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Condition Monitoring of Permanent Magnet Synchronous Motor- A Review Abstract: In the present time, Permanent Magnet Synchronous Motors (PMSMs) are extensively used in many industrial applications due to its advantages over conventional synchronous motor. In the PMSM, the rotor is made of a special-shaped rare- earth permanent magnet instead of the field windings. This motor has some certain advantages such as simple structure, small size, light weight and large overload capacity. Therefore, this motor becomes compact and efficient with high dynamic performance. These motors are failed during operation and consequently large revenue losses for industries.

Hence, it is essential to diagnose these faults before occurring for protection of any industrial plant. Therefore, Condition Monitoring of PMSMs are extremely studied in the past and also essential for safe guarding of an industrial plant. In the past, PMSMs faults have been analyzed and diagnosed with help of many Condition Monitoring techniques. In this paper, a comprehensive review has been done for permanent magnet synchronous motor faults and their diagnostics techniques. Keywords: Permanent Magnet Synchronous Motor (PMSM), Condition Monitoring, Methods of Condition Monitoring, Faults Classification, Need of Condition Monitoring I.

INTRODUCTION The PMSM motor has many advantages over conventional synchronous motor because of field windings absence. The stator of PMSM contains symmetrical three phase windings as conventional synchronous motor but the rotor is different. The rotor of PMSM is made of special shaped rare-earth permanent magnet instead of field windings [1]. The PMSM is widely used in many industrial applications such as wind generators, ship propulsion engine [2], electric vehicles, manufacturing systems etc. [3]. The main advantage of PMSM is their high dynamic performance and high torque density [4].

In the industries, due to imbalance power supply and load conditions many faults occur during long term continuous motor operation. Since, the motor works in the industrial environment with different stresses therefore, faults occur reported in [5]. These faults are very dangerous for reliability and safety of motor operation. If faults are not diagnosed in time, it leads to large revenue losses for industry because of equipment damage and plant shut down [6]. Hence, it is most important to study about Condition Monitoring of PMSM. In the present paper, a comprehensive review of faults and Condition Monitoring techniques of PMSM has been discussed. II.

CLASSIFICATION OF PMSM FAULTS Normally, the PMSM faults can be classified as magnetic faults, mechanical faults and electrical faults [7] and these faults are identified as per their nature. A. Electrical Faults Main reasons of occurring electrical faults in PMSM are as follows [8]: ? Incorrect connection of motor windings ? Grounding errors ? Short circuit of stator phase winding ? Open circuit of whole phase The stator faults contributed around 38 % of all PMSM faults [9]. The most common stator winding fault of PMSM is inter-turn short circuit [10]. The insulation of the stator winding is damaged due to overheating, overload and insulation wear for long running time of the motor.

If insulation is breakdown then stator turns short circuit fault occur [11]. This fault is most dangerous and if not corrected and diagnosed in time then it will create more stator winding faults. In this fault, large circulating current flows in the shorted path with excessive heat [12]. This fault is able to generate other stator winding faults such as phase-to-phase fault, phase-to-ground faults and even demagnetization [13]. In the drive system, phase open circuited fault takes place and reported in [14]. This fault produces large mechanical vibrations and large electromagnetic torque fluctuations of the PMSM.

This fault can damage the entire system due to secondary damage [15]. B. Mechanical Faults In this section mechanical fault of PMSM has been explained one by one: a). Bearing Fault The bearing fault is a common mechanical fault and contributed around 40-50 % of all PMSM faults. The mechanical faults are bending of the shaft, loosening of the bolts, damage to the magnet, air-gap eccentricity fault and bearing faults [16].

The bearing fault occurs due to overload, corrosion, poor lubrication, vibrations, shaft misalignment and environmental mechanical vibrations [17]. The common bearing faults are inner raceway fault, outer raceway fault, cage fault, and ball fault of the bearing [18]. Purnima Singh1, Pradeep Kumar Gupta 2, Irshad Ahmad Mir 3, Tariq Ahmad Ganie 4 and Dr. Khadim Moin Siddiqui 5 1-2 Final Year Undergraduate Student, Electrical Engineering

Department , BBDITM, Lucknow 3-4 Final Year Undergraduate Student, Electrical & Electronics Engineering Department , BBDITM, Lucknow 5 Assistant Professor , Electrical Engineering Department , BBDITM, Lucknow b). Eccentricity Faults The inconsistent air gap between the rotor and the stator is called eccentricity fault.

This fault is takes place due to misalignment of the shaft, rotor imbalance, improper installation, lack or missing of the bolts [19]. The eccentricity fault is classified as: static eccentricity, dynamic eccentricity and mixed eccentricity [20]. The center line of the shaft is offset from the center of the stator by a constant value is called static eccentricity. The minimum distance of the air gap rotates with the rotation of the rotor is called dynamic eccentricity. Actually, both eccentricities are co- exist and it leads to mixed eccentricity. C. Magnetic Faults The demagnetization fault comes in the category of magnetic fault in the PMSM and it is a unique fault of this motor.

The magnet used in the PMSM is demagnetized due to large short circuit current produced by stator faults or inverter, large stator current and the aging of magnet itself [21]. However, the armature reaction is the main source of magnetic demagnetization fault. The stator current generates a reverse magnetic field and it is constantly opposes the magnetic field of the permanent magnet during the normal operation of the PMSM [22].

Authors reported in the [23, 24] that the PMSM specific demagnetization fault occurs due flux linkages ripples, the torque will be insufficient and it will raise the temperature. Due to the raising temperature, demagnetization of the magnet will take place. At the same time, the fluctuation of the torque will produce abnormal vibration and acoustic noise consequently reduces motor performance and efficiency. III. CONDITION MONITORING AND NEED OF CONDITION MONITORING Condition Monitoring is the evolution of health of the PMSM components during its service life and it is needed for diagnosis of motor faults when they are growing and called incipient failure detection.

The incipient failure detection gives safe environment of the motor. The Condition Monitoring provides complete prior warning of the failure to be happening in the PMSM. Accordingly, future preventive maintenance can be scheduled [25]. The Condition Monitoring and fault diagnosis scheme allows the machine operator to have necessary spare parts before the machine is stripped down, thereby reducing outage times. Therefore, effective Condition Monitoring of electric machines can improve the reliability, safety and productivity of the machine.

Condition Monitoring has great significance in the business environment due to the following reasons [25]: ? To reduce cost of maintenance ? To predict the equipment failure ? To improve equipment and component reliability ? To optimize the equipment performance ? To improve the accuracy in failure prediction Due to the above motioned advantages of the Condition Monitoring of the PMSM, now, it has been most important to find out the best suitable monitoring technique of induction machine. IV. CONDITION MONITORING METHODS OF PMSM In the past, many fault diagnosis methods have been used for PMSM Condition Monitoring purpose. One can understand each method from the Fig.1. All techniques are described below one by one. Fig.1.

Condition Monitoring Methods of PMSM A. Model Based Fault Diagnosis Methods In this method, a motor model is made which containing a certain fault. The fault should be based on physical principles. From the model, one compares the predicted output from actual detected output. It determines the fault occurring condition of the motor. The same simulation model may be used to diagnose any motor fault with the help of other diagnostics methods. In the reference [26], authors stated that the model based fault diagnosis method can enter the internal laws and physical nature of motor faults. For achieving best results, the motor model ought to have high accuracy.

In this method, analytical mathematical models, digital simulation models and magnetic Equivalent Circuit Models (ECM) can be used and all these methods have been compared in [26]. The mathematical modelling for healthy three phase permanent magnet synchronous motor has been discussed in [27] and the modelling of multiphase permanent magnet synchronous motor is reported in [28]. The inter-turn short circuit fault of PMSM has been diagnosed by model based fault diagnosis method and is reported in [29].

For creating inter-turn short circuit fault, authors have added resistance and inductance and due to this voltage and magnetic equations will be changed. Similar model based fault diagnosis method has been reported in [30] and with dq reference frame is reported in [31]. In these models, limited study has been done because they are based on electrical equivalent circuit, which is fast but accuracy is less. Magnetic Equivalent Circuit (MEC) has been used to diagnose electrical faults is reported in [32, 33]. In these models, magnetic equivalent circuit equations are solved and magnetic fluxes and potentials in all branches have been determined.

Since, the MEC models are more accurate than EEC models. MEC and EEC simulation gives less accurate results rather than digital simulation models. The digital simulation models are widely used in the diagnosis of PMSM faults. The Finite Element Model (FEM) is the example of digital simulation model. Therefore, coupling between FEM and MEC is reported in [34]. In the past, FEM has been used for demagnetization, eccentricity and inter-turn short circuit fault diagnosis purpose and reported in [35-37].

The main advantage of FEM is that for finite element field calculation, both physical and geometric details are considered. Due to this, mechanical faults of motor is modelled [38], also the digital simulation accuracy of the machines is high than analytical model with linear parameters. In the [39] authors reported that the digital simulation models has highest accuracy and highest computational cost. A FEM model has been used for different PMSM fault diagnosis purpose and compared with experimental data.

The harmonics and amplitude analysis has been done for fault identification purpose [40]. B. Signal Processing Methods In signal processing methods, many electrical quantities such as current, voltage, power and frequency are used for different PMSM fault analysis purpose. Many non-electrical quantities are also used with signal processing methods such as light, sound, heat, gas, radiation, vibration for fault diagnosis and analysis.

The signal processing method is based on processing of the raw signal means motor signal with the suitable signal processing technique and may extract required information related to fault. The signal processing methods can analyze the performance of faults and can extract hidden feature from the motor signal. The information may be extracted though motor current [41], vibration [42] etc. With signal processing techniques, Motor Current Signature Analysis Technique (MCSA) is reported in [43] has been broadly studied. Some researchers have made a PMSM fault diagnosis system with the combination of different signals [44,45].

In general, there are three types of signal processing methods, time domain, frequency domain and time-frequency domain. In the next section, all used signal processing methods is discussed one by one. a). Time Domain Methods The time domain signals are used in this method for fault diagnosis and analysis purpose. These methods are used mean, peak, root mean square, kurtosis values etc for fault diagnosis purpose. These methods are not accurate [46-47]. b). Frequency Domain Method The Fast Fourier Transform (FFT) method comes in the category of frequency domain method. This method clearly displays the frequency distribution of the signal.

The FFT represents a signal as a superposition of a number of sine and cosine functions. In this method, the amplitude and harmonics components of frequency have been used for different faults diagnosis purpose [48]. With FFT, current and vibration signals are used as the motor parameter for extraction of fault. The Condition Monitoring of PMSM has been done by stator current imbalance and amplitude, reported in [49]. When the fault takes place side lobes corresponding to fault frequency will be increased [50]. Therefore, by non-invasive approach, fault diagnosis can be done. If fault is occur the third harmonics will be increased [51].

The mechanical fault cause distortion in the flux distribution inside the motor, and will also lead to some current harmonics in the stator current in turn [52]. Ebrahimi et. al.[20] has generated a equation of eccentricity fault frequencies for PMSM and is given in equation (1). (1) Ebrahimi also reported in his paper that the harmonic for static eccentricity faults is at fs(1-3/p) whereas the harmonic for both static eccentricity and dynamic eccentricity is at fs(1 + 1/p).

In [53] an equation is proposed for three phase current balance by three phase current balance indicator and is given in equation (2). (2) For demagnetization fault, the MMF will not be sinusoidal therefore, two MMF will be generated one is the normal portion and next is failed portion. Both MMF together will produce current with multiple frequencies. For demagnetization condition, low frequency component come in the effect and it will near to fundamental wave in the current signal [54]. Therefore, harmonic frequencies for demagnetization fault in given in equation (3), reported in [55].

(3) The equation 3 is independent on slip unlike asynchronous motors. It means all the fault pattern will be in the same point in the current spectrum. Authors of reference [56] has addressed this issue and written that the 0.25th, 0.5th and 0.75th harmonics is the ideal indicators to separate a demagnetization fault from the static eccentricity fault. Vibration signal can also be used to find out PMSM fault by FFT method. The stator vibration frequency will be two times than the frequencies of the power supply in the healthy condition.

In the stator winding fault, the unsymmetrical motor windings will be the reason of magnetic field asymmetry and it results abnormal vibration, which will create the harmonics in the harmonics components of 4fs and 8fs in addition to the vibration fundamental frequency of 2fs[57]. For the mechanical fault, the vibration signal analysis is highly considered. It is because when a local mechanical failure occurs in the motor, it comes into contact with another part of the machine and produces a shock pulse in the vibration [58]. C.

Short-time Fourier Transform The short time Fourier Transform does not provide time information. Hence, it is quite hard to differentiate same harmonics precisely. This method does not give at what time which frequency exists. There are many time-frequency techniques and each technique has their own merits and demerits. The Short time Fourier Transform (STFT) is an improved technique based on FFT. It divides the signal into small windows and available window functions are Hamming, Hanning, Rectangular, Gauss etc.

The discrete expression of STFT for an input signal x(n) is given in equation 4 and reported in [59]: (4) We (the ofnctio ifruey e is number of FFT points, m is position of window and H represents the jump distance between two consecutive windows. STFT method is very suitable for non-linear complex signal. But, the time and frequency resolution is depends upon the selected window. One may observe from above equation, the window H is fixed consequently resolution is fixed in entire time and frequency range. Hence, their time resolution is poor. For good resolution, this method needs large computational cost.

This method is not much suitable for transient analysis. In [60] authors reported that the STFT performs the most awful in numerous time-frequency analysis. Therefore, authors of [68] have overcome this problem by using STFT with Gabor spectra jointly to analyze PMSM current signal. [61]. D. Wavelet Transform The wavelet is a small wave and it is classified as Continuous Wavelet Transform (CWT) and Discrete Wavelet Transform (DWT).

The wavelet transform generates wavelet coefficients by convolving the input signal f(h moherwafnctio?(6] he scaling factor a and displacement factor b of the mother wavelet function are related to frequency and time respectively. The expression of wavelet transform is as follows: (5) In the wavelet transform, the window size is varying in nature with the frequency unlike STFT. Therefore, the signal can be decomposed into signals at different frequency bands with different resolutions. This makes WT for accurate and flexible fault detection of PMSM [9] The discrete wavelet transform has been used for PMSM fault diagnosis purpose. Authors calculated energy of detailed signal [61].

The short circuit winding fault of PMSM has been diagnosed by wavelet transform [63]. The wavelet analysis cannot further decompose the high frequency bands of the signal. One point should be noted that the fault characteristics of motors often appear at high frequencies. This drawback was overcome by wavelet packet transform and it was reported in [64]. Authors extracted the useful information for PMSM inter-turn short circuit fault and calculated energy for appropriated frequency bands as the attribute vector of the fault.

In the wavelet transform, mother wavelet function should be chosen correctly because it makes wavelet transform more sensitive to transient shocks. For each wavelet results will be different, therefore, most appropriate mother wavelet should be chosen. E. Hilbert-Huang Transform This technique combines Empirical Mode Decomposition (EMD) with Hilbert Transform. This technique does time- frequency analysis. In this technique, the raw signal is decomposed into multiple internal mode functions (IMF) through EMD, each of which is a single component function.

The instantaneous energy is calculated of the raw signal from the internal mode function [74] is called Hilbert Transform [65]. The expression of the Hilbert transform for an input x(t) is: (6) The stator short circuit fault of PMSM has been diagnosed by Hilbert energy spectrum and reported in [56]. The Hilbert Transform approach is suitable for dynamic signal analysis due to its sensitivity to transient frequencies.

In the [66], authors applied Hilbert Transform technique for diagnosis of demagnetization fault, and authors concluded that the obtained results are good for high speed and dynamic operating conditions. F. Wigner-Ville Distribution The definition of Wigner-Ville distribution (WVD) for an input signal x(t) is: (7) Where transient correlation is x(t+ /2) x(t- /2). From WVD, one can obtain time-frequency energy density. Authors reported in [61] that the WVD is best and better than other time-frequency calculation methods with less cost. In WVD, cross-term interference will occur for signals contains more than one frequency component.

Therefore, this method is not favorable in electric machine fault diagnosis. This problem overcome by a joint method with WVD, EMD and Hilbert Transform [67,68]. For eliminating interference in WVD based PMSM fault, Rosero et. al. has proposed a smoothed pseudo Wigner Ville distribution (SPWVD) and Zao-Atlas-Marks distribution (ZAM) [69,70]. Nonetheless, its purpose on PMSM faults will always be studied additionally. V. DATA-DRIVEN INTELLIGENT DIAGNOSIS ALGORITHM Prior knowledge is relied in traditional artificial intelligence algorithms.

Authors of [71] reported that the rule basis of fuzzy logic can be based on the knowledge and experience of experts about permanent magnet synchronous motor faults. Many data-driven intelligent diagnosis algorithms have been proposed recently for machine learning and artificial intelligence. Some statistical methods such a principal component analysis reported in [72] and independent component analysis reported in [73] are used a basic data driven approaches. This method is used to diagnose faults through feature extraction technique.

But, the PMSM fault type and its severity can be automatically identified by the input data based on the given training data is called data- driven intelligent diagnosis algorithms. These techniques mostly comprise the support vector, sparse representation, neural network and deep learning etc. A. Neural Network With the development of artificial intelligence, Neural Networks (NN) or Artificial Neural Networks (ANN) was proposed. These techniques are mostly used in the fields of automatic control, pattern recognition and fault diagnosis reported in [74]. The human brain is simulated to identify the fault type by NN.

Traditional NN consists an input layer, a hidden layer and an output layer; each layer containing many modes [75]. The output is obtained from the activation function after calculation of fully connected nodes from multiple layers. The goal of NN is to minimize the classification errors on the training set and to react appropriately to new inputs, which requires adjusting the initial values of the parameters and training the network multiple times. Therefore, different training algorithms and network models are used in fault diagnosis studies, such as back-propagation (BP) network [76], dynamic recurrent NN [77] and so on.

Ebrahimi trained feed-forward perceptron ANNs for the static eccentricity fault of PMSM [78]. Çira et al. used the third harmonic in the PMSM current as the input to the ANN to achieve a good diagnosis result for the inter-turn short circuit [79]. However, it also has the disadvantage of relying on a large amount of input data, easy over- fng,“bk bx” n. B. Support Vector Machine The Support Vector Machine (SVM) was proposed in 1999 by Vapnik [80] and is a commonly used machine theory [81]. In this technique, the distance between training data and a decision boundary in feature space is maximized. By separating the hyper plane and training vectors forms decision boundary.

The training vectors must be closest to the decision boundary and is called support vectors. This support vector determines position. Following equation is solved in SVM technique. (8) SVM is more suitable than NN for small sample classification. Though, the fundamental model of support vector machine may merely be employed to crack the two- class problem. For practical needs, Ebrahimi et. al. used one versus all SVMs for the PMSM inter-turn short circuit fault classification [82]. For complex mechanical fault signals the wavelet SVM considered very good [83]. Authors reported in [84] that the support vector regression (SVR) to map the feature vectors from torque and current into the different demagnetization levels of PMSM.

In addition, the performance of SVM depends largely on the choice of SVM parameters, parameter optimization algorithms, such a particle swarm optimization (PSO), should also be noted. C. Sparse Representation For linear representation methods, the sparse representation is an advanced theory and the most representative methodology. It is used to compress signals for anti- interference, de-noising with reduced data space. Its principle is to use the sparse linear combination of over complete dictionary atoms to represent the original signal [85]. The expression of the sparse representation for given input signal x=[x1, x2,x 3,.

xn]T of length n is as follows: (9) Where, D is the dictionary matrix and T is the sparse representation coefficient of the original signal. The sparse representation mainly includes dictionary design [86-88] and sparse coefficient solving. A sparse representation classification (SRC) in the field of face recognition is reported in [89], the training data is used as the dictionary to compare the residuals of deferent categories data and input data. In widens the sparse representation application and scope. In recent years, the sparse representation is used in the feature extraction, signal de-noising and fault classification applications.

Matching Pursuit (MP) algorithm is reported in [90], this method obtained largest N sparse coefficients of PMSM with different faults and considered them as the features [91]. Liang et. al. has taken the reference [92] and built an orthogonal matching pursuit and sent the feature vectors into SVM. One point to be noted here, the SRC is not accurate than SVM although it is faster. Ren et. al. has proposed SRC and SVM jointly model and diagnosed bearing fault [93]. D.

Deep Learning In the deep learning, first one extract feature vectors as the input by any one suitable signal processing technique then apply machine learning algorithm such as SVM. Recent deep learning method can automatically study the capability to classify and represent raw data features [94] and it can imitate the deep features of the original data. The convolutional neural networks (CNNs), deep stacking network (DSN) [95], deep belief network (DBN) [96], long short term memory (LSTM) [97] etc are deep learning methods and these methods are used in the field of fault diagnosis.

In all above methods, the convolutional neural network (CNNs) is widely used method for motor fault diagnosis in the effective way. The CNNs comprises ReLU layers, convolutional layers, pooling layers and a fully connected layer. In the training process, The input samples are forwardly propagated for feature learning and classification, and the errors are reversely propagated until the model is finally completed. It is a bite like NN but can reduce the tendency to over fit. Since CNN is a method developed in image processing, some researchers first converted the features extracted by time-frequency analysis technology into two-dimensional, and then input them into 2D-CNN for diagnosis [98].

Authors proposed a method for converting the time domain signal into 2-D gray images and this abolish the necessity of additional feature extraction steps [99]. They have compared DBN and SVM and sparse filter methods from CNNs and concluded that the CNN based fault diagnosis is more accurate. The main shortcoming of this method is that it too much time consuming and more hardware requirements. The fault has been diagnosed by 1D-CNN in [100], authors have sensed time domain signal from the motor and applied to 1D-CNN. This method is compared in [101] with WPT for extracting features and the applied into ANN.

Authors concluded from results that the CNN has a somewhat better accuracy in the fault diagnosis of PMSM [102]. Hence, the research on deep learning is promising for fault diagnosis of PMSM. VI. CONDITION MONITORING PROCESS The online Condition Monitoring process can be understood by the fig 2. The PMSM can be operated by direct mains or inverter. Nowadays, inverter based machines are popularizing therefore; inverter fed machine is considered and shown in fig.2. The current transducer senses the morcrandth rwill e o differentiating healthy and faulty conditions of the motor.

For fast and high accuracy response, the closed loop sensor may be used. The anti-aliasing filter may used before a signal sampler to limit the bandwidth of a signal to approximately or completely satisfy the sampling theorem over the band of interest. Finally, the analog stator current signal will be processed through the analog to digital converter and it will Fig.2. Process of Condition Monitoring give required digital signal and this data may be used to diagnose any particular fault by non-intrusive technique. Conclusions In this paper, PMSM faults and its diagnostics techniques have been discussed.

Some advanced methods have also been discussed such as data driven intelligent algorithms. In recent years, deep learning method has become a burning topic due to its high intelligence features but in this method hardware is required. Though, by deep learning method, the data can be classified correctly but must have the knowledge of necessary characteristics of the data and internal laws. Since, the speed of SRC is faster because in this method training process is not required. Therefore, fault diagnosis by signal processing techniques also needs further research. For low computational time and small sample of data, the SVM technique is still used broadly.

Thus, more research is happening on ensemble learning algorithms and multi-classification algorithms. Hence, time-frequency based signal processing techniques are still important area of research for extracting information in extra assorted and specific features. Presently, the necessity of fault diagnosis increases in terms of intelligence and accuracy therefore this paper will be very useful for future researchers.

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