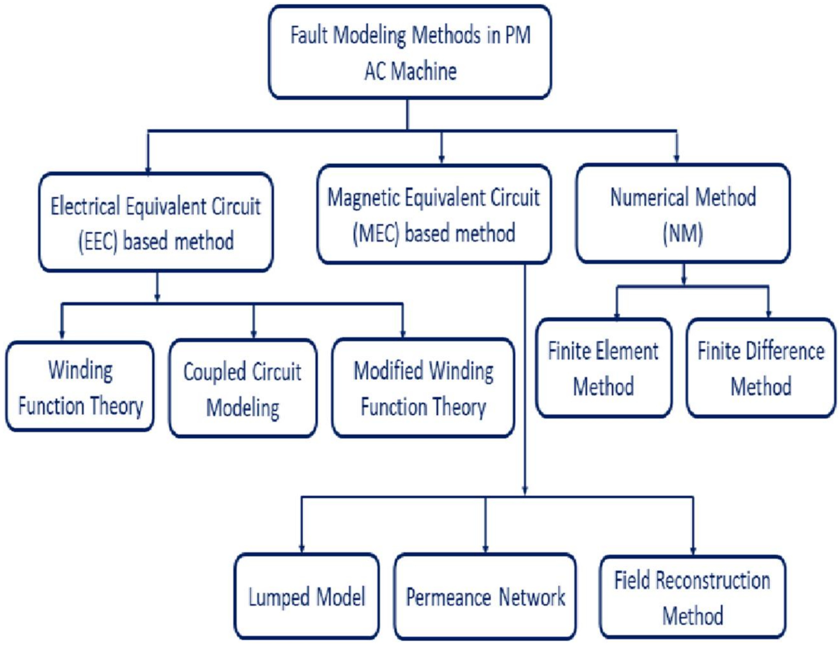

FIGURE 12 Classification of fault modelling methods in permanent magnet (PM) AC machines.

frequency components in the current during fault conditions help in diagnosing the motor faults.

4.2 | Motor Back-EMF estimation

The motor back-EMF estimation requires the estimation of the stator resistance, neglecting the stator inductance. The advantage of this method is that the estimated magnet strength is independent of other asymmetric faults, such as rotor eccentricity, and therefore the variation of modelled inductance is used only as an *indicator of demagnetisation fault* [33–36]. The mathematical expressions in Equations (5) and (6) can be used for estimation.

4.3 | Magnetic flux indices

With the evolution of PM AC machines, which are susceptible to rotor demagnetisation faults, estimating magnetic flux has become more vital. For any type of rotor demagnetisation faults (*partial*, *irreversible*, or *broken PM bars*), the ϕ or B_M produced by the magnets is reduced (shown in Figures 7 and 11) [33, 37, 39], signifying the effect of rotor demagnetisation faults in the machine. Thus, the magnetic flux signature is used as an index for the detection of rotor faults in the PM AC machine.

Since all the aforementioned fault indices include only machine-based quantities as fault indicators, the provided solutions are found to be more reliable and accurate. However, there are other emerging fault indices used for diagnosing faults. These include thermal analysis [14, 29], acoustic noise, and vibrations [15, 45, 46].

4.4 | Thermal analysis

Most of the motor faults discussed above cause changes in motor operating temperatures, leading to the generation of heat in the machine. Such changes in thermal conditions of the machine under fault operating conditions can be analysed numerically through NM- or FEM-based techniques. For instance, during the stator winding short-circuit faults, the temperature rise of the motor fault winding can be estimated through *thermal analysis* of the fault winding. The authors in [14, 29] discuss the thermal model of a PM AC machine and the sharp rise in temperatures under SITF conditions at different fault winding resistances. The short-circuit current increases sharply with the changing fault resistance value, and the generated heat causes the temperature at the short-circuit fault to rise sharply [29], thereby diagnosing and estimating the SITF severity.

4.5 | Acoustic and vibration analysis

Additional fault indices, such as acoustic noise, frequency, and vibrational analysis, are carried out to diagnose PM AC machine faults more efficiently [45, 46]. For a more comprehensive classification between stator and rotor faults, frequency analysis on the stator currents and motor back-EMF is carried out in [45, 46, 56], along with new techniques like random pulse-width modulation approaches [46]. However, in [56, 57], the forces on the rotor shaft are analysed, which are subjected to forces at natural frequency, calculated in a FEM-Maxwell 3D tool. The harmonic analysis on the motor's vibrational spectrum is used to study the deformation state of the machine under fault conditions. Figure 13 [56, 57] shows the total deformation of a motor

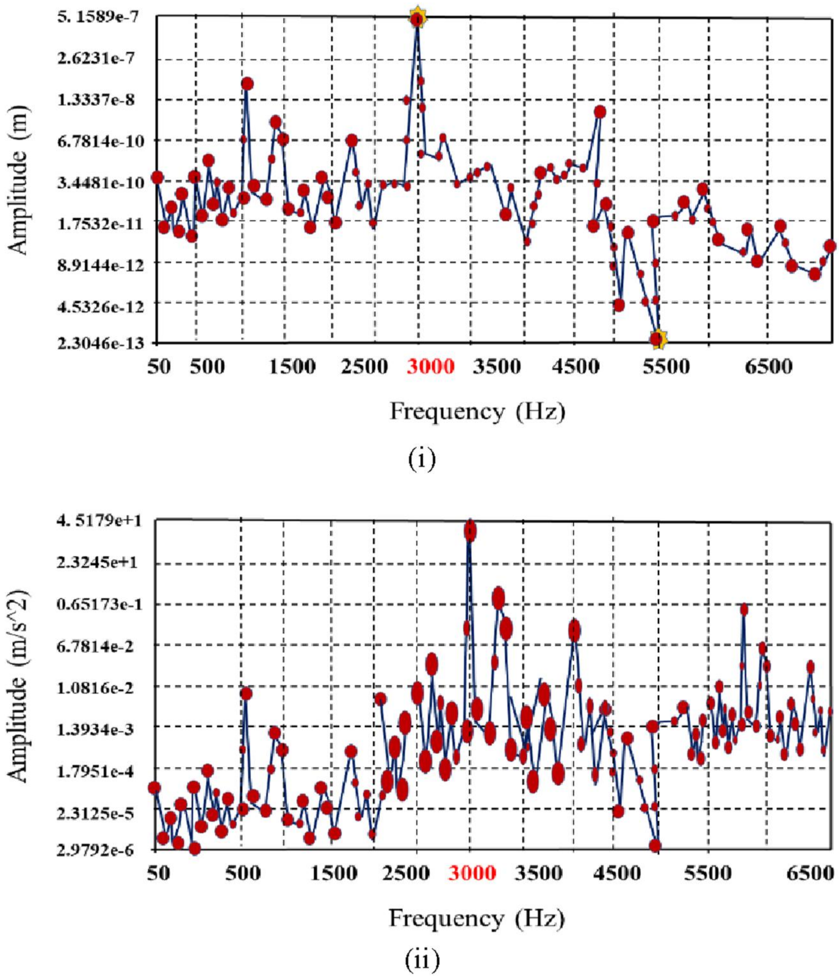

FIGURE 13 Amplitude versus frequency response of the vibrational spectrum for (i) displacement (m) and (ii) acceleration (m/s^2) at the rotor of a permanent magnet (PM) AC motor under fault conditions [56, 57].

geometry under fault conditions, in terms of *frequency-amplitude* response for *displacement* and *acceleration* on brushless PM AC motor shaft. For the motor under study, it is observed that the effect of the vibration varies with frequency, and therefore, the maximum vibrations for both *displacement* (m) and acceleration (m/s^2) are encountered at frequency f = 3000 Hz as shown in Figure 13 (i) and (ii), respectively, thereby signifying the effect of faults in the machine.

4.6 | Emerging trends in motor fault diagnosis

Thermal, acoustic, and vibrational analyses are some of the fast-emerging fault indicators being widely used in condition monitoring and fault diagnosis of electrical machines. In addition, more advanced and cost-effective approaches have been established, as reported recently in 2023 [58–74]. For instance, advanced computational intelligence-based mechanisms and machine learning-based approaches are used for diagnosing the stator winding related faults like SITFs [58–60] in the machine. Similarly for the PM AC machines, employed in domestic and household applications, the fault diagnosis is done using Internet of things-based mechanisms as reported in [61, 62]. In addition, the new techniques, which involve interval-based nested optimization framework, are employed for estimating the SOH of the EV system [63].

For the rotor-related faults in the machine such as demagnetisation faults, the advanced technique of using rotor displacement signals [64, 65], temperatures-based analysis/thermal characteristics [66] and flux-based signatures [67, 68] are being widely employed.

Similarly, for the rotor eccentricity and mechanical defects in the machine-like bearing faults, vibrations and acoustic-based analysis [69, 70] are extensively used. The temperature-based evaluation using thermography [71], harmonic and spectral analysis [72, 73] and advanced computational intelligence-based approaches [74] are also employed recently in 2023 for diagnosing the mechanical faults in the machine. In addition, these analyses are translated into energy storage, electricity markets, and smart buildings-based applications as reported in 2023 in [75, 76].

Table 1 summarises all the faults related to PM AC machines, including fault modelling methods, diagnostic techniques, measurement tools, and signatures involved in condition monitoring of faults. Table 2 illustrates the comparison between the proposed methodology with the recent works (year 2023) conducted in the same field.

TABLE 1 Types of faults in PM AC machines: Fault modelling methods, diagnostic techniques, measurement tools, and indices.

Types of faults	Subcategory	Fault modelling methods	Fault indices	Detection of faults	Fault measurement tools
Electrical faults (stator short-circuit winding faults)	SITF [16–19, 24–26]	EEC-based methods and NMs [2, 16–19, 47–49] WFT and MWFT [37, 47–49]	Stator phase currents (i_s) [16–19, 37, 39, 47–49]	Significantly high rise in stator winding currents. Approximately three times the value of rated current	MCSA, frequency spectrum
	Coil-to-coil faults [17–19, 24–26]	Multiple coupled circuit modelling [49]	Motor E_B [33–36]	For the corresponding short-circuit stator winding turns, there is equivalent % change in motor back-EMF.	Back-EMF estimation techniques
	Inter-phase faults [16–19]	WFT and MWFT [37, 47–49]	Temperature $(\Delta°)$ [14, 29]	The temperature rises sharply with the rise in fault currents	Thermal analysis, infrared images
	Open-circuit faults [19, 20, 27, 28], [23–29]	WFT and MWFT [37, 47–49]	Acoustic noise and vibrations (mm) [15, 45, 46]	With the commencement and intensification of electrical faults, the magnitude of deformation changes with different amplitude at higher frequencies	Amplitude-frequency spectrum, random pulse-width modulation techniques
Magnetic faults (rotor demagnetisation faults)	Partial demagnetisation faults [33, 34, 39]	MEC-based methods and NMs [2, 33, 37, 39, 52–54] Lumped model and PN [52, 53]	Motor E_B [33–36]	Reduction in motor back-EMF is in proportion to the change in magnetic coercivity, Hc. The characteristic demagnetisation curve is for a machine without saturation	Back-EMF estimation techniques
	Irreversible demagnetisation faults [12, 33, 36, 38, 39]	Lumped model, PN, field reconstruction model (FRM), and hybrid EEC-NM-based approaches [33, 52–54]	B_M [33, 37, 39]	The rotor magnetic flux density changes in accordance with the change in demagnetisation effect, corresponding to the % demagnetisation factor (magnetic coercivity)	Magnetic flux analysis, flux measurement using Hall sensors
	Broken PM faults [33, 34, 38, 39]	Field reconstruction method (FRM), hybrid EEC-NM-based approaches [33, 54]	Temperature $(\Delta°)$ [14, 29]	The temperature of the machine surface (rotor) rises sharply with the rise in temperature of the magnets, tending towards demagnetisation effects	Thermal analysis, infrared images, BH curves
Mechanical faults (eccentricity faults)	Eccentricity faults [40–44]	PN and NM [43, 53]	Stator phase currents (i_s) [16–19, 37, 39, 47–49]	Significant change in stator phase currents accompanied with harmonics.	MCSA, frequency spectrum
			B_M [33, 37, 39]	Due to change in airgap length, the magnetic flux distribution will change significantly	Magnetic flux analysis, flux measurement using Hall sensors
			Acoustic noise and vibrations (mm) [15, 45, 46]	Deformation with different amplitude at higher frequencies	Amplitude-frequency spectrum, random pulse-width modulation techniques

TABLE 2 Comparison of proposed methodology with recent works done in the same field.

Motor faults under study	Fault sub-category	Currently used fault diagnostic approaches	Proposed fault diagnostic approaches	Recent work in the same field (year 2023)
Electrical faults	Short-circuit winding faults: Stator inter-turn fault (SITF), coil-to-coil faults, open-circuit faults, inter-phase faults	Winding function theory (WFT)	Hybrid electrical equivalent circuit EEC-numerical method (NM) based approaches.	Search coils, computational intelligence and machine learning-based approaches [58–63]
		Modified winding function theory (MWFT)	Machine learning (ML) based diagnostic approaches.	
		Multiple coupled circuit modelling method (MCCMM)	Computational intelligence - artificial neural network (ANN)	
Magnetic faults	Rotor demagnetisation faults: Partial demagnetisation faults, irreversible demagnetisation faults, broken PM faults	Magnetic equivalent circuit (MEC)	Hybrid electrical equivalent circuit EEC- numerical method (NM)-based approaches	Rotor displacement signals [64, 65]
		Lumped model (LM)	Numerical method (NM)	Temperature analysis [66]
		Permeance network (PN)	Thermal analysis	Harmonic analysis [67, 68]
		Field reconstruction model (FRM)		
		Numerical method (NM)		
		Finite element analysis (FEA)		
Mechanical faults	Bearing and eccentricity faults		Numerical method (NM)	Acoustic and vibrational signals [69, 70]
		Permeance network (PN)	Finite element analysis (FEA)	Thermography [71]
		Numerical method (NM)	Thermal analysis, vibrations and acoustic	Harmonic and spectral analysis [72, 73]
			Machine learning (ML)-based diagnostic approaches.	Computational intelligence and machine learning-based approaches [74]
			Computational intelligence- artificial neural network (ANN)	
			Harmonic analysis	

5 | CONCLUSIONS

This paper presents a comprehensive review of the state of the art on the condition monitoring of PM AC machines, which is a part of energy system integration. The current study takes into account EVs or all electric transportation as an example of energy integration system. The study includes significant types of machine faults, fault diagnostic methodologies and techniques, fault indices/signatures, and fault measurement tools employed in diagnosing the PM AC machines fault. All the relevant reports over the past 2 decades have been discussed in this paper. The study includes major fault mechanisms on the stator and rotor side of the machine, which comprise stator winding short-circuit faults, rotor demagnetisation effects, and faults related to rotor eccentricities. Different fault modelling approaches and their formulation, such as electrical equivalent circuit, MEC, and NM-based approaches, are discussed in detail. Fault indices and measurement tools, including analysis in terms of motor current signatures, magnetic flux distribution, thermal and acoustic noise, and vibrational analysis, which are emerging fault monitoring mechanisms, are also discussed thoroughly in this paper.

For instance, with the given NM-based approaches (finite element analysis) in modelling the rotor faults, the measurement and monitoring of *magnetic flux data* are used to evaluate and estimate the motor fault conditions. As shown in Figure 11, the change and reduction in the magnetic flux density (Bg) characteristics for the corresponding half-cycle signify the equivalent % change in magnetic coercivity (magnetization) for that PM in the rotor. The flux density of the PM located at the rotor position (θ = 150–200°), that is, Pole-4 of the machine, undergoes an irreversible demagnetisation fault. The flux density (B_g) of the Pole-4 magnet decreases from 0.425 to 0.300 T, indicating the rotor demagnetisation faults occurring in the corresponding PM of the machine.

This paper summarises all the types of machine faults, its condition monitoring techniques, and the corresponding effects on motor performance in terms of change in machine quantities/indices, thereby giving a significant inference to the carried-out literature study. Since all the diagnostic techniques discussed in this paper mostly include machine-based quantities as fault indicators, the provided solutions are therefore found to be more reliable and accurate. The study seems to be very useful for online monitoring of faults in the PM AC motor while under operation in any type of energy-integrated systems like commercial EVs or all electric transportation systems. In addition, the latest emerging fault diagnostic methodologies as discussed by the authors add significant values to the existing fault diagnostic techniques currently used in industrial and commercial practices. Hence, all the given condition monitoring schemes seem significantly vital in estimating the SOH of PM AC machines while under employment in all-electric transportation systems.

This comprehensive review can therefore be relevant while studying and investigating the faults occurring in PM AC machines when employed in all-electric transportation systems.

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[Correction added on 11 Dec 2023, after first online publication. The acknowledgment section is updated.]

CONFLICT OF INTEREST STATEMENT

None.

DATA AVAILABILITY STATEMENT

Data sharing is not applicable—no new data are generated.

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