# Health Monitoring, Fault Diagnosis and Failure Prognosis Techniques for Brushless Permanent Magnet Machines

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***Abstract*****—** Over the past few years, many researchers have been attracted by the challenges of electrical machines' fault diagnosis and condition monitoring, which provide early warnings that could help schedule necessary maintenance to avoid catastrophic consequence. With advancements in the use of rare-earth magnets, Brushless Permanent Magnet Machines are widely used in industry recently, which has led to the development of numerous fault diagnosis techniques. Considerable papers have presented reviews and compared condition monitoring and fault diagnosis methods for induction machines, but none for Brushless Permanent Magnet Machines. To make a difference, this paper presents a comprehensive survey of modern research advancements and state-of-the-art in health monitoring, fault diagnosis and prognosis techniques for Brushless Permanent Magnet Machines. The symptoms of each type of fault and the principles of diagnosis process are also described and discussed.

***Keywords—Brushless permanent magnet machine, Health monitoring, Fault diagnosis.***

## I. INTRODUCTION

Over the past decade, Permanent Magnet Synchronous Machines (PMSMs) and Brushless DC machines (BLDCs) have gained significant popularity in the industry, especially where high performance is required, owing to higher efficiency, high output power to volume ratio, high torque to current ratio, etc. Some of the commonly occurring faults in PMSMs are eccentricity, bearing failure, demagnetization of permanent magnets, short circuit in the stator or armature winding, etc. Health monitoring and fault diagnosis of the machine could help in scheduling preventive maintenance to length their lifespan and avoid catastrophic system failure. Basic steps for a machine diagnosis scheme are illustrated in Fig.1, where dashed lines indicate non-necessary steps. Considerable papers have presented reviews and compared condition monitoring and fault diagnosis methods for induction machines [1]-[4], but none for Brushless Permanent Magnet Machines. The goal of this paper is to provide a comprehensive review in this area to help fellows to consider what have been done, where we are now, and which direction we might go.

This paper is organized as follows. In Section II, the classification of the common faults is presented. Their causes are explained and their influence on machine parameters is discussed. In Section III, various signatures extraction

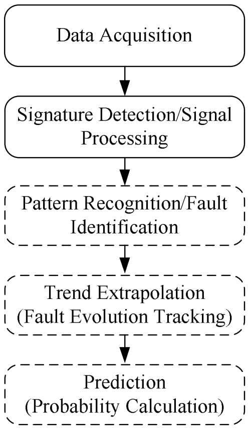


Fig. 1. Basic steps for electric machine diagnosis

schemes are presented, analyzing their pros and cons. Section IV discusses various artificial intelligence algorithms for distinguishing different signatures. In Section V, the concept of prognosis is introduced. The summary and conclusions are presented in Section VI.

## II. TYPES OF FAULTS IN PM MACHINES

In an electric machine, faults can occur in the rotor/field, stator/armature, inverter, or mechanical components connected to it. This paper discusses a permanent magnet machine without focusing on associated inverter faults and bearing faults. Fig. 2 illustrates the most frequently encountered problems for electric machines [5]. Their causes and symptoms are presented in this section.

### *A. Armature Faults*

Armature faults are usually caused by winding insulation failure, which frequently happens in the regions where end windings enter the slots. The reasons which cause insulation

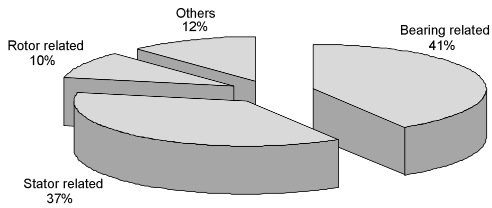


Fig. 2. Failure of components

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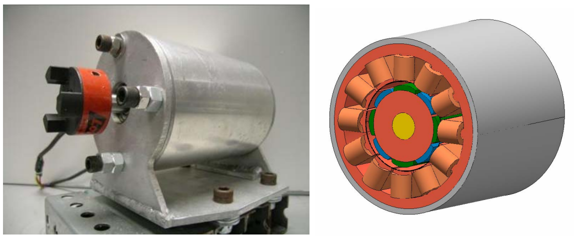

Fig. 3. Test brushless permanent magnet machine and its FEA model

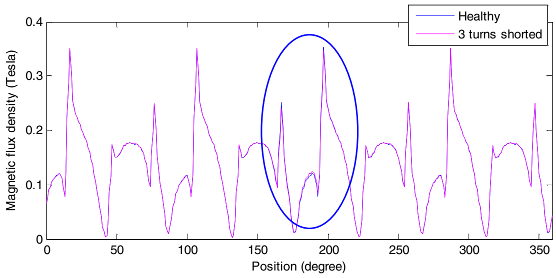


Fig. 4. Magnetic flux density around the air-gap with winding short circuit

failure could be

1) Manufacturing defect
2) High operation temperature/Cooling system malfunction
3) Machine overloading
4) Transient high voltage
5) Vibration caused rubbing

This fault usually starts as an incipient turn-to-turn short circuit and could grow to a ground-to-phase or phase-to-phase short circuit if no preventive maintenance is done. A bolted turn-to-turn short circuit behaves similar to a same system with less number of turns. To illustrate multi-faults' effect on the magnetic flux in air-gap, finite element analysis (FEA) is used to simulate a three phase eight pole brushless permanent magnet machine shown as Fig. 3. Figure 4 shows the difference of flux density in the air gap for a healthy machine and a machine with three turn shorted respectively, under a condition that 30% rated load is applied. It can be seen that the difference is very small and not obvious. The notches in this figure are caused by slot effect.

From the electromagnetic perspective, change in the number of turns affects phase self-inductance, phase-to-phase mutual inductance, winding resistance, and back EMF of a PMSM. For both the inductor models as Fig.5, the relationship between inductances and number of turns are described as

$$L_s = \frac{N^2}{R + R_m} \tag{1}$$

where $L_s$ is phase self inductance, $R$ is reluctance of the back iron, $R_m$ is the reluctance of the permanent magnet. And

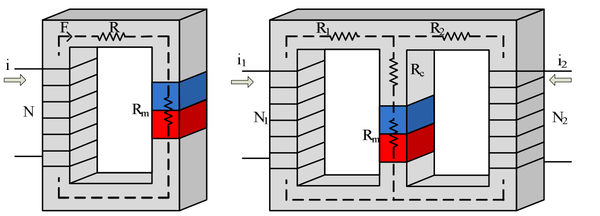


Fig. 5. Model of self-inductance and mutual inductance in a PM machine

$$L_m = \frac{N_1 N_2 R_c}{R_1 R_2 + R_1(R_c + R_m) + R_2(R_c + R_m)} \tag{2}$$

where $L_m$ is mutual inductance, the $R_1$ and $R_2$ are reluctance of each phases and $R_c$ is reluctance of their common path. It can be seen from above equations that self inductance is proportional to the square of number of turns, while mutual inductance is proportional to the number of turns, under ideal conditions.

### B. *Permanent Magnetic Faults*

For permanent magnet machines, field fault typically refers to a failure in the permanent magnets, where demagnetization is the most common issue. The demagnetization could be uniform over all poles or partial over certain region or poles. Conditions that could cause permanent magnets in a PMSM to demagnetize include

1) High operation temperature/Cooling system malfunction
2) Aging of magnets
3) Corrosion of magnets
4) Inappropriate armature current

Commonly used sintered rare-earth magnet materials such as NdFeB and SmCo have straight demagnetization curves in the second quadrant in their B-H loops. Influence of temperature on the magnetic remanence is approximately linear below Curie temperature [6] expressed in equation (3)

$$B_r(T) = B_r(T_0)[1 + \Delta_B(T - T_0)] \tag{3}$$

where $T$ is magnet's operation temperature, $T_0$ is the preferred temperature, $B_r(T_0)$ is the remanence at $T_0$, and $\Delta_B$ is the reversible temperature coefficient, which is a negative number. The moving of operating point due to increasing temperature is illustrated in Fig. 6.

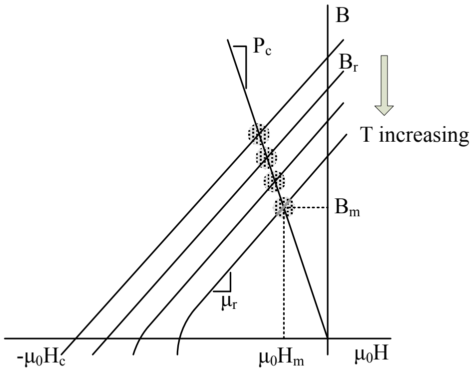


Fig. 6. Effect of increasing temperature on the operating point

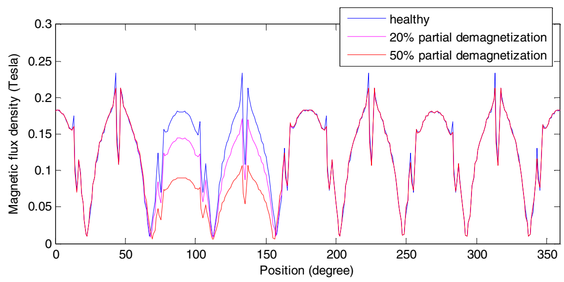


Fig. 7. Magnetic flux density around the air-gap with demagnetization

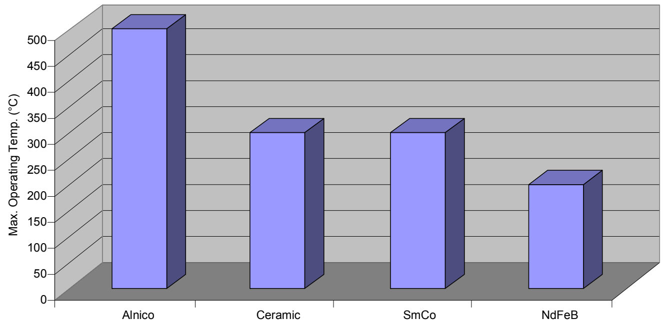

Fig. 8. Maximum operating temperature of different magnet materials

Magnet's permeance coefficient $P_c$ is a function of magnet length, air gap length, and armature current. It is usually greater than one to keep the operation point far away from the knee point. Operation around the knee area will cause irreversible demagnetization. A partial demagnetization FEA simulation result is illustrated in Fig. 7, which shows the changes of flux density with 20% and 50% demagnetization respectively.

The approximate maximum operation temperature of commercial magnets is illustrated in Fig. 8. To evaluate the effect on the parameters of the machines under demagnetization conditions, various analytical models have been proposed [7]-[11], which are discussed in Section III.

### C. *Mechanical Faults*

Mechanical faults typically refer to bearing failure and eccentricity in most machines. Bearing is a mechanical component which consists of two rings and a set of balls rolling between them and it has been recorded as one of the dominant causes for electric machine failure [5]. It could be caused by

1) Metal fatigue
2) Unbalanced stress
3) Improper installation
4) Corrosion/Contamination

These problems could result in vibrations and noise during machine operation, which are usually measured and processed as diagnosis indicators [12]. Since bearing fault manifest itself as a vibration of rotor and unbalance air gap length, it is sometimes also classified in the eccentricity category. However, it has its own frequency signatures related to its number of balls, ball diameter and ball pitch [13], which is not the same as eccentricity. This is a common issue to all machines with similar effects on performance. Nandi *et al.* [1], [2] have presented a review of fault diagnosis in an induction machine, therefore it has not been discussed in detail in this paper to avoid repetition.

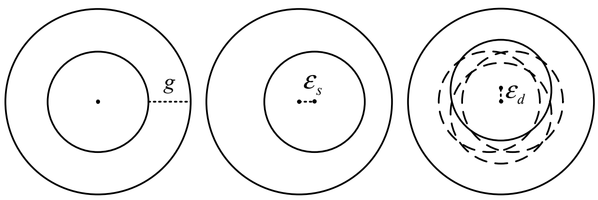

Fig. 9. The air-gap of a healthy machine, a static eccentricity machine and dynamic eccentricity machine

Eccentricity in a machine is a condition of uneven air-gap between the stator and rotor. If the condition is severe, the Unbalanced Magnetic Pull (UMP) could cause stator and rotor contact [14]. Generally, eccentricity is classified into three types: Static eccentricity, dynamic eccentricity and mixed eccentricity. Static eccentricity is the case where there is a displacement in the axis of rotation. This could be caused by an oval stator or misaligned mounting of bearings, rotors or stators. In this case, the air gap is length is fixed in space. Static eccentricity ratio is defined as [15]

$$\vec{e}_s = \frac{\vec{\varepsilon}_s}{g} \tag{4}$$

where $\varepsilon_s$ is the radial distance between rotor axis and stator axis, and g is the uniform air-gap length.

Dynamic eccentricity is the condition in which the stator axis and the rotor rotation axis are identical, but the rotor's axis is displaced to some extent. Therefore the minimum air-gap length position rotates around. This case is usually caused by bent shaft, misaligned mounting of bearings, etc. Similarly, the dynamic eccentricity ratio is defined as

$$\vec{e}_d = \frac{\vec{\varepsilon}_d}{g} = \frac{|\vec{\varepsilon}_d| \angle \omega t}{g} \tag{5}$$

where $\varepsilon_d$ is the radical distance between rotor's axis and stator's axis. Combination of both static and dynamic eccentricities is called mixed eccentricity. Their vector sum can be expressed by equation (6) and (7).

$$|\vec{e}_m| = \left| \frac{\vec{\varepsilon}_s}{g} + \frac{\vec{\varepsilon}_d}{g} \right| = \sqrt{|\vec{e}_s|^2 + |\vec{e}_d|^2 + 2|\vec{e}_s||\vec{e}_d|\cos(\omega t)} \tag{6}$$

$$\angle \varphi = \angle \vec{e}_m = \tan^{-1} \frac{|\vec{e}_d|\sin(\omega t)}{|\vec{e}_s| + |\vec{e}_d|\cos(\omega t)} \tag{7}$$

where $\varphi$ is the angle of the mixed eccentricity, with a reference to static eccentricity direction. It is a time dependent variant with the same period as the rotor's mechanical speed. Thus, the air-gap length $l$ can be calculated as

$$\begin{aligned} & l_{air}(\zeta, t) = \\ & R_s - |\vec{e}_m| g \cos(\zeta - \varphi) - \sqrt{R_r^2 - |\vec{e}_m|^2 g^2 \sin^2(\zeta - \varphi)} \end{aligned} \tag{8}$$

where $\zeta$ is the position around the air-gap, from 0 to 360 degree.

In a machine's magnetic circuit, reluctance is a function of the air-gap length and back iron equivalent length $l_{iron}$. Therefore magnetic flux is given by equation 9.

$$\Phi(\zeta, t) = \frac{F}{R_{air} + R_{iron}} = \frac{F}{\frac{l_{air}(\zeta, t)}{\mu_o A_{air}} + \frac{l_{iron}}{\mu_o \mu_r A_{iron}}} \tag{9}$$

where $\Phi$ is magnetic flux through a search coil, $F$ is MMF produced by permanent magnets, $R_{air}$ and $R_{iron}$ are reluctance of air-gap and back iron respectively, and $\mu_o$ is the permeability of the air, $\mu_r$ is the relative permeability of the back iron. If only static eccentricity exists, $l_{air}$ is just a function of position, so $\Phi$ is also time irrelevant. If dynamic

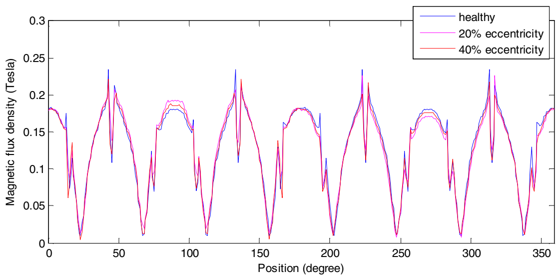

Fig. 10. Magnetic flux density around the air-gap with eccentricity

eccentricity exists, $\Phi$ will be a function of both position and time.

Figure 10 shows the magnetic flux density distribution around the air gap with 20% and 40% eccentricity in the FEA model, from which the unbalance can be found. Besides of FEA, instantaneous magnetic flux density distribution in air gap region can also be calculated by solving the governing Laplacian/quasi-Poissonian field equations and associated boundary conditions with analytical methods. Zhu *et al.* [16] reported a 2D analytical method to predict magnetic flux density of PMSM under different scenarios. Kim *et al.* [17] also presented a perturbation method to predict the air gap magnetic flux density distribution to analyze eccentricity faults based on a model in polar coordinated, with and without considering slotting effect, where analytically calculated results were verified by corresponding FEA results.

## III. Fault Signature Detection Techniques

### A. *Frequency Signature Analysis*

Stator current frequency analysis is the most frequently used technique for machine fault diagnosis. It is usually called Motor Current Signature Analysis (MCSA). Fast Fourier transform (FFT) method is widely used for frequency analysis. Some specific harmonics in the stator winding current spectrum can be detected as a signature of specific fault. Since only current measurement is required, this method can be used for simultaneous multi-fault detection. In addition, this technique is also non-invasive, and cost-effective.

In dynamic eccentricity case, frequency components in the order of 1/P exist in the inductance versus position profile, where P is the number of pole pairs. Since the position of minimum air gap rotates, harmonics can be found in the stator current spectrum. The frequencies due to dynamic eccentricity are given in equation (10)

$$f = f_e(1 \pm \frac{k}{P}) \tag{10}$$

where $f_e$ is the electrical fundamental frequency, and k is an integer.

It has been observed in [18] that the additional frequencies due to partial demagnetization are as same as dynamic eccentricity signature frequencies given by equation (10), and they cannot be distinguished. In the case of demagnetization, a machine's inductance profile does not contain any new spectral contents, since the permeance of permanent magnet is approximately one. However, the flux profile contains the 1/P component; therefore the integer multiples k/P can also be found. In reality not only partial demagnetization, but also other asymmetric problems like load unbalance, misalignment, or oscillating load can produce the same harmonics [19].

Since FFT doesn't contain the information about time, for non-stationary operated machine, short time Fourier Transform (STFT) can be applied. However, the selection of suitable FFT window type and window size is still a critical issue for STFT. A fixed length of window will provoke an inconsistent treatment of different current frequencies [20], and changing motor speed makes it harder to determine harmonic orders, therefore STFT has limitation for non-stationary operated machines.

To overcome the tradeoff between time and frequency resolution of STFT, Rajagopalan *et al.* applied other algorithms such as Windowed Fourier Ridges, Wigner-Ville Distributions, [21], Choi–Williams distribution, Born–Jordan distribution and the Zhao–Atlas–Marks distribution [22] to improve the readability of the time-frequency spectrum. These transformations has a general form as

$$\begin{aligned} D(t,\omega) = \iiint e^{j(\xi\mu - \tau\omega - \xi t)} \varphi(\xi,\tau) \\ \times f(\mu + \frac{\tau}{2}) f^*(\mu - \frac{\tau}{2}) d\mu d\tau d\xi \end{aligned} \tag{11}$$

where $t$ is the instantaneous time, $\omega$ is the instantaneous frequency; $\tau$, $\xi$ and $\mu$ are variables for integration; and $\varphi(\xi, \tau)$ is a kernel which is given by Table I. In this table, $h(\tau)$ is a window, and $\sigma$ is a constant.

TABLE I
Comparison of Time–Frequency Representation Algorithms

| Distributions | Kernel |
|---|---|
| Wigner-Ville | 1 |
| Windowed WV | $h(\tau)$ |
| Choi–William | $e^{-\xi^2\tau^2/\sigma}$ |
| Born–Jordan | $\varphi_1(\tau)\frac{\sin(\xi\lvert\tau\rvert/a)}{\xi/2}$ |
| Zhao–Atlas–Marks | $\frac{\sin(\xi\tau)}{\xi/2}$ |

For machines operated with a rapidly changing speed profile, wavelet analysis is another option to avoid the dilemma between time resolution and frequency resolution. Rosero *et al.* [20] applied both continuous wavelet transform (CWT) and discrete wavelet transform (DWT) to detect demagnetization faults in machine running under non-stationary condition. Similar method is also used to detect dynamic eccentricity in PMSM and to monitor their health condition [23].

Similarly to current frequency, indications of several faults are also found to be hidden in other spectrums, such as noise, vibration and torque, etc [24]-[26]. However, due to the high cost of accelerometer or torque meter, they are usually implemented in relative larger machines.

The limitations of these frequency analysis based algorithms are relatively time consuming to some certain extent, and it is too hard to determine the source of specific harmonics, so it cannot discriminate faults that have the same signature frequencies, like partial demagnetization, dynamic eccentricity and unbalanced load.

### *B. Model Based Methods*

For model based machine diagnosis methods, an accurate machine model is required. Modeling of a balanced three-phase healthy PMSM is widely recognized, as presented by researchers in [27]

$$\begin{cases} u_d = R_s i_d + L_d \dfrac{di_d}{dt} - \omega L_q i_q \\ u_q = R_s i_q + L_q \dfrac{di_q}{dt} + \omega L_d i_d + \omega \psi_{PM} \end{cases} \tag{12}$$

$$T_e = \frac{3}{2} p i_q [\psi_{PM} + (L_d - L_q) i_d] \tag{13}$$

where $u_d$, $u_q$ and $i_d$, $i_q$ are stator winding voltage and current in d-q coordinate system respectively; $R_s$ is the stator winding resistance; $L_d$ and $L_q$ are the $d$, $q$ axis stator winding inductances; $\Psi_{PM}$ is the permanent magnetic flux linkage; ω is the angular speed of the rotor; $T_e$ is electromagnetic torque. In faulty cases, specific parameters changes accordingly.

Negative/zero current [28], negative/zero impedance [29], or negative/zero voltage [30] are utilized as indicators for fault detection. These indicators are sensitive to machine asymmetry so that faults due to unbalance signals can be discriminated. However, any asymmetry caused by the machine structure or the power supply's unbalance could also influence the fault detection.

Parameter estimation is another scheme that can be used for online fault diagnosis through detecting abnormal physical parameters. Usually current, voltage and speed are measured, while other parameters are estimated so that faults can be found from any change in magnitude or asymmetry. For parameter estimation, various algorithms are used in literatures. X. Liu *et al.* [31] utilized least-squares method to estimate the stator resistance, inductance, rotor inertia, friction, and back EMF constant from a liberalized PMSM model for multi fault detection. W. le Roux *et al.* [32] determined the strength of the permanent magnets to distinguish rotor magnet defect from dynamic eccentricity, by estimating the mean value of the torque constant. Liu *et al.* [33] implemented an evolutionary computation technique, called particle swarm optimization approach, to estimate two parameters which indicate stator winding inter-turn short circuit fault severity and fault location.

Besides frequency based and model based methods, pros and cons of some other types of methods are compared in Table II.

## IV. Fault Identification Techniques

Sometime, extracted fault features are not easily distinguished from fault-free cases or other fault types, especially when disturbances and noise are not negligible. Therefore, several researchers have reported artificial intelligence (AI) algorithms for faults isolation. This approach maps extracted features to specific fault categories. Some frequently used fault identification tools are: artificial neural network (ANN), fuzzy logic, expertise system, support vector machine, etc.

ANN mimics the structure of human brain, which consists of numerous processing unit-neurons, to form a complex adaptive network to perform multi-input/multi-output mapping, even though every neuron has a very simple function. Usually, complex systems will have many hidden layers or feedbacks to enhance the ANN performance. However, the main challenges are that such a system often requires massive computational device and large storage memory. In real application, commonly used ANNs in literatures are three layers feed forward structure in order to simplify the implementation and lower the hardware requirements. Various ANN structures are approved successful in brushless permanent magnet machine fault diagnosis [31], [34]-[39]. For machine condition monitoring and faults identification, the input could be current, voltage, vibration signals, or other estimated parameters. To perform this task, a training data which covers different operating conditions from simulation or experiments are applied to ANN for the offline training procedure to determine the weighting coefficients. After being trained, ANNs need to be tested at some operating points with the testing data from either the training data set or other data sets. Once the offline training and tests are finished, the ANNs can be implemented on hardware to perform fault identification tasks. Besides fault identification, ANNs' nonlinear mapping ability is also implemented for parameter estimation in a supervised learning environment [31], [40], [41].

Fuzzy logic is another AI tool in pattern recognition field. In contrast to crisp logic, it has a truth value between 0 and 1. For machine fault identification, it works as an inferential engine for classification based on a mother function set and

TABLE II
COMPARISON OF CLASSES OF DIAGNOSIS TECHNIQUES

| Types of methods | Types of Failures | | | | Hardware Requirement | Drawbacks |
|---|---|---|---|---|---|---|
| | Bearing | Eccentricity | Winding short circuit/open circuit | Partial Demagnetization | | |
| Current frequency Analysis | √ | √ | √ | √ | Current sensor, Raster encoder | Not good for various speed operated machines. Eccentricity and demagnetization have same frequency signature. |
| Vibration/Noise frequency Analysis | √ | √ | | | Accelerometer/Sound recorder, Raster encoder | |
| Parameter estimation based on current and voltage monitoring | | | √ | √ | Current sensor, Raster encoder | Fault-free machine accurate parameters are required. |
| Temperature Monitoring | | | √ | | Thermograph | Temperature is affected by many factors. |
| Direct Flux Monitoring | | √ | √ | √ | Search coils, Raster encoder | Additional built-in flux sensors are required. |

an if-then rule set [42]-[44]. These sets are needed to be formed before the diagnosis process by expertise based on experience. To make it more adaptive to achieve more accurate solutions under different operation conditions, hybrid neural/fuzzy machine fault detectors are also under research [45]-[48], which take advantage of the learning capability of ANNs to optimize fuzzy sets.

## V. FAILURE PROGNOSIS TECHNIQUES

With emerging applications in hybrid electric vehicles and renewable energy systems, failure prognosis has become an active area of interest for electric machines and drives. S.J. Engel *et al.* [49] have defined this word as follows: *Prognostics is the capability to provide early detection of precursor and/or incipient fault condition (very "small" fault) of a component and to have the technology and means to manage and predict the progression of this fault condition to component failure. However, so far, understanding of this word is still diverse.* Some papers define "*prognosis*" as the estimation of Remaining Useful Life (RUL) [49], [50]. Since fault evolution is a stochastic process influenced by factors which could have unknown future values, it is impossible for one to know exactly when a component will fail. However, one can find an extrapolated trend of fault evolution, or a Probability Density Function estimating the failure time's probability.

In [51]-[54], prognosis is defined as the prediction/forecasting of future state during the evolution of a fault. In these papers, state prediction algorithms such as Kalman Filter, Hidden Markov Model, are utilized for state prediction based on known state conditions. However, the state transition matrix is assumed to remain same throughout the progression of the fault, which might not be true in reality. In [55], [56], prognosis is defined as small transient signal detection. It must be noted that there is no prediction process that has been specifically cited in these papers. They refer to prognosis since the faults detected are transient signal existing during a short time, which can be considered as incipient fault. It is based on an assumption that specific conditions leading to faults produce short transients on the currents of electrical motors. The analysis and transient fault detection tools developed in these papers might better fall into diagnosis category rather than prognosis.

## VI. CONCLUSION

A brief review of armature, field and mechanical faults occurs to PMSM and their diagnosis schemes have been presented in this paper. So far spectrum signature analysis based methods and machine model based methods are the mostly preferred. Apart from Fourier Transform based techniques, other spectrum manipulation algorithms, such as higher order spectrum, wavelet transforms show better performance for various speed conditions. Artificial intelligence algorithms are also discussed in this paper, which is necessary to distinguish the fault signatures. This paper also discusses the concept of prognosis, which holds the potential for machine life time estimation and incipient fault warning.

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