Condition Monitoring of Brushless DC Motors with Non-Stationary Dynamic Conditions

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Abstract—This work introduces a new multi-sensor measurement framework for condition monitoring of brushless DC motors (BLDCM) with bearings. An experimental platform for equipment health monitoring is used for producing different faults on BLDCMs and log the measurement data. This work is oriented to maximize the life-cycle of industrial machinery and prevent catastrophic failures and their environmental consequences through reliable behavior classification. A public benchmark data set containing key failure scenarios is being built based on this work. This data set will be unique with respect to other available data sets due to the different sensors used and include more extensive scenarios such as non-stationary (time varying) conditions. A BLDCM with a bearing is tested under non-stationary conditions, and the scenario for their failure is developed. Supervised learning classifiers such as back propagation neural network and support vector machine are used to identify the fault state in the equipment.

Index Terms - Multi-sensor Measurements, Condition Monitoring, Signal Processing, Brushless DC Motors

I. INTRODUCTION

Safety standards, asset optimization and environment protection are some of the main reasons for preventing failures in industrial machinery. Catastrophic failures on electromechanical equipment have significant consequences that could be avoided if effective predictive maintenance could be implemented. Condition Based Maintenance (CBM), which is based when the failure has occurred, is not sufficient to address these concerns. A field with growing relevance to address them is prognosis, an statistical and signal analysis approach to deliver effective predictive maintenance.

Due to the ubiquity of rotatory machinery across several industries it is common to find electrical motors failing under particular applications caused by external conditions and fatigue. Our research uses an experimental platform designed for simulating different testing scenarios as described in [1] and presented in Figures 1 and 3. Brushless DC motors are proposed as the one in Figure 2 due to their multi-phase similarity to AC induction motors. This is done while safety concerns were addressed by operating with DC for compliance with the Workplace Health and Safety (WHS) standards.

Part of the main constraints for the progress of prognosis research is the lack of reliable data sets that demonstrate the performance of machinery working under different conditions. Some data sets for predictive maintenance are publicly available such as the NASA IGBT Accelerated Aging Data Set [2] and the CMAPS Data Set [3]. However, as other public data sets, these are not detailed enough or do not specify degradation parameters appropriately to replicate the testing settings. Our work is aimed to test equipment under well defined testing settings and validate the conditions under which failure happens. We refer to non-stationary dynamic conditions to those physical settings such as rotating speed and external forces that are applied on the BLDCM and mechanical components of our platform. Moreover, a more precise tracking of the equipment behavior can be achieved by using a multi-sensor measurement system. As a result, a benchmark data set is built from the testing measurements of this work.

In addition to specify well defined testing conditions this paper discusses recent relevant research towards signal processing and analysis for failure identification. The upcoming sections discuss the related work, experiment design and results.
II. RELATED WORK

Bearing related cases are the most frequent causes for failure in BLDCMs [4]. Different methods for signature extraction and analysis are discussed in [5]. In that work signature extraction based on the magnetic flux density $\Phi$ is used to detect variations, which are due to the arise of a mechanical fault linked with the bearings. Therefore, potential failures can be predicted based on monitoring $\Phi$. Stator current signature analysis is proposed by [6] to detect faults in induction motors and bearings. Similarly, the monitoring of phase-currents can be used to detect turn to turn failures caused by heating as the turns drastically modify their resistance when they overheat and lead to a turn to turn shortcut [5]. Our work inspired in these cases uses signal analysis to evaluate faults that can be derived from different causes in the BLDCMs and bearings.

Cost effective techniques for estimating different failures such as bearing related ones are proposed by [7]. Rotor bearing tests FFTs are used in their research to detect harmonics in the current caused by unbalanced loads and misalignments on the shaft of the motor. Then, the current rms increases with the magnitude of the angular and linear shaft deviation. With respect to insulation faults, some derived from heat, artificial neural networks (ANN) are fed with measurements of the voltage and current for the detection of stator insulation faults. However, the learning of the ANN like in [8] might be based on stationary conditions in order to discriminate from the inherent electrical measurements representing a constraint. Therefore, when the physical conditions change over time some of these algorithms are no longer accurate. Conversely, we propose to evaluate fault leading behaviors with time varying conditions such as rotating speed and load.

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Fig. 3: Main components and connections of testing platform.
Monitoring of load and bearing faults in BLDCMs operating under time invariant (stationary) and time variant (non-stationary) conditions are discussed by [9]. Their work shows how it is possible to detect faults in electromechanical devices by monitoring their voltage and current, this in contrast to vibration-based diagnostics that requires expensive equipment as dedicated accelerometers. Moreover, current-based detection techniques available to detect rotor faults in transient (non-stationary) operating conditions are discussed. In order to address the case of non-stationary temporal conditions, [9] uses different signal analysis algorithms such as time frequency methods, Hidden Markov Models (HMMs) and time-series methods. Different metrics such as quantifying the rms are proposed to aid in fault detection, which defines the direction of our work in selecting some particular features from the acquired signals.

The challenges of time variant conditions are addressed by [10] and presents different methods for signal analysis based on frequency sidebands, harmonics and rms vibration among others. Further bearing testing scenarios with time variant conditions are discussed in [11] to build this handful data set for prognostics research. The framework for monitoring failures based on phase voltage and current measurements with spectral analysis is correlated with multi-sensor data such as vibrations and noise. This has led our work to extend the failure identification with different sensors.

III. EXPERIMENT DESIGN

In this section the testing apparatus described in [1] is used. Figures 1 and 2 show the diagram of the testing platform mechanical components and the motor to be used for the multi-sensor testing. The multi-sensor measurements are meant to be correlated with the failures of the monitored BLDCM and bearing. The motor under test is a 17.5 turn BLDCM manufactured with hall sensor by Turnigy TrackStar. Moreover, the platform was conceived for non-invasive measurement techniques allowing quick motor replacement without unnecessary sensor reconfiguration. This ensures the extensibility of the platform to more complex testing scenarios. This setup was also designed to be used with minimal customization and easy to use. As shown in Figure 1, there is a force load cell which is in charge of measuring the perpendicular force applied on the shaft of motor for bearing testing. This testing takes place in the upcoming experiment. The main goal is to detect signatures on the signals that intensify over time (non-stationary). In this case, the force applied varies (which is the one applied perpendicular to the shaft of the motor).

Figure 3 shows the main components of this testing platform and Figure 4 presents our data processing scheme for fault identification, which is described in the upcoming sections.

The different sensors that compose this measurement system are incorporated into a data acquisition system to allow the user to focus maximum effort on data analysis instead of signal conditioning and acquisition. The sensing data was composed of 18 channels including voltages of each of the phases with respect to GND (3), and with respect to each other (3); shunt resistors for the current through each phase (3); microphone for sound (1); RTD for temperature (1); strain gage for torque (1); accelerometer for vibrations in X,Y and Z (3); hall sensor for motor speed (1); sensor for power supply (1); load cell for perpendicular force applied on bearings (1). A summarized list of the used equipment consists in:

- NI PXIe chassis and modules
- Maxon Motor controller
- NSK 10 mm bearing of 7 balls
- Electronic load
- Three dimensional accelerometer
- Microphone
- RTD unit
- Tension and compression load cell
- Printed Circuit Board (PCB)
- Reaction torque sensor
- Miscellaneous
- Custom made holder for Bearing
- Brushless DC generator

A. Bearing test

The bearing fault testing consists in monitoring the operation for increasing the perpendicular force while performing accelerated wear from the stresses on the raceways of the bearing.

The current software and hardware platform allows the control of 3 variables, which are the desired rotational speed in revolutions per minute (RPMs), the axial load to apply to the motors and the perpendicular force on the bearing. By increasing the perpendicular force with respect to time it is achieved a non-stationary testing scenario for the motor. For future use, additional motors of the same model have been allocated to perform further tests. These tests results compose the data set to be available.
B. Fault classification

In order to validate the contribution of the data set been built, several BLDCMs like the one in Figure 2 were put under test. Five BLDCMs were used (one per test) to generate several sets of data. With an increasing perpendicular force on the bearings at a rotating speed of 2000 RPMs, the bearings were led to failure.

The raw data from the 18 different sensors acquired at a high sample rate has to be pre-processed before been used for fault classification. Software-based second-order butterworth filters were implemented on measurements. To remove the effects of the BLDCM driver switching at 50kHz [12] a 10 kHz cut-off was used for the voltage and current measurements. With respect to the vibration channels a 2kHz-10kHz band pass filter was used according to the bearing vibration energy content [13]. Feature extraction is proposed to determine relevant content of the signal with respect to failure detection. The features to be used are the rms, the kurtosis and the mean value of the 18 channels that compose the measurement logged data.

By applying spectral analysis on each of the phase current signals, it can be seen on Figure 5 that there was a noticeable change on the motor behavior before and after failure. A similar test was performed to measure the average rms of the signals as a reference of the health of the motor. It was found that most of the mentioned features (kurtosis and mean value and rms) of each of the sensor signals reflect variations after the failure with respect to their original values.

The following stage is to feed with the extracted features a classifier such as an artificial neural network (ANN) or a support vector machine (SVM). A parameter vector to feed the classifiers is defined as $s = s_1, s_2, ..., s_m$ where $s_n$ is a parameter derived from the multi-sensor instrumentation setup. Given the available sampling data from the current data set, it is proposed to use these supervised learning classifiers, with primarily 2 class labels: healthy behavior and faulty behavior. Off-line learning will take place first to explore the data and then the classifier would be used for failure detection.

A back-propagation artificial neural network is used to classify the health condition based on the collected data sets. The fact that reliably it was possible to estimate the force on bearings and motor speed through the load and hall sensors respectively, allowed to ensure that time varying conditions were taken into account. ANNs are based on empirical risk minimization which is centred on the content of the data to model non-linear functions. An ANN is found to work efficiently to model non-linear functions by using a non-linear activation function of the sum of several weighted inputs:

$$c_m = \vartheta \left(\sum_{i=1}^{n} w_i a_i\right),$$

(1)

where $n$ is the number of inputs, $w_i$ is the weight for input $a_i$ and the sum determine which class $c_m$ is triggered or identified. The backpropagation algorithm then is in charge of updating the weights $w_i$ iteratively by computing the derivative $\vartheta$ and a non-linear activation function like the logistic regression:

$$c_m = \frac{1}{1 + e^{-z}}.$$  

(2)

A different classifier is the support vector machine (SVM). The SVM is an statistical classifier developed to model accurately high dimensional data and non-linear functions. Different from other classifiers used in bearings and gears prognostics such as ANNs, the SVM is based on structural risk minimization. This prevents the SVM from being over trained from the data and generalize functions more accurately than ANNs. For this research the SVM is used as a two class classifier, representing the faulty case of the equipment and
the healthy case. Starting with a training set of class-labelled data \((x_i, y_i)\), \(i = 1, \ldots, l\), with training vectors \(x_i \in \mathbb{R}^n\) and the class label \(y_i \in \{1, -1\}\), it is required to optimize the problem:

\[
x_{\text{new}} = \min_{w, b, \xi} w^T w + C \sum_{i=1}^{l} \xi_i,
\]

subject to

\[
y_i (w^T \phi(x_i) + b) \geq 1 - \xi_i, \quad \xi_i \geq 0,
\]

where \(\phi\) is function that maps \(x\) into a higher dimensional space. The solution is a separating hyperplane that divides the classes and \(C\) is a penalty parameter. The SVM has been used in diverse fault diagnostic cases as presented by [14].

These classification methods are used in the failure detection process described in Figure 4. The process can be applied on several models besides the back-propagation ANN and SVM classifiers. This method can be extended to detect failures under other non-parametric models and unsupervised learning for non-labelled training data.

IV. EXPERIMENTS

A. Testing Conditions

The testing of the BLDCM consisted in reproducing a bearing fault and contrast the motor behavior before and after the fault. The rotational speed and axial load (from the E-Load) were kept constant (2000 RPMs and 0, respectively), while increasing the perpendicular force in the experiment. By monitoring the current on each of the phases, it is expected to observe a change on their frequency components due to the occurrence of a failure.

Regarding sampling rate, previous documentation on similar settings define a suggested maximum time period of 10ms to apply actions before the propagation of a failure [15] derived from heat transfer that can damage electronic equipment. Therefore, it was decided to use the maximum sampling rate that can be supported by the hardware in order to prevent any failure propagation. The maximum sampling rate supported by the data acquisition modules for each of the insulated voltage channels is 51000 samples/s. Hence, for plotting analysis and convenience the sampling rate for the experiments was defined to be 50000 samples/s., this while having the motor rotating at 2000 RPM.

A bearing test was performed by sampling data at the mentioned rotating speed and sampling rate. The bearing attached to the BLDCM was led to fail after increasing the perpendicular force on the gradually up to 460 Newtons. This force was measured by the load cell shown in Figure 1. Figure 6 shows the main measurements performed on each of the 18 sampling channels of 4.5 hours or 510 minutes of testing leading to the bearing failure. The rms of the perpendicular force value reflects how the perpendicular force on the bearings was increased from 360 N. to 464 N. Then at the end, after approximately 480 minutes of testing, the bearing failed and the speed shown by the Hall sensor channel decreased from 33.3 to 18 revolutions per second: decreasing the torque, sound pressure and vibration measured by the accelerometer; but still increasing the temperature and current on each phase.

B. Failure discrimination

In order to validate the usability of the multi-sensor setup, several tests for failure detection were performed. By extracting the mentioned features (rms, kurtosis and mean values) of

<table>
<thead>
<tr>
<th>TABLE I: Measurements for failure discrimination</th>
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<tbody>
<tr>
<td>Feature</td>
</tr>
<tr>
<td>Perpendicular force</td>
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<tr>
<td>Hall sensor (speed)</td>
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<tr>
<td>Voltage PhaseA-Ground</td>
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<tr>
<td>Voltage PhaseB-Ground</td>
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<tr>
<td>Voltage PhaseC-Ground</td>
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<td>Current PhaseA</td>
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<td>Current PhaseB</td>
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<td>Voltage PhaseA-B</td>
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<td>Voltage PhaseC-A</td>
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<td>Torque</td>
</tr>
<tr>
<td>Sound Pressure</td>
</tr>
<tr>
<td>Temperature</td>
</tr>
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<tr>
<td>Vibration-X</td>
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<tr>
<td>Vibration-Y</td>
</tr>
<tr>
<td>Vibration-Z</td>
</tr>
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</table>
the data acquired, three data sets, subsets of our main data set, were generated as identified in Table I.

A feature vector was defined as \( s = s_1, s_2, \ldots, s_n \) where \( s_n \) is a parameter derived from the multi-sensor instrumentation setup. The vector is composed of the rms, kurtosis and mean values computed over 8192 data points of each signal. The vectors then feed the ANN and SVM classifiers with primarily 2 target classes: healthy and faulty. Off-line learning was used to analyse the data and then the classifiers were used to perform the fault identification. For the ANN the training stop criterion consisted on reaching a mean square error of \( 10^{-6} \) reached before 4000 training iterations. The SVM was based on a Gaussian kernel.

The generated data sets were to be used by the classifier to identify the health condition of the equipment as shown in Table II. \( T1 \) includes only the essential perpendicular force, speed, voltage and current channels that have been used in previous testing scenarios [7]; \( T2 \) includes the \( T1 \) plus the torque, sound pressure and temperature values next to the bearing; and \( T3 \) includes \( T2 \) plus the power supply of the sensors and the vibration in X, Y and Z measured by the accelerometer next to the bearing. Since each data set is a subset of the others they differ in the amount of channels but have the same length of parameter vectors, 300 for each motor tested over 4.5 hours. With a time varying perpendicular force on the bearings at a rotating speed of 2000 RPMs, five tests leading each to a bearing failure with a BLDCM took place.

A classification test was performed using the data set of another failed BLDCM with a healthy and faulty bearing. The experiment was repeated five times using different training and testing data vectors. By inputting several testing feature \( s_k \) vectors form this data set it was achieved different degrees of classification accuracies. This can be seen on Table II. For the accuracy of the classification it was more determinant the amount of channels employed than the length of the data set to discriminate whether it is a faulty or non-faulty behavior. For both the ANN and the SVM adding more vectors and channels in the shown order allowed higher classification accuracy and lower classification variance. These results demonstrate the inherent value of the multi-sensor data obtained from the testing platform for reliable failure detection.

### V. SUMMARY AND FUTURE WORK

This paper presents a summary of this novel approach using a multi-sensor data acquisition platform for predictive maintenance. Different testing conditions have been discussed. Under well defined sampling conditions and spectral components it was possible to quantify the behavior of a BLDCM with a bearing before and after failure. Failure discrimination using two different supervised learning classifiers was improved with the addition of more sensing channels. The failure identification was more reliably by using features such as rms, mean value and kurtosis. Therefore, the multi-sensor data set derived from this work will contribute significantly towards new models for failure prediction of BLDCM equipment. Future work involves reproducing gears and stator failures. More details of the project can be found on http://www-personal.acfr.usyd.edu.au/zubizarreta/index.html. In addition, dimensionality reduction and feature selection will be addressed to improved the performance of the classifiers.

### ACKNOWLEDGMENTS

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### REFERENCES


<table>
<thead>
<tr>
<th>Classifier</th>
<th>Test</th>
<th>Data Vectors</th>
<th>Classification Accuracy</th>
<th>Variance</th>
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<td></td>
<td>T2</td>
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<tr>
<td></td>
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<tr>
<td></td>
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<tr>
<td></td>
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<tr>
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<tr>
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