

PAPER • OPEN ACCESS

Fault detection and classification of permanent magnet synchronous motor in variable load and speed conditions using order tracking and machine learning

To cite this article: Jagath Sri Lal Senanayaka *et al* 2018 *J. Phys.: Conf. Ser.* **1037** 032028

View the [article online](#) for updates and enhancements.

Related content

- [A robust method for detection and classification of permanent magnet synchronous motor faults: Deep autoencoders and data fusion approach](#)
Jagath Sri Lal Senanayaka, Van Khang Huynh and Kjell G. Robbersmyr
- [Research on Torque Ripple Suppression of Permanent Magnet Synchronous Motor](#)
Kening He, Weijie Zhu and Lei Xu
- [The Numerical Calculation and Experimental Measurement of the Inductance Parameters for Permanent Magnet Synchronous Motor in Electric Vehicle](#)
Chao Jiang, Mingzhong Qiao and Peng Zhu



IOP | ebooks™

Bringing together innovative digital publishing with leading authors from the global scientific community.

Start exploring the collection—download the first chapter of every title for free.

Fault detection and classification of permanent magnet synchronous motor in variable load and speed conditions using order tracking and machine learning

Jagath Sri Lal Senanayaka, Van Khang Huynh, Kjell G. Robbersmyr

Department of Engineering Sciences, University of Agder, 4879 Grimstad, Norway

E-mail: jagaths @uia.no

Abstract. Permanent magnet synchronous machines have gained popularity in wind turbines due to their merits of high efficiency, power density, and reliability. The wind turbines normally work in a wide range of operations, and harsh environments, so unexpected faults may occur and result in productivity losses. The common faults in the permanent magnet machines occur in the bearing and stator winding, being mainly detected in steady-state operating conditions under constant loads and speeds. However, variable loads and speeds are typical operations in wind turbines and powertrain applications. Therefore, it is important to detect bearing and stator winding faults in variable speed and load conditions. This paper proposes an algorithm to diagnose multiple faults in variable speed and load conditions. The algorithm is based on tracking the frequency orders associated with faults from the normalised order spectrum. The normalised order spectrum is generated by resampling the measured vibration signal via estimated motor speeds. The fault features are then generated from the tracking orders in addition to the estimated torque and speed features. Finally, support vector machine algorithm is used to classify the faults. The proposed method is validated using experimental data, and the validated results confirm its usefulness for practical applications.

1. Introduction

Condition monitoring (CM) is necessary to guarantee the healthy and safe operation of critical rotating machines. The CM is an important part of condition-based maintenance (CBM) program and based on CM results the maintenance schedules can be arranged. Moreover, by analysing the CM data with failure mechanisms, the remaining useful life (RUL) of the component can be estimated. This complete process is covered in the Prognostics and Health Management (PHM) of engineering systems.

In wind turbines, vibration and current sensors are widely used for CM. The mechanical faults can be detected by investigating the trends of root mean square (RMS) of measured vibration signal. but, the overall RMS of vibration signal can be only used to detect faults, and the classification of multiple faults is not possible. Mechanical faults produce forcing frequencies associated with the faults which can be differentiated by searching those forcing frequencies in the vibration spectrum. Therefore, Faults can be classified by further analysing the frequency spectrum of the vibration signal [1]. Signal processing and statistical detection methods are useful for the analysis, due to the noise and stochasticity of vibration signals and machine behaviour. With spectrum analysis, good performances can be expected for individual fault classification tasks, but multiple faults classification can be difficult. Understanding complex spectrum regions is required for the classification of multiple faults. Statistical and machine learning methods have been used in the multiple-fault classifications. Fault-related features can be derived using the statistical methods, or domain knowledge of forcing frequencies, and those features can be used in statistical and machine learning algorithms to classify the faults. A review on



different signal processing, statistical and machine learning algorithms can be found in [2]. Decision tree algorithm [3] and support vector machine (SVM) algorithm [11] are used for bearing fault detection under a constant load and speed or in the steady state. Most of the existing fault diagnosis algorithms are mainly implemented at such conditions, which are not the case for wind turbine applications. This work focuses on fault classification for a permanent magnet synchronous motor (PMSM) working in variable load and speed conditions.

The rest of this paper is organised as follows. The details of proposed fault diagnosis Algorithm are discussed in Section 2. The experimental results are presented in Section 3. Finally, the conclusion is given in Section 4.

2. Proposed fault diagnosis algorithm

A block diagram of the proposed algorithm is shown in Figure 1, in which the rotational speed and torque of PMSM are estimated using the current measurements. For the fault classification, features of the variable speed and load torque are required. The speed can be estimated from the Hilbert transformation, and the torque is calculated from the measured currents [4-5]. Since the mechanical rotational speed of a PMSM is directly proportional to the AC supply frequency, it is possible to estimate the rotational speed by estimating the frequency of the current waveform. First, the complex-valued analytic signal of the current signal is extracted using the Hilbert transformation, and the phase angle of the current signal is derived. Next, the rotational speed is calculated by taking the first order derivation of the cumulative angle of the current waveform and multiplying with the number of pole pairs. The collected vibration signal is resampled based on the estimated rotational frequency, and the order normalized frequency spectrum is calculated from the resampled signal.

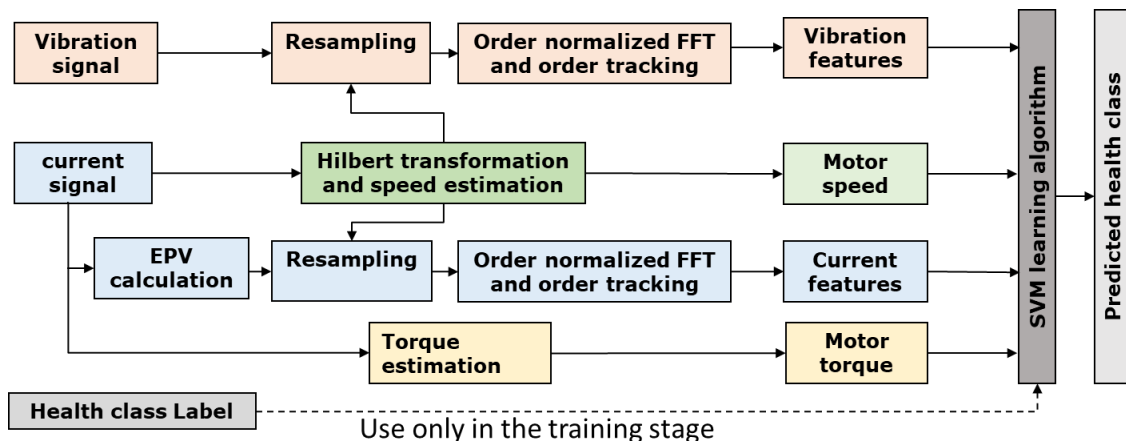


Figure 1. The block diagram of proposed fault diagnosis and classification algorithm

Several features based on vibration and current signals are calculated from the order normalized spectrogram. The faults related orders of the vibration spectrum are tracked. Furthermore, additional features of speed and torque are produced based on measured currents and calculated rotational speed. In this study, a nonlinear SVM algorithm is used as the classifier. Gaussian radial basis function (RBF) kernel is used in the SVM algorithm, which produces a better nonlinear classification in the feature space. This study focuses on 4 types of health classes based on the health status of stator winding and bearing on a PMSM. The first class is the healthy class where both stator winding and bearings are healthy. In health class 2, the stator has 10% inter-turn winding short-circuit fault, and bearing is healthy. In health class 3, the stator is healthy, and an outer-race defect occurs on the bearing. In health class 4, both the stator winding and bearing fault are defective. As shown in Figure 2, the SVM algorithm is trained using labelled training data. After the training process, the algorithm can be employed for predicting the health statuses using new current and vibration signals.

2.1 Hilbert transformation and motor speed estimation

In a PMSM, the current signal is usually sinusoidal with varying frequency and amplitude. Therefore, the current signal can be considered as a mono-component signal and Hilbert transformation can be used to extract the instantaneous frequency, amplitude and the phase.

The instantaneous frequency and the angle estimation example of a mono-component signal using Hilbert transformation are given in Figure 2. An analytic signal of the original signal is required to extract the instantaneous frequency, amplitude and the phase of the original system. The analytic signal is a complex-valued function, which has no negative frequency values shown as follows [6].

The Fourier transform $S(f)$ of a time-domain signal $S(t)$ has a Hermitian symmetry at zero frequency axis, which is $S(-f) = S(f)^*$, where $S(f)^*$ is the complex conjugate of $S(f)$. The analytic function in the frequency domain is defined as:

$$\begin{aligned} S_a(f) &= \begin{cases} 2 S(f), & \text{if } f > 0 \\ S(f), & \text{if } f = 0 \\ 0, & \text{if } f < 0 \end{cases} \\ &= 2u(f) \cdot S(f) \\ &= S(f) + \text{sgn}(f) \cdot S(f) \end{aligned} \quad (1)$$

where $u(f)$ is the unit step function and $\text{sgn}(f)$ is the sign function. The analytic function holds only non-negative frequency components of $S(f)$ and the operation is reversible due to the Hermitian symmetry of $S(f)$.

$$S(f) = \begin{cases} 0.5 S_a(f), & \text{if } f > 0 \\ S_a(f), & \text{if } f = 0 \\ 0.5 S_a(-f)^*, & \text{if } f < 0 \end{cases} \quad (2)$$

The analytic signal of $S_a(t)$ can be derived using the inverse Fourier transform of $S_a(f)$:

$$\begin{aligned} S_a(t) &= F^{-1}[S_a(f)] \\ &= F^{-1}[S(f) + \text{sgn}(f) \cdot S(f)] \\ &= F^{-1}[S(f)] + F^{-1}[\text{sgn}(f)] * F^{-1}[S(f)] \\ &= S(t) + j \left[\frac{1}{\pi t} * S(t) \right] \\ &= S(t) + j\hat{S}(t) \\ &= S_m(t)e^{j\phi(t)} \end{aligned} \quad (3)$$

where $\hat{S}(t) = H[S(t)]$ is the Hilbert transformation, $*$ is the convolution operator and j is the imaginary unit operator. $S_m(t) = |S_a(t)|$ is called the instantaneous amplitude or envelope, and $\phi(t) = \arg[S_a(t)]$ is called the instantaneous phase. The instantaneous angular frequency in hertz can be extracted by differentiating the unwrapped $\phi(t)$.

$$f(t) = \left(\frac{1}{2\pi} \right) \frac{d}{dx} \phi(t) \quad (4)$$

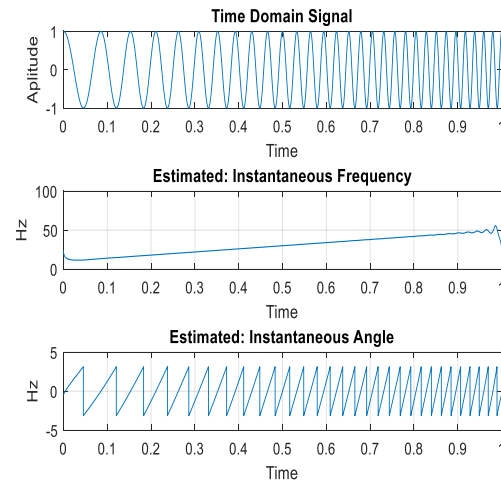


Figure 2. Frequency and angle estimation of a mono-component signal: Hilbert transformation

2.2 Resampling order normalized FFT and order tracking

In steady-state fault diagnoses, the frequencies are assumed as constants, and the constant time sampling rates can be used. Therefore, Fourier transform can be used for such a frequency domain analysis. However, in variable speed operations, the Fourier transform cannot be used because the analysis signals are not stationary or the frequencies change in time. To deal with nonstationary signals, short time Fourier transform (STFT) with constant time sampling may be used as it assumes that the frequency is constant for a small-time period and Fourier transform is performed for those short time signal windows. However, using STFT requires a wise selection of window sizes in advance to archive the best resolution, which is not a solution to tackle the characteristic frequencies in variable speed operations as the characteristic frequency is changed according to the shaft speed.

The solution is instead of using constant time sampling, using the constant angular sampling and order normalised FFT which is demonstrated in Figure 3 for a simple frequency varying sine wave. The constant angle sampling method can be used to capture the underline constant-frequency sine wave from a varying frequency sine wave where the signal is resampled using the rotor position information, which is calculated in the previous section. More details on this method can be found in [7-8]. This method can be extended for complex vibration and current signals in variable speed operations.

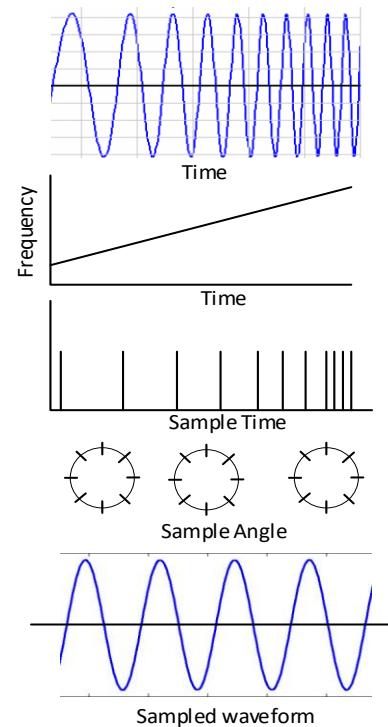


Figure 3. Constant angle sampling of a variable speed signal

2.3 Torque estimation

The voltage equations of a PMSM in $dq0$ transformation can be expressed as [9]:

$$\left. \begin{aligned} v_{sd} &= R_s i_{sd} + \frac{d\lambda_{sd}}{dt} + \omega_r \lambda_{sq} \\ v_{sq} &= R_s i_{sq} + \frac{d\lambda_{sq}}{dt} + \omega_r \lambda_{sd} \end{aligned} \right\} \quad (5)$$

where R_s is resistance of the stator windings. ω_r is the rotational speed of the motor. λ_{sd} and λ_{sq} are the flux linkages in the d and q axes, respectively.

$$\left. \begin{aligned} \lambda_{sd} &= L_s i_{sd} + \psi_{PM} \\ \lambda_{sq} &= L_s i_{sq} \end{aligned} \right\} \quad (6)$$

where L_s is the inductance of the stator windings. ψ_{PM} is the flux of rotor permanent magnets. The electromagnetic torque generated by a PMSM with n_p pole pairs and m_s phases can be expressed as:

$$T_e = \frac{m_s n_p}{2} (\lambda_{sq} i_{sd} - \lambda_{sd} i_{sq}) = -\frac{m_s n_p}{2} \psi_{PM} i_{sq} \quad (7)$$

Based on (7), the electromagnetic torque can be estimated and used as a feature for the classification algorithm.

2.4 Feature generation

Based on estimated rotor speed and measured vibration and current signals features are derived. As given in Table 1, the devised features are used as inputs to the SVM algorithm. The motor speed is calculated by (4), and the motor torque is calculated by (7).

Table 1: The features used in the SVM classification algorithm

Signal Source	Feature name	Description
Current	Speed	Represent the speed
	Torque	Represent the torque
	$2f_s$	Characteristic frequency of Inter-turn winding fault from the Park's vector current i_p in (9)
	Torque Variance	Moving variance of 10 consecutive values of the torque signal
Vibration	3.05X order	Characteristic frequency of outer-race bearing fault
	1X	Motor rotating speed
	8X	Motor rotating speed *No of rotor pole pairs
	16X	Motor rotating speed *2nd harmonics of no of rotor pole pairs

An inter-turn stator winding fault can be analysed by calculating the extended Park's vector (EPV) of the motor current as below [10].

$$\left. \begin{aligned} i_d &= \sqrt{2/3} i_a - \sqrt{1/6} i_b - \sqrt{1/6} i_c \\ i_q &= \sqrt{1/2} i_b - \sqrt{1/2} i_c \end{aligned} \right\} \quad (8)$$

$$i_p = |i_d + j i_q| \quad (9)$$

where i_d and i_q are the direct and quadratic components of the Park's vector i_p . i_a , i_b and i_c are the stator currents in each phase. A stator winding fault can be detected by analysing the frequency spectrum i_p since the inter-turn fault results in an increase in $2f_s$ (two times of supply frequency) components of the i_p . Further, moving variance of 10 consecutive values of torque signal is also used as a feature, which represents any short-term variation of the torque profile. The vibration signals can be used to detect bearing faults. The characteristic bearing outer-race fault frequency is the ball pass frequency outer-race (BPFO), which can be calculated as [11]:

$$\text{BPFO} = \frac{N_b}{2} f_s \left(1 - \frac{D_b}{D_c} \cos\theta\right) \quad (10)$$

where N_b is the number of rolling elements in the bearing, D_b represents the diameter of a rolling element, D_c denotes the pitch diameter, θ is the contact angle between the outer-race and rolling element, and f_s is the shaft speed. above BPFO frequency can be divided by the shaft rotational frequency, and a frequency order can be found which is a constant for any rotational speed. The related order of the bearing fault studied in this study is the 3.05 order (3.05X) of the shaft speed. In addition, the 1X, 8X and 16X frequency components are also used as the features for SVM classification algorithm.

2.5 SVM classification algorithm

SVM is a vector-space-based machine-learning method where the goal is to find a decision boundary between two or more classes that are maximally far from any point in the training data. The simplest SVM algorithm can be built to separate data linearly into two classes. This concept can be extended for multi-class cases and for nonlinear classification tasks [12-14]. In this study the fault, classification problem is solved as a nonlinear SVM classification problem. First, the linear case is studied.

Consider a set of training data points in Figure 4 with inputs x_i and two output class labels $y_i \in \{\pm 1\}$; $i = 1, \dots, N$. A linear classifier can be defined as:

$$f_{w,b}(x) = \text{sgn}(w^T \cdot x + b) \quad (11)$$

where the decision hyperplane is defined by an intercept term b and a decision hyperplane normal weight vector w , which is perpendicular to the hyperplane. A value of -1 specifies one class, and a value of $+1$ the other class. For a given data set and decision hyperplane, the functional margin of the i^{th} example x_i with respect to a hyperplane (w, b) can be measured by $y_i (w^T \cdot x_i + b)$.

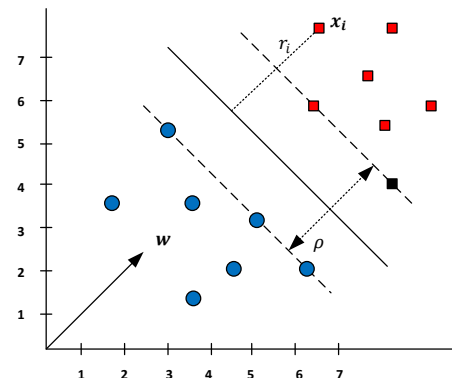


Figure 4. Linear SVM classification

The functional margin can be scaled to solve SVM problems, $|w|$ can be set to 1. The functional margin of all data points is at least 1 and there exist support vectors for which the inequality is equality.

$$y_i (w^T \cdot x_i + b) \geq 1, i = 1, 2, \dots, N \quad (12)$$

For each sample, distance from the hyperplane is $r_i = \frac{y_i (w^T \cdot x_i + b)}{|w|}$ and the geometric margin is $\rho = \frac{2}{|w|}$. The objective is to maximise the geometric margin. This means finding w and b such that $\rho = \frac{2}{|w|}$ maximising for all (x_i, y_i) and $y_i (w^T \cdot x_i + b) \geq 1$. Maximising the $\rho = \frac{2}{|w|}$ is the same as minimizing $\frac{|w|}{2}$ and the final optimisation problem with a hard margin (without tolerating for wrong classification) is given in (13) and the solution is in (14).

$$\text{Minimise } \frac{1}{2} w^T w \text{ and for all } \{(x_i, y_i)\}, y_i (w^T \cdot x_i + b) \geq 1 \quad (13)$$

$$f_{w,b}(x) = \text{sgn}(\sum_i \alpha_i y_i x_i^T x + b) \quad (14)$$

where most of α_i are zero and the each non-zero α_i represents that the corresponding x_i is a support vector. If a data set is not linearly separable, a soft margin can be assigned where wrong classifications are allowed when solving the optimisation problem. The new optimisation problem is:

$$\text{Minimise } \frac{1}{2} w^T w + C \sum_i \epsilon_i \text{ and for all } \{(x_i, y_i)\}, y_i (w^T \cdot x_i + b) \geq 1 - \epsilon_i \quad (15)$$

where the parameter C is the regularisation term, ϵ_i is the slack variable and non-zero ϵ_i allows x_i to not meet the margin requirement at a cost proportional to value of ϵ_i . The linear SVM classifier solution in (14) depends on the dot product. By using a function $K(x_i, x_j) = x_i^T x_j$, the equation (14) can be modified as:

$$f_{w,b}(x) = \text{sgn}(\sum_i \alpha_i y_i K(x_i, x) + b) \quad (16)$$

The original data points can be mapped into a higher dimension space via some transformation $\Phi: x \rightarrow \phi(x)$. Then dot product become $\phi(x_i)^T \phi(x_j)$. Therefore, by using a proper transformations (kernels) the solution in (14) can be solved efficiently. With this kernel trick, the solution can be extended to nonlinear classification also. A kernel function K is such a function that related to a dot product in some extended feature space. The radial basic function (RBF) kernel [12-14] is used in this study. An RBF is equivalent to mapping the data into an infinite dimensional Hilbert space, which is defined as

$$K(\mathbf{x}, \mathbf{z}) = e^{-(\mathbf{x}-\mathbf{z})^2/(2\sigma^2)} \quad (17)$$

where σ is a constant and $(\mathbf{x} - \mathbf{z})^2$ is the squared Euclidian distance between two feature vectors.

3. Experimental setup and results

3.1 The experimental setup

Experimental results are used to validate the proposed algorithm. Figure. 5 shows the experimental setup used to collect the data. There are two 400V, 2.5 kW, 375 rpm, 16 poles PMSMs which are directly coupled each other. One motor is used as the test motor, and another one is used as the load motor. The load motor is connected to a resistor bank. The vibration sensor is located on top of the bearing housing of test PMSM.

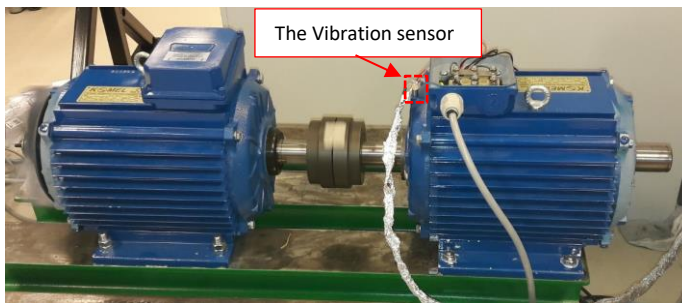


Figure 5. The experimental setup

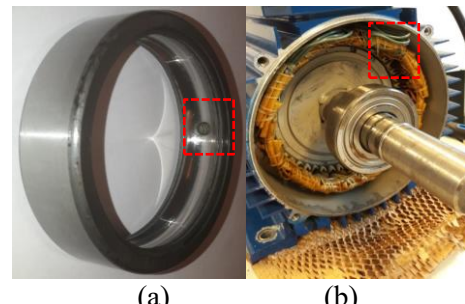


Figure 6. Faulty components (a) outer race bearing fault (b) stator winding fault

Manually seeded faults are introduced for the bearing and the stator winding. The seeded faulty components of the PMSM are given in Figure 6. The faults are tested at constant speeds (150, 250 and 350 rpm) and 2 types of variable speed profiles. A variable speed profile of 120 seconds used in the study is given in Figure 7. 10 repeated testes have been conducted with this speed profile. Therefore, 50 samples of 2-minute data are recorded. Both vibration and current signals have been collected at the 20 kHz sampling rate. After making the order normalisation, the number of samples per 2-minute signal is approximately 360. This value is selected by balancing both order and time resolutions. Finally, a table of 18000 sample rows and 9 columns (8 features and the health class label) have been generated, and the proposed algorithm is used to generate features. Then 75% of available data in the table is used to train the SVM algorithm, and 25% data is used to validate the algorithm.

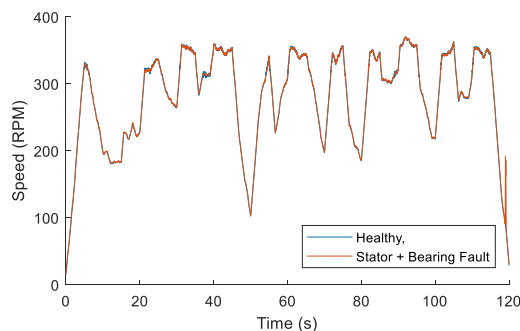


Figure 7. The variable speed profile used in experiments

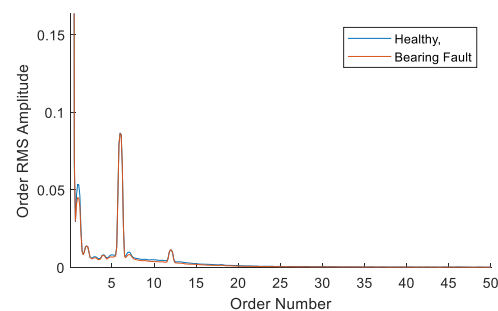


Figure 8. Average i_p order spectrum

3.2 Order normalized spectrum and order tracking for a bearing outer-race fault

The average i_p order spectrum is given in Figure 8. There is no any significant difference of the i_p order spectrum in healthy and fault cases. Figure 9 shows the average order spectrum of the vibration signals in the healthy and faulty conditions, where 3.05X order and its 2nd harmonic (6.1X) has a significant increase when the outer-race bearing fault is present. The tracked 3.05X frequency component over time is given in Figure 10 where the instantaneous amplitude is varying over time due to variable speed, load and noise conditions. Therefore, a simple decision based on threshold values will not work well and may produce many false or missing alarms. Therefore, a machine learning or statistical detection method is required and, in this work the SVM algorithm is trained to detect these variations.

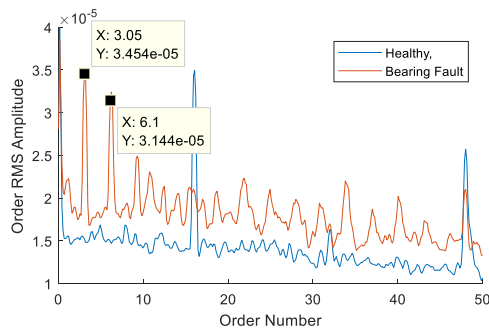


Figure 9. Average vibration order spectrum

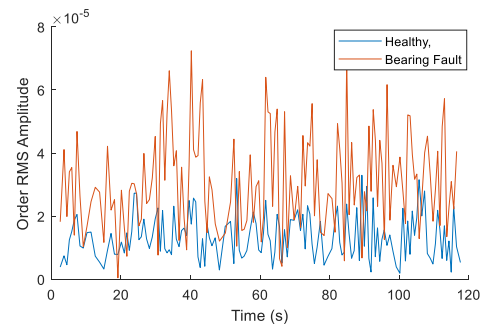


Figure 10. Tracked 3.05X order

3.3 Order normalized FFT and order tracking for stator winding fault

The average i_p order spectrum is given in Figure 11, where there is a significant increase in the 2nd and 4th orders with a stator winding fault over healthy case. Figure 12 shows the tracked 2nd order from the i_p spectrum over time, and which shows a clear variation for variable speed, load and noise over the healthy case. In the average vibration order spectrum given in Figure 13, the 16th order shows a significant increase for stator winding fault. When this 16th order is tracked over time a significant increase of instantaneous amplitudes can be seen from Figure 14. The 8th order has a similar behaviour. Therefore, both current and vibration information are useful for detecting stator winding faults.

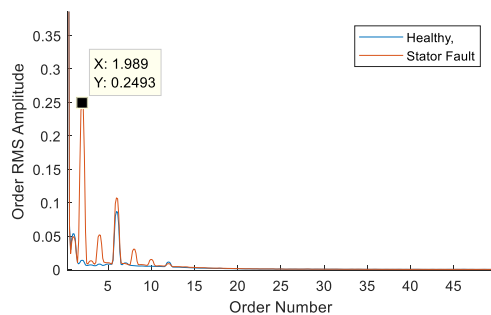


Figure 11. Average i_p order spectrum

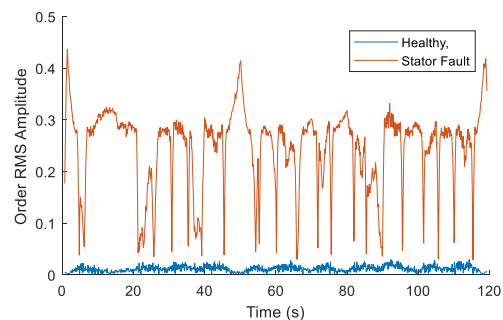


Figure 12. Tracked 2nd order

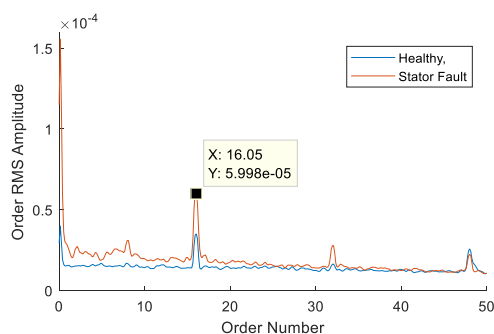


Figure 13. Average vibration order spectrum

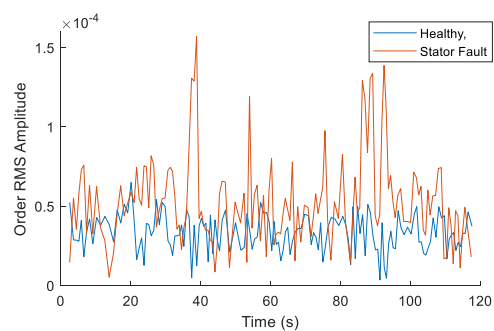


Figure 14. Tracked 16.05 order

3.4 Order normalized FFT and order tracking for stator winding and bearing outer-race fault

The analysis conducted in previous sections is focused on individual fault cases. In this section, the order spectrums are applied to multiple fault cases where both stator winding and bearing faults occur.

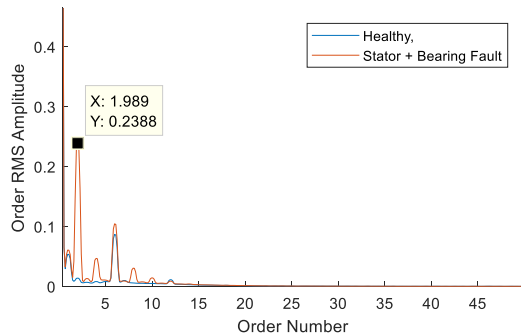


Figure 15. Average i_p order spectrum

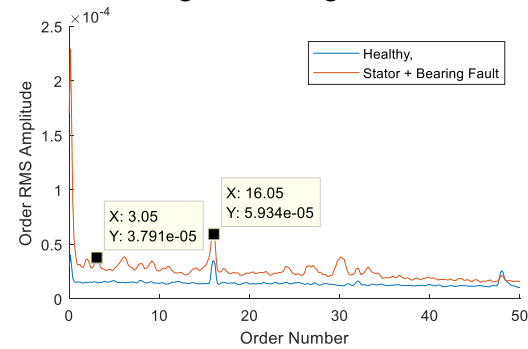


Figure 16. Average vibration order spectrum

The average i_p order spectrum is shown in Figure 15 where only the 2nd and 4th orders of the supply frequency have significantly increased amplitudes when both faults exist. This is mostly like the individual stator winding fault since only the stator winding fault related information can be found. However, the average vibration spectrum in Figure 16 shows both the bearing fault related characteristic order of 3.05X and the stator winding fault related order at 16X. These results show that it is possible to detect multiple faults and individual faults from the same order tracking method discussed in the previous Sections for individual faults.

3.5 Performance SVM classification algorithm

The confusion matrix for validating dataset is given in Figure 17. Four fault classes are predicted by SVM namely HB (Stator winding healthy and bearing fault), HH (both stator winding and bearing are healthy), SB (both stator winding and bearing are defective) and SH (stator winding is faulty and bearing is healthy). The overall accuracy of the SVM classifier is about 92.9%. For all the fault classes more than 90% classification accuracy is obtained and the highest classification accuracy is 94%. These results are highly acceptable, and the SVM can detect and classify considered two faults in variable speed and load conditions.

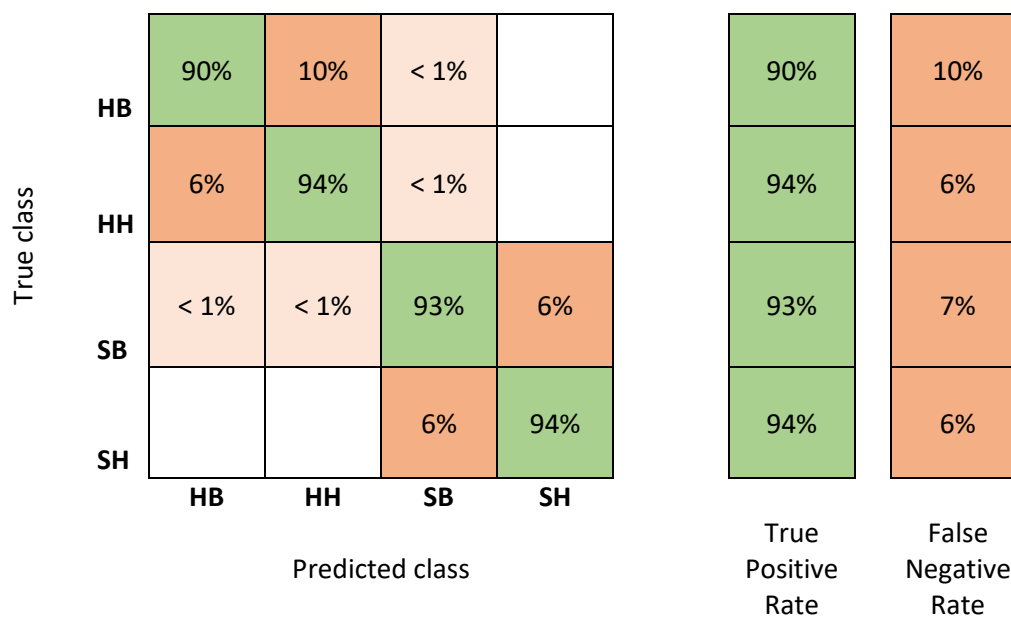


Figure 17. The confusion matrix for the test dataset

4. Conclusion

In this paper, a fault classifier is introduced for fault diagnosis of PMSMs in variable speed and load conditions. Features for the fault classification are produced based on the resampled vibration, current signals and estimated torque and speed. The fault detection and classification are implemented by a supervised machine learning algorithm, namely Support Vector Machine. The proposed method is validated by variable speed experimental data, and excellent performances have been obtained. Following contributions are provided in this study;

- (1) The proposed method is based on estimated rotor speeds and separate speed sensor is not required. In PMSMs, the rotor speed can be accurately estimated using the measured current signals.
- (2) In a real wind turbine, the generator is also vibrating on a flexible frame. This vibration can be very different depending on the operating conditions. However, in proposed method, only the fault related characteristic frequency bands of vibration signal are considered for fault diagnosis purpose and other parts of the signals are neglected. Also, current signal may not affect much by additional vibration and the feature level fusion method can give a robust result.

Therefore, the proposed method can be implemented in wind turbines and other similar industrial applications. In this study, only two types of individual faults and one multiple fault cases are considered. However, the proposed method can be extended to other types of faults in both motoring and generating operations.

References

- [1] Norton M and Karczub D 2003 *Fundamentals of Noise and Vibration Analysis for Engineers* (Cambridge: Cambridge University Press)
- [2] Nandi S, Toliyat H. A, and Li X 2005 Condition monitoring and fault diagnosis of electrical motors-a review *IEEE Trans. on Energy Conversion* **20** 719-29
- [3] Senanayaka J S L et al 2017 Towards online bearing fault detection using envelope analysis of vibration signal and decision tree classification algorithm *2017 20th International Conference on Electrical Machines and Systems* (Sydney: NSW) pp. 1-6
- [4] Senanayaka J S L et al 2015 Sliding-mode observer based sensorless control of a small wind energy conversion system *Recent Advances in Sliding Mode (RASM) 2015 Int. Workshop* (Istanbul: Turkey) pp 1-6
- [5] Baccigalupi A and Annalisa A 2016 The Huang Hilbert Transform for evaluating the instantaneous frequency evolution of transient signals in non-linear systems *Measurement* **86** 1-13
- [6] Justice J 1979 Analytic signal processing in music computation *IEEE Trans. on Acoustics Speech and Signal Processing* **27** 670-84
- [7] Brandt A 2011 *Noise and Vibration Analysis: Signal Analysis and Experimental Procedures* (Chichester UK: John Wiley and Sons)
- [8] Blough J 1998 *Improving the analysis of operating data on rotating automotive components PhD Thesis* (USA: College of Engineering University of Cincinnati)
- [9] Kinnunen J et al. 2006 Analysis of directly network connected non-salient pole permanent magnet synchronous machines in *Proc. Int. Symp. Ind. Elect.* (Montreal: Canada) pp 2217–2222
- [10] Cardoso A M, Cruz S and Fonseca D 1999 Inter-turn stator winding fault diagnosis in three-phase induction motors by Park's vector approach *IEEE Trans. Energy Conversion* **14** 595-98
- [11] Senanayaka J S L et al 2017 Early detection and classification of bearing faults using support vector machine algorithm *IEEE Workshop on Electrical Machines Design, Control and Diagnosis* (Nottingham,UK) pp 250-255
- [12] Manning C D et al 2008 *Introduction to Information Retrieval* (Cambridge university press)
- [13] Vapnik, V 1998 *The nature of Statistical Learning Theory* (New York: Wiley)
- [14] Scholkopf B et al 1997 Comparing support vector machines with Gaussian kernels to radial basis function classifiers *IEEE Trans. on Signal Processing* **45** 2758-65