A Data Mining based Approach for Electric Motor Anomaly Detection Applied on Vibration Data

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***Abstract*—**

In many industrial settings, a significant amount of data is generated from electromechanical systems and stored, without processing to gain valuable insights that could enable optimised production while bringing down maintenance cost to its barest minimum. Data mining techniques offer potential solutions to address this concern. In this paper, anomaly detection techniques using machine learning models such as K-Nearest Neighbour (KNN), Support Vector Regression (SVR) and Random Forest (RF) have been applied to vibration sensor data for early fault detection of industrial electric motors. The models relied on vibration data collected from sensors mounted on four bearings. Initial results suggest that the RF model outperformed SVR and KNN for the data set analysed, and can be a candidate data mining technology to implement for condition monitoring of electromechanical systems.

Keywords*— *Vibration Analysis, condition monitoring, anomaly detection, Fault Detection

I. INTRODUCTION

The increasing overlap between information technologies (IT) and operational technologies (OT), computing is playing a significant role in the development of advanced sensors installed in industrial settings. Data mining techniques form the backbone for the operational functionality of these sensors', which are deployed for performance monitoring of electromechanical systems [1] [2].

Electromechanical systems are processes and machines that consist of electrical and mechanical components. They convert electrical energy into mechanical movements and sometimes vice versa. Designing a complex electromechanical system can take time, and the cost of maintenance of these systems are high [3]. Paper [4], classified the costs of production failure to a company into two categories, namely intervention and downtime cost. The intervention cost includes labour and material; while the downtime cost includes the production cost and other consequential costs such as loss in raw materials, reduced production quantity and quality, and finding alternative production lines. The savings that can be accrued in preventing a system failure/breakdown are enormous. The commonly adopted traditional maintenance strategy are either preventive or reactive maintenance.

The preventive maintenance requirement is a time-based maintenance strategy, where components are replaced according to standard mechanical wear as a function of operating time. This approach cannot predict the future condition of a critical component where repair may be necessary to preserve equipment lifespan [6]. Reactive maintenance is based on the catastrophic breakdown of the machines [5]. This maintenance strategy can be expensive and prone to human error. Thus, the deployment of an automated early fault detection system will reduce plant downtime and maintenance cost by preventing unexpected breakdowns.

Vibration data analysis is commonly used for early fault detection in machines as they provide rich information regarding the health status of many industrial machines. Some of the techniques applied to analyse vibration data include Fast Fourier Transform [7], envelope spectrum [8] and Support Vector Machine (SVM) [9].

This paper utilised anomaly detection techniques to identify bearing faults of an industrial electric motor. It relies on features extracted from four vibration sensors attached to the bearing.

This paper is divided into 6 sections. Section II describes related work; Section III and IV presents the experimental setup and the research methodology, respectively. The results and analysis are presented in section V and the conclusion in section VI.

II. PREVIOUS WORK

Many machine condition monitoring studies often consider the implementation of either supervised or unsupervised learning methods to address the drawbacks of traditional maintenance strategies – preventive and reactive [10],[11], [12].

Supervised learning fault detection approach often requires large historical data sets which is labelled, i.e. healthy machine condition data are annotated from the faulty condition data. For this approach, the assumption is that such data sets contain every possible fault characteristic [13]. Although this is not the case in many industrial environments [14], in a scenario, where it is challenging to gather large historical and representative data, an option may be to simulate fault conditions [15]. However, it may not be feasible to model every possible fault characteristics

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of an industrial equipment accurately. Often, there is a shortage of faulty machine data samples, whereas healthy example data are readily available [14]. This data disparity may present a performance problem for many machine learning classifiers. Hence, it becomes beneficial to adopt an appropriate learning approach such as anomaly detection, that can be modelled using only healthy machine data samples.

Moreso, unsupervised learning can address some of the limitations of the supervised learning approach [16]. Unsupervised techniques do not require data to be labelled, instead learns from an unlabelled data set.

Anomaly detection techniques are mostly used where anomalies in the data are rare, and there is a significant difference in its inherent behaviour as compared to those that are considered the norms. The objective of this process is to find patterns in data that do not conform to the healthy (normal) machine condition. The commonly used anomaly detection techniques include the one-class support vector machine, K-means, Self-organizing Maps (SOM) [17].

According to [18], most fault defects in rotating motors will show a distinct vibration pattern; hence, they can be detected by using vibration signature analysis techniques. The authors analysed the vibration signature of multiple devices that included a Direct Current (DC) Motor. The signature of the DC motor with no load showed a maximum dominant frequency of 422 Hz with all its energy centred at 70 Hz. When load was applied, the dominant frequency decreased to 66 Hz. The dominant frequency further reduced to 25 Hz when a more significant load was placed on the shaft of the motor to cause an out-of-balance scenario resulting in increased vibration amplitude. Another study [19], used temperature and vibration data of a DC motor collected from a controlled laboratory environment to train an Artificial Neural Network (ANN). They combined various parameters from two neutral network paradigms: Dynamic Neural Network (DNN) model and Non-Linear Autoregressive Neural system (NARX).

A condition-based monitoring system called MPROS (Machinery Prognostics/Diagnostics System) was developed for the US Navy by The DLI Engineering Corporation [20]. The goal of the system was to accurately evaluate system conditions, detect/identify fault severity, and predict the machine's remaining life under various operating states. The system integrates data from vibration, motor current, wear particle analysis and other sensors such as temperature and pressure for online prognostic/diagnostic. Data analysis techniques such as state-based future recognition, neural networks, signal processing (e.g. wavelet and Fast Fourier Transform (FFT)) were applied to process the data from the multiple systems.

The authors [8], compared various data analysis techniques to find the most suitable for detecting oil whip vibration faults. The data analysis techniques include Short-Time Fourier transform (STFT), Wigner–Ville Distribution (WVD), Wavelet Transform (WT) and Hilbert–Huang Transform (HHT). The HHT time-frequency was the most effective tool in diagnosing faults of rotational machines (non-stationary and non-linear) as it can detect components of low energy, and it displayed distinct time-frequency distributions.

This paper presents a simplified approach for early fault detection that is computationally efficient when deployed in real-world industrial applications. This study examines the performance of Support Vector Regression (SVR), Random Forest Tree and K-Nearest Neighbour (KNN) for anomaly detection in electric motor vibration data.

III. Experimental setup and Data overview (Test Rig Setup)

The architecture is based on the concept that measuring and monitoring the changes in energy consumption and vibration levels in real-time would detect faults in their early stages of development. It could support better scheduling of emergency and maintenance work, as well as potentially avoid sudden catastrophic breakdowns. Failure of any of the bearing in an industrial setting can cause a complete stop of production and loss of revenue. The experiment consists of four bearings (Rexnord ZA-2115 double row bearings) attached to a shaft, as shown in Fig. 1. The bearings were run at a constant speed of 2000RPM by an AC motor coupled to the shaft via rub belts. The four bearings were force lubricated, and a radial load of 6000 lbs was applied by a spring mechanism unto the shaft [4]. Vibration sensors (High Sensitivity Quartz ICP) were placed on the bearing housing, as shown in Fig. 1. The failure on bearing 3 occurred after exceeding designed lifetime, which is more than 100 million revolutions.

The dataset describes a test-to-failure experiment. This paper used the 4th (Also, Set No. 3) bearing failure test, which consists of 4,448 files. The test ran for 45 days and an extra 02:42 hours until the bearing failed. Individual files consist of a 1-second vibration signal snapshots recorded at the 10-minute interval; which is approximately 20,480 data points collected at a sampling rate of 20 kHz. The National Instrument DAQ card 6062E facilitated the data acquisition. An outer race failure occurred in bearing 3 at the end of the test-to-failure experiment.

As outlined in the related work section, various data analysis techniques have been applied for processing vibration data. However, this paper proposes an anomaly detection methodology which relies on optimised features extracted from the bearing vibration data, enabling a more computationally efficient system performance.

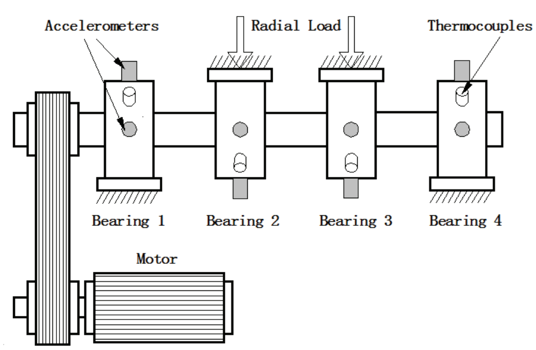

Fig. 1: Bearing test rig and sensor placement illustration [21]

A. Feature Extraction

Raw sensor data are prone to noise; hence additional pre-processing is required to reduce the effect of noise. The assumption is that the bearing degradation gradually evolved; therefore, each of the 4,448 files can be considered a 1-second window for statistical features extraction. Using this approach 6 features per bearing are generated, consisting of the standard deviation, variance, skewness, kurtosis, minimum and maximum sensor reading for each window (20,480 data point). A total of 24 features was generated for the 4 bearings. The extracted statistical features for kurtosis and skewness are shown in Fig. 2 and Fig. 3, respectively. As shown in the figures, there is no underlying trend until after the 44th day of the experiment when an outer race failure occurred at bearing 3. Due to the test rig setup in Fig. 1, the vibration from the faulty bearing 3 was transmitted to the healthy bearing 1, 2 and 4. These transmitted faults can be identified by the higher vibration level at bearing 3 as compared to the others, as shown in Fig. 2 and Fig. 3, respectively.

A positive kurtosis value indicates a heavier tail, a higher peak level, and a spikier profile. While, a negative kurtosis indicates a lighter tail, a lower peak level, and a flatter profile. The skewness defines the extent to which a distribution differs from a normal distribution. Care must be taken when assessing the health of the machine that the data are collected when the machine is running at a constant speed.

The threshold-based approach has been commonly used for condition monitoring in some industry. This approach requires setting a minimum or maximum threshold for individual sensors reading, and when the reading exceeds that threshold, a fault instance is considered to be present. However, this has shown to cause false alarms, which can result from the sensors inaccuracies, human error. Hence, an approach that is more robust to these limitations is required.

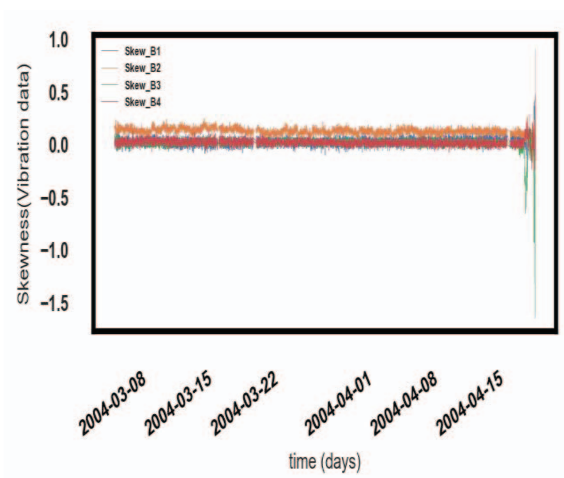

Fig. 2: Time Series Data: Skewness of Vibration

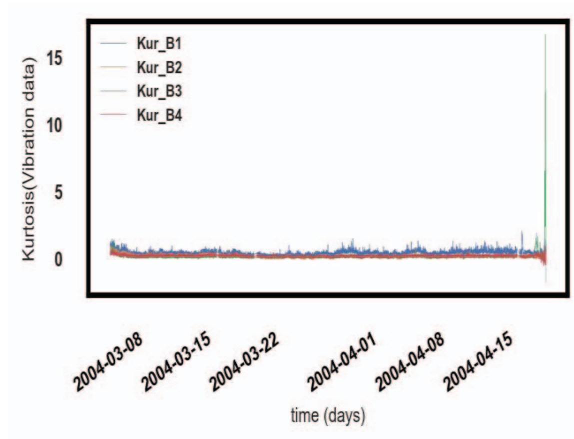

Fig. 3: Time Series Data: Kurtosis of Vibration

IV. METHODOLOGY:

The research methodology consists of the data collection/assembling, pre-processing and feature engineering, train/test data split, feature scaling, dimension reduction, modelling (applying machine learning model) and finally, the model evaluation and analysis. Fig. 4 illustrates data flow in the research methodology.

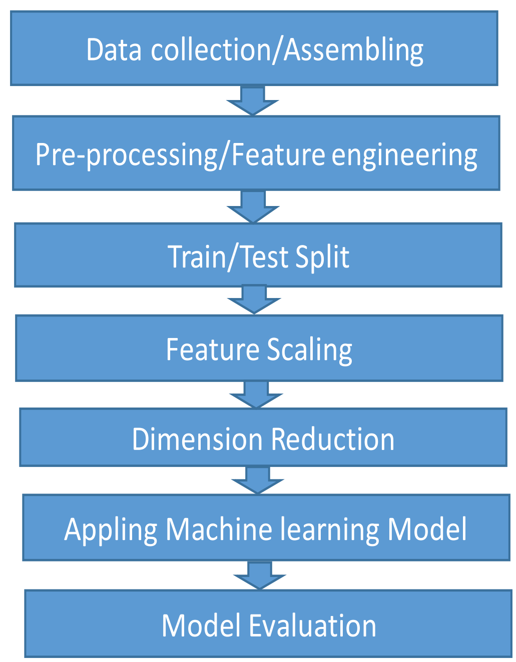

Fig. 4: Flow chart of research methodology

The extracted features from healthy time-series sample data were used to train the machine learning model. Dimension reduction using Principal Component Analysis (PCA) [22] was applied to reduce the feature from 24 to 1 dimension space. This was a much-preferred approach to averaging as it seeks a linear combination of the original variables weighted by their contribution to explaining the variance in a particular orthogonal dimension. The output from the PCA is used as an input to a regression model whose goal is to reconstruct the input variable. In the training phase, the Mean Absolute Error (MAE) of the healthy data sample and the standard deviation is computed. Using the MAE as a standalone threshold is not robust to detect anomalies, as it results in many false alarms. Hence, any input element that is more than two standard deviations from the mean (95% confidence interval) is considered an outlier/fault in the bearing. The pre-trained machine-learning model and estimated threshold using the healthy data sample were used to detect anomalies on the test data sets. The test data is considered an anomaly when the loss is greater than the estimated threshold from the healthy data sample. For this study, the training and test data split is as follows: training split: ' 04/03/2004 09:27:46':'2004-03-31 23:59:59' and the test split: '2004-03-31 23:59:59': '2004-04-18 02:42:55'.

V. RESULTS AND ANALYSIS

The computed threshold for KNN, SVR and RF model are 0.0080, 0.1740 and 0.0128, respectively. Hence, as shown in Fig. 5, Fig. 6 and Fig. 7, an input data point is considered an anomaly when the MAE reconstruction loss is higher than the threshold. The reconstruction loss and threshold are represented in the figures by a blue and red graph legend, respectively.

The bearing failure occurred on the 18/04/2004 02:42:55; thus, the three machine learning approach (KNN, SVR and random forest tree) were able to detect the bearing failure at least a day before it occurred.

The KNN model sparsely detected 7 anomalies (between 04/03/2004 12:32:46 and 04/03/2004 18:32:46) towards the start of the experiment. It also sparsely detected 4 anomalies (between 05/03/2004 03:32:46 and 15/04/2004 22:22), 11 anomalies (between 16/04/2004 01:02 and 16/04/2004 23:52) before consistently detecting the sensors data anomaly from the 17/04/2004 00:02 up until failure occurred on the 18/04/2004 02:42:55. The SVR model sparsely detected 8 anomalies (between 04/03/2004 12:42:46 and 04/03/2004 18:32:46) before consistently detecting anomalies from the 16/04/2004 23:32:55 up until the failure occurred on the 18/04/2004 02:42:55. The RF model sparely detected 2 anomalies (between 04/03/2004 12:42 and 04/03/2004 13:22) before consistently detecting all sensor data (from 16/04/2004 23:32:55 to 18/04/2004 02:42:55) as an anomaly.

High vibration level of the main gearbox was observed during start/stop of the electric motor, resulting in all three predictive models sparsely detecting anomalies at the start of the experiment. This increased vibration levels during start/stop operations is mainly due to the huge forces (much higher than nominal) generated as the machine accelerates/decelerates. This is expected for electric motors operation in many industrial settings, although a suitably sized and installed vibration damper can help to limit the vibration levels during start/stop operations.

For this study, increased vibration levels during start/stop operations are considered not to be indicative of a bearing fault. Hence, the bearing is deemed to be healthy on the start day (04/03/2004) of the experiment. The RF model is the best performing machine learning algorithm because it has the lowest false positive, as compared to SVR and KNN. SVR is the second-best followed by KNN. However, the RF and SVR model consistently detected the bearing fault 1630 minutes (translates to a day, 3 hours and 10 minutes) before it occurred. While the KNN model consistently flagged the fault, 1480 minutes (translates to a day and 40 minutes) before it occurred. This early detection will allow for better maintenance and repair schedule.

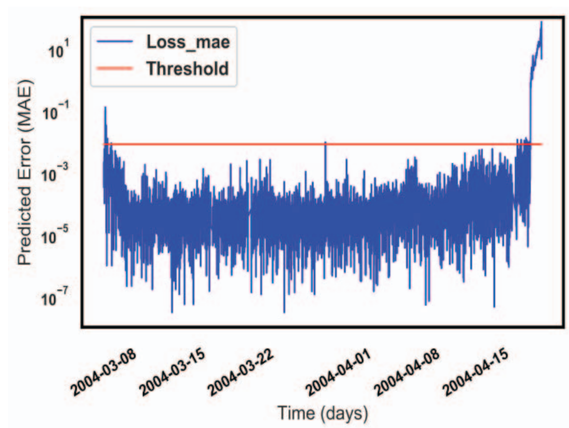

Fig. 5: Predicting bearing failure using KNN

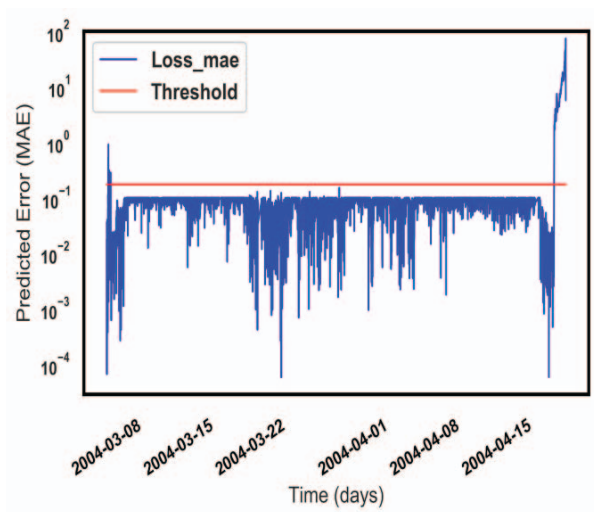

Fig. 6: Predicting bearing failure using SVR

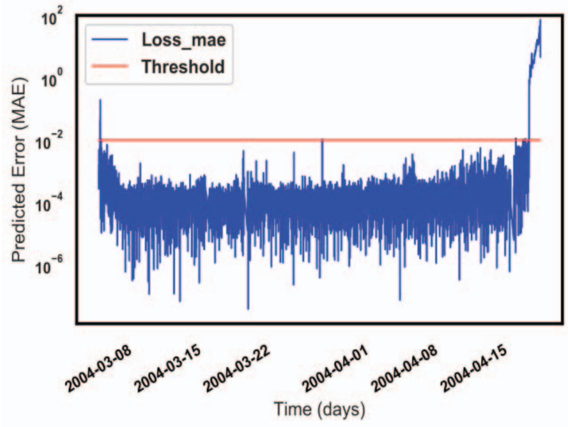

Fig. 7: Predicting Bearing failure using Random Forest Tree

VI. Conclusion:

This paper examined the use of data mining approach for anomaly detection of an electric motor. It utilises statistical features extracted from the vibration data as an input to a one-dimensional PCA. The output of the PCA is used to train the machine learning model. The machine learning model is trained on the healthy dataset and tested on unhealthy dataset.

The performance of three machine learning models (KNN, SVR and RF) were presented. The RF showed the best performance as compared to the SVR and KNN as it has the lowest false positive and a better detection time than KNN. Further work would be necessary to transform the methodology described in this paper into a useful tool to assist engineers in the health monitoring of electric motors, as well as other critical components; enabling the capturing of performance trends that provide valuable insights on component's health history. This will eventually feed into any maintenance strategy in an industrial setting and potentially facilitating robust and effective equipment fault diagnosis.

The savings from adopting an appropriate early fault detection system can be enormous over time as downtime cost is significantly reduced. Hence, appropriate data mining techniques can be integrated into industrial production systems to help drive process optimisation and efficiency.

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