Bearing wear prognosis based on Hidden Markov Model

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ABSTRACT

Condition-based maintenance (CBM) is a maintenance program that recommends maintenance decisions based on the information collected through condition monitoring. There are two substantial factors to support CBM, machine fault diagnosis and machine condition prognosis. In this paper deal with an estimation of the Remaining Useful Life of bearing based on the Hidden Markov Models. The Prognostic process is done in two phase: a learning phase and evaluation phase. In first process, the sensors' data are processed in order to extract appropriate features, which are used as inputs of learning HMM. During second phase the extracted features are continuously injected to the obtained model to represents the current health state of mechanism system and to estimate its remaining useful life. The proposed method is tested on bearing wearing test of Rotor kit RK4.

1. INTRODUCTION

The plant process consists of combining a number of different types of equipment with varying capacities and different characteristics for generating power generation. Even if one of these machines is stopped, it is important to maintain a significant loss of power, resulting in a system of maintenance and management of individual devices. Most initial problems or failures occur during the initial operation of the plant in the event of multiple failures, which causes the symptoms to be caused by chronic failure.

The Condition based maintenance is currently widely used in machine maintenance with the use of signals that occur during the device's operational data. Three key process of effective CBM are data acquisition, data processing and decision making. There are two substantial factors to support CBM, machine fault diagnosis and machine condition prognosis, isolating and identifying a failure condition of a part or system, while the affected components are still operating even though they are in a degradation mode.

In the case of faulty diagnosis, there is a limit to the efficacy of the sensor technology, although it is generally implemented in the field of industrial technology, but it is normal to detect if the performance degradation has already progressed to some extent. To compensated for this, The Prognostics technology is conducted in the current state of prediction of the residual useful life of mechanical equipment or systems, depending on the method of estimating the life span of the system. It can be divided into three main methods, which include methods based on data-driven, knowledge-based and model-based prognostics approaches. The data-driven approach drills into the input load and damage relationships and predicts future failures. It has the advantage of being able to apply for various system failures, but it needs a lot of data for training. The model-based or physics based prognostics approach use explicit mathematical representation to formalize understanding of a degrading system. The model based approach provides accurate prediction of long-term damage and has the advantage of predicting only small amounts of data. However, it cannot be applied for failures without physical model.

This study has developed algorithms that predict the wear life of bearings using a hidden Markov model, as a data-driven method, as one of predictive techniques. For acquiring training data, the rotating mechanism system was constructed to express bearing wear acceleration test.

2. BEARING DEFECT ACCELERATED LIFE TEST

To measure the abnormalities of the rotary motion, a rotary laboratory simulator was constructed such as Fig. 1. The device is driven by a motor, and the motor axis is equipped with 12 teeth for use as a trigger (trigger) signal for measuring the frequency of the A/D conversion, and the coupling shaft and the rotating axis are connected to the flexible coupling.

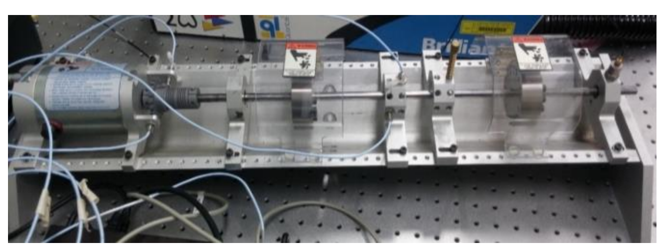

Figure 1. bearing wear test set up

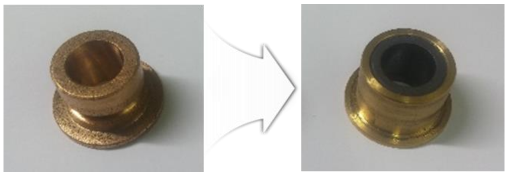
Figure 2. carbon bearing

At the end of the rotation shaft, the bearings and housings supporting the rotation shafts were installed and the discs were installed in the center of the shaft. Two displacement sensors near the bearing shaft were recorded with the vertical and horizontal displacement of the rotational axis of the rotating axis 12 times per revolution, recording the data for 2000 (approximately 166.7 rotations) on the experiment. The rotation speed was fixed at 1200 rpm and stopped at 10 minutes, 20 minutes, and 30 minutes, and the degree of wear was checked.

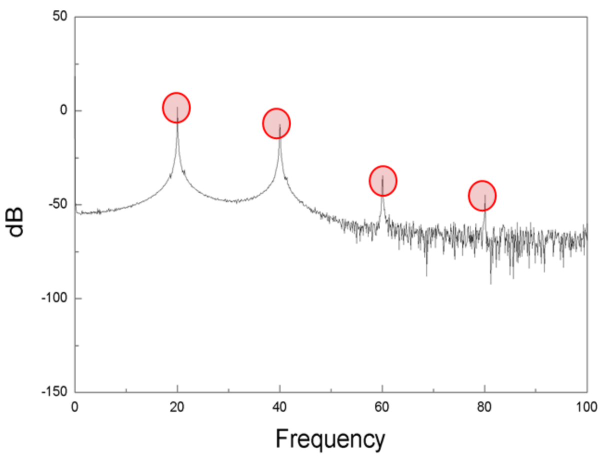

Figure 3. (a) FFT of acquired sensing data (horizontal direction displacement)

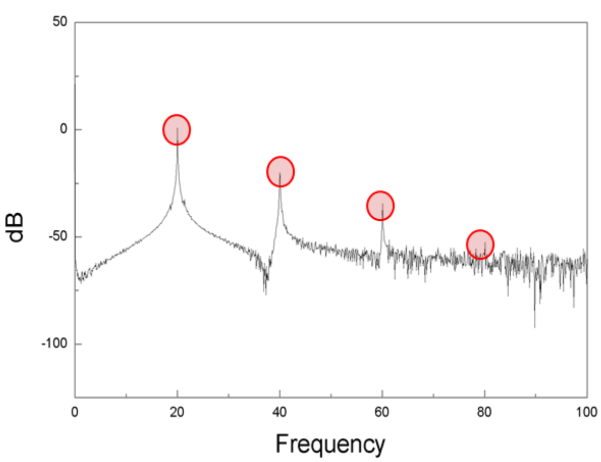

Figure 3. (b) FFT of acquired sensing data (vertical direction displacement)

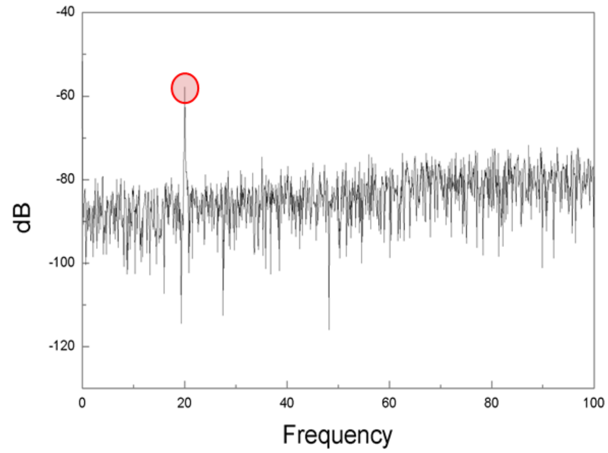

Figure 3. (c) FFT of acquired sensing data (vertical direction acceleration)

3. PROGNOSIS BEARING REMAINING USEFUL LIFE USING HMM

In order to training HMM, a feature vector should be chosen which best describes the state of rotating system. So The measured data from the sensor was converted for each sampling time. The peak value from FFT graph was used as a feature vector, and a total of 9 feature vectors were selected through the classification operation.

Trained Model is an important indicator of the life expectancy of the system. As gradually failures occur gradually from initial failures, the probability of a fatal defect increases gradually. Using this trend, we gradually estimated the residual lifetime from the initial wear of the learned model. By the time a fault was made about 60 %, the remaining life expectancy was relatively accurate.

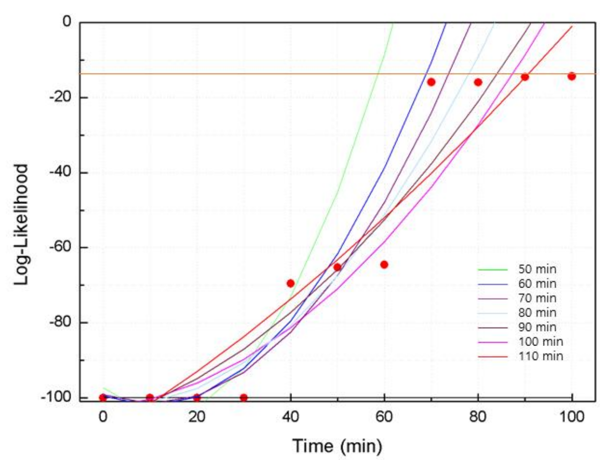

Figure 4. Predict RUL of Bearing Wear

4. CONCLUSION

In this study, we applied HMM techniques, which are statistical techniques, to assess the life expectancy of a rotating body. HMM is suitable for detecting subtle changes in the rotational system because it is suitable for detecting subtle changes. Moreover, it was noted that the relative probability of a fatal failure could be used to substantially estimate the remaining lifetime of the residual probability of a fatal defect.

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BIOGRAPHIES

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