Prediction of Drive-End Bearing Faults

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***Abstract*— This project aims to explore the different machine learning methods of fault prediction in a three phase induction motor. The CWRU bearing dataset for Drive-End Bearings will be used to train a Support Vector Machine that will classify the vibrations generated by a motor as either normal or as containing a specific type of fault. The results obtained through this experiment will be compared with other machine learning algorithms.**

Keywords—condition monitoring, vibration analysis, drive-end bearing faults, machine learning, support vector machine

I. Introduction

Condition Monitoring refers to a preventive maintenance technique that involves the constant monitoring of the various attributes of electrical devices, such as vibrations or temperature. The data is collected using sensors on the machines and is analyzed in real time to detect anomalies. This is a vital process that allows manufacturing firms to reduce down-time by detecting possible faults in a timely fashion.

This project will perform condition monitoring using vibration analysis of three phase induction motors. Three phase induction motors are motors that use electromagnetic induction to generate mechanical energy from electricity. They are very popular in industry due to their high efficiency and low maintenance costs.

While these motors are known to be very durable, their failure is still a possibility, especially over large periods of time. Given the scale of operation of any industries using these motors, unexpected failure can cause thousands of rupees of losses within minutes. Thus, condition monitoring becomes a necessary process for these motors.

Each part of the motor is vulnerable to failure, and can cause huge damage, both monetary and in some cases physical. However, it is very difficult to monitor all parts with a single algorithm. It is therefore prudent to focus on a single part of the motor at a time. Therefore, the specific area of interest of this project is drive-end bearing faults.

Bearings are parts of the motor that "are designed to support the rotor and maintain a consistent air gap between the rotor and the stator as well as transferring the loads from the shaft to the motor frame"[1]. They are some of the most sensitive parts of the motor, and timely detection of bearing faults can prevent motor failure and greatly reduce downtime losses for a manufacturing firm.

Bearings are present on both the drive-end and the fan end of the rotor. This project will specifically focus on the drive end bearing faults. A subsection of the The Case Western Reserve University Bearing Dataset [2] will be used to obtain a trained model for fault prediction in drive end bearings.

Figure 1 - Parts of Motor Bearings; this project focuses on the inner and outer raceway faults[3]

Motor bearings (Figure 1) have three parts that are most prone to failure. Those parts are the inner raceway, rolling element and outer raceway. This particular project will focus on inner raceway and outer raceway faults. Two locations of the outer raceway will be considered for robustness of the model. This is due to the fact that outer raceways are generally static, and the difference in location with respect to the load zone often results in significantly different vibration patterns.

The model built for this project will be able to predict induction motor failure due to drive-end bearing faults in the specific motor, and classify the fault as inner raceway fault, outer raceway fault in the load zone, outer raceway fault orthogonal to load zone, or normal condition.

This information can be useful in preventing motor failure in industry. Timely detection and classification of the fault can help the operator execute quick repairs, and prevent severe damages to life and property. The specificity of the information provided by the model can also provide greater insight into the reasons for the occurrence of bearing faults.

II. Materials and Methods

A. Motor and Bearing selection

This project will focus on predicting Drive-End Bearing Faults in a 2 HP, Class - 1 horizontally-mounted Reliance electric motor. Under the conditions of the experiment, the motor will be rotating at 1750 rpm with a load of 2 horsepower. The readings will be recorded using accelerometers with a sampling frequency of 48kHz.

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Industry Mentor: Arun Kumar S
Faculty coordinator: Ashwin K.P.

The drive-end bearing model I will focus on is 6205-2RS JEM SKF, deep groove ball bearing. The specifications of the bearing are as follows:

- Inner Diameter: 0.9843 inches
- Outer Diameter: 2.0472 inches
- Thickness: 0.5906 inches
- Ball Diameter: 0.3126 inches
- Pitch Diameter: 1.537 inches

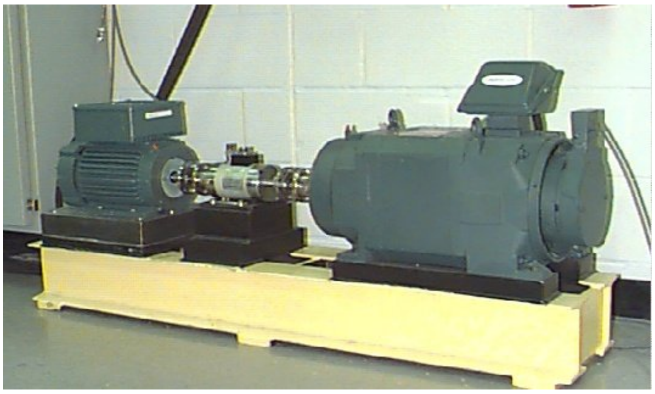

Figure - 2: Apparatus used to collect the test data for the CWRU Dataset, which is used for training and testing the model for this project

The setup for the data collection process (Figure 2) involved consists of a 2 hp motor (left), a torque transducer/encoder (center), a dynamometer (right), and control electronics (not shown). The test bearings support the motor shaft [2].

B. Dataset

This project will use a subsection of the Case Western Reserve University Bearing dataset.The dataset has been widely used to validate and improve several condition analysis models and techniques for induction motors.

The data was collected by introducing faults into the inner raceway, rolling element, and outer raceway of the motor through the technique of electro-discharge machining. Faults were introduced into the raceways and rolling element of bearings and each faulty bearing was installed on the setup, one at a time, to get accelerometer readings.

Data is available for drive-end and fan-end bearings, with faults of 0.007, 0.014 and 0.040 inch diameters. The vibrations have been recorded for 0 to 3 horsepower of motor load. The data has been collected using accelerators at the frequency of 18,000 samples per second for both fan-end and drive-end bearings, as well as 48,000 samples per second for the drive-end.

The focus for this particular study shall remain on the Drive - End bearing faults of 0.021 inch diameters. The rotational speed of 1750 rpm is being studied, with readings collected at a frequency of 48kHz. Inner raceway faults and outer raceway faults, both in the load zone and orthogonal to it, were studied in this project.

The data was taken from the official website of the dataset[2] in .mat format. It was then preprocessed using the Multivariate CWRU Bearing Package[4] in Python. This converted the data into time-domain waves of 3600 readings each., which amounts to about 0.075 seconds of data, with a sampling frequency of 48kHz. The various categories of faults outside the scope of the project were dropped using the pandas library in Python.

C. Implementation

The model built for this project takes a two step approach towards solving the problem statement. The first step involves feature extraction and the second step involves classification on the basis of those features.

For feature selection, [5] was used as a reference point. The paper analyzed various sets of features in the time-domain and frequency domain to determine the optimal features for fault analysis. Their results show that frequency domain features peak frequency, peak amplitude and total band power would be most useful for this problem.

To extract these features, the time-domain wave was converted into a frequency domain wave using Fast Fourier Transform (FFT). FFT was applied using the Numpy library in Python.

The peak amplitude was found by finding the maximum magnitude of the frequency domain readings in each wave. The peak frequency was the frequency corresponding to the peak amplitude. The total band power was calculated by finding the power spectrum of each wave, then adding the resultant series. All of these operations were performed using simple mathematical functions available in the Numpy library.

Data visualization of the extracted features in Python clearly showed stark differences in the composition of vibrations generated by normal bearings, bearing with inner raceway faults and bearings with outer raceway faults. The differences between the composition of outer raceway faults in the load zone and orthogonal to it are less significant in comparison. This visualization was executed using the Matplotlib library.

The extracted features were classified using a Support Vector Machine (SVM) Classifier. The SVM works by creating a line or a hyperplane that separates instances of different classes. This particular model used a linear kernel for the purpose of classification. 90% of the available data was used for classification, the other 10% was used for testing the model. The basic structure of the SVM was imported from the Sci-kit Learn library, which is widely used for a variety of machine learning operations.

The model is able to classify motor vibrations into four categories according to the bearing condition of the motor. The categories are Normal, Inner Raceway Fault, Outer Raceway Fault in load zone, and Outer Raceway Fault orthogonal to the load zone.

The trained SVM has been saved in the form of a .sav file using pickle, to enable future use without the need of retraining the model each time.

III. Discussions and Future Work

A. Discussion

The Support Vector Machine is a classification algorithm that works by finding a line or hyperplane that demarcates different classes. This action is augmented by selection and extraction of relevant features from the raw wave. This model has been chosen due to its effectiveness and efficiency.

This particular model was able to achieve an accuracy of 96.296% under the aforementioned conditions. This is the same accuracy that was achieved in [5], hence validating the correctness of the execution of this method.

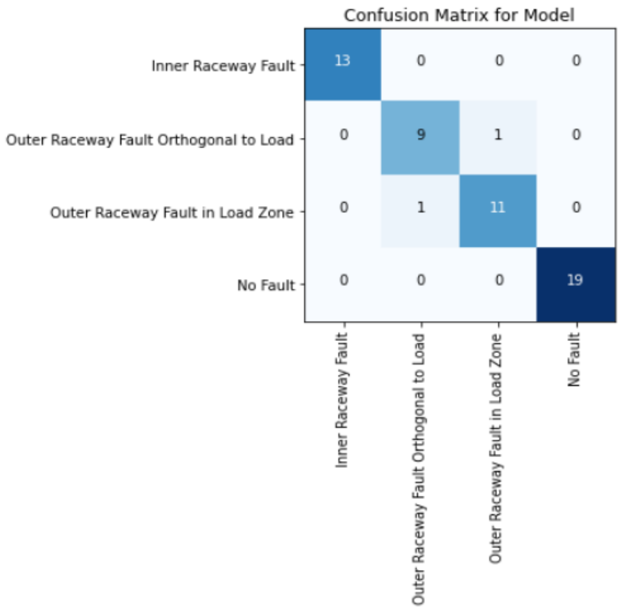

Figure 3 - Confusion matrix of the model, a plot displaying the accuracy and error for each class in the test data.

The confusion matrix of the model (Figure 3) shows that the error made by the model was largely in differentiating between the two locations of the fault relative to the load, in case of an outer raceway fault. Thus, even when the model is inaccurate in its findings, the results are not far from the truth, and in a real world scenario, would result in the investigation of the correct part of the bearing.

Moreover, in a real world setting, several waves of 3600 readings will be analyzed each second, thus resulting in a higher probability of correct continuous classification by the model.

Since the probability and impact of the error are both quite low, this implementation should serve well in an industrial setting, if scaled and optimized for the same.

B. *Future work*

There are currently several limitations to this project, the model built will have to incorporate several new features before it is fit for industrial deployment. This model is only a prototype, built on one specific motor and bearing type. Practical use of this technique would require retraining and optimization for the particular application.

This model requires static data input from a .csv file and has not been optimized for a continuous data pipeline that receives new data in real time. This is currently a major drawback because industrial use will require real-time results to effectively prevent losses.

This project uses secondary sources for feature selection, and focuses only on three frequency domain features. The process could be modified to train on various sets of relevant features to obtain an even higher accuracy, as well as gain assurance that the features used are truly the most appropriate for this application. Machine learning methods, such as an auto-encoder decoder setup can also be used to extract appropriate features from the waveform data.

Moreover, this project is built completely in Python, and is limited to the functionality provided by the various libraries in that language. There may be a need to transform the data preprocessing parts of the code into a LabVIEW model to enable the specific waveform analysis that might be required in some applications.

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