Commentary

Development of Remaining Useful Life Prediction Technology for Rolling Bearings Under Flaking Progression

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In recent years, due to aging equipment and the lack of maintenance personnel, there is increasing interest in advanced predictive maintenance, and rolling bearings are attracting attention as a target. In general, rolling bearings are replaced when some kind of damage occurs. However, in some cases where maintenance is not easy, they may continue to be used even after the damage has occurred as long as it does not affect peripheral equipment. This paper introduces a developing AI method for predicting the remaining useful life of rolling bearings under flaking progression.

1. Introduction

Interest is growing for enhanced functionality and automation of maintenance technologies amid the backdrop of increased maintenance costs due to long-term deterioration and the increasing burden on workers due to the lack of maintenance personnel in manufacturing, infrastructure and similar related equipment. In recent years much attention has been given to technology relating to “predictive maintenance”, a method which involves detecting abnormal signs of operation so that maintenance can then be performed. This method is more efficient than “preventive maintenance”, which involves regularly maintaining equipment regardless of its condition or “corrective maintenance”, which involves maintaining equipment after a failure has occurred. **NTN** has increased activity in this area by introducing these technologies in maintenance using IoT and AI[1].

Rolling bearings are machine elements that is vital to equipment and are a key element in supporting machine rotation. In cases of equipment failure, it is said that roughly 30 % of failures are caused by rolling bearings[2]. Based on this fact, it is desirable to estimate the condition of rolling bearings and repair or replace them at the proper time to reduce maintenance costs for the entire machine.

Vibration acceleration is often used to diagnose rolling bearings because it can be measured without interrupting the machine and is highly sensitive to damage[3]. Diagnostic methods that use vibration acceleration predict damage conditions using statistics such as the root mean square value and kurtosis, as well as specifying areas of damage using frequency analysis. There has been much recent activity in R&D development to predict the damage conditions and remaining useful life of rolling bearings in line with the development of AI technology such as deep learning[4), 5), 6)].

This paper introduces AI technology[7] developed to predict remaining useful life up to when it is necessary to replace the bearings and is applicable to rolling bearings after damage has occurred.

2. Development background

Generally, the life of a rolling bearing is often considered to be when some type of damage occurs on the bearing raceway surface, such as flaking or indentation. However, depending on the environment and conditions in which the bearing is used, it is not easy to replace rolling bearings and these bearings may continue to be used even after minor damage has occurred because of the significant maintenance costs involved.

If rolling bearing damage progresses, there will be a sudden increase in vibration, which will cause damage to the machine as well as other elements and will likely lead to increased downtime. Therefore, it is desirable to be able to predict the remaining useful life up to when the bearing needs to be replaced by estimating the extent of damage on the rolling bearing (hereafter, damage condition). However, most research into remaining useful life prediction of rolling bearings mentioned above does not describe the damage condition of rolling bearings.

Therefore, this paper will introduce the technology that was developed with the aim of predicting the remaining useful life with high accuracy, by expressing a regression model of the relationship between the damage condition and remaining useful life for rolling bearings where damage is in progress.

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3. Flaking progress and vibration acceleration on rolling bearings

Fig. 1 shows the relationship between the operating time and vibration when using a cylindrical roller bearing. Operation continued until the circumferential length of flaking that occurred on the inner ring raceway surface exceeded the rolling element pitch length[8]. The horizontal axis shows the load count while the vertical axis shows the change relative to the root mean square (RMS) initial value of the vibration acceleration (RMS relative value). The figure also shows an external view of the flaking on the inner ring raceway surface for a specific time. Flaking occurred at a load count of approximately 900 thousand times. Flaking on the raceway surface first develops mostly in the axial direction (range A in **Fig. 1**), and when the length of flaking in the axial direction reaches the rolling element contact length, flaking mostly progresses along the circumference after this (the direction in which the rolling element moves) (range B in **Fig. 1**). RMS increases quickly while flaking progresses in the axial direction, and while flaking mostly progresses along the circumference, RMS increases slower and fluctuations follow the same trend. As flaking progresses further, if the length of flaking along the circumference reaches the rolling element pitch length (range C in **Fig. 1**), RMS increases rapidly once again and the fluctuation range also increases.

When this type of vibration increases, displacement between the inner and outer rings of the rolling bearing increases the risk of exceeding the range of acceptable clearance for peripheral components, which will result in damage to the peripheral components. Consequently, it is best to stop operation before the flaking circumferential length reaches the rolling element pitch length. This study regarded the bearing replacement time to be when the circumferential flaking length reaches half of the rolling element pitch length.

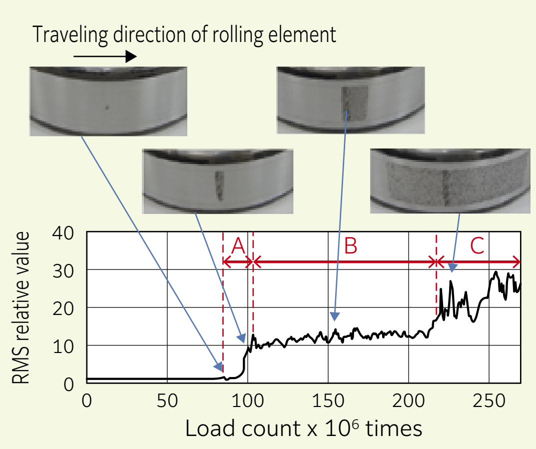

Fig. 1 Relationship between flaking progress and vibration acceleration[8]

4. Characteristics of development technology

This chapter describes the overview for development technology.

4.1 Development technology

Fig. 2 shows an overview of development technology. Development technology consists of a combination of Feature Fusion Network (FFN)[7] as indicated in section 4.2 and Hierarchical Bayesian Regression, HBR[9] as indicated in section 4.3. Using a short time Fourier transform (STFT) (see **Fig. 3**)[10] spectrogram to input vibration acceleration time series data, FFN can predict maximum circumferential flaking length (hereafter, flaking size) and remaining useful life (hereafter, SS remaining life) as a snapshot (a single output for a single input data set). Next, from the flaking size and SS remaining life predicted by FFN, HBR can be used to output the remaining useful life regression equation, remaining useful life and its distribution.

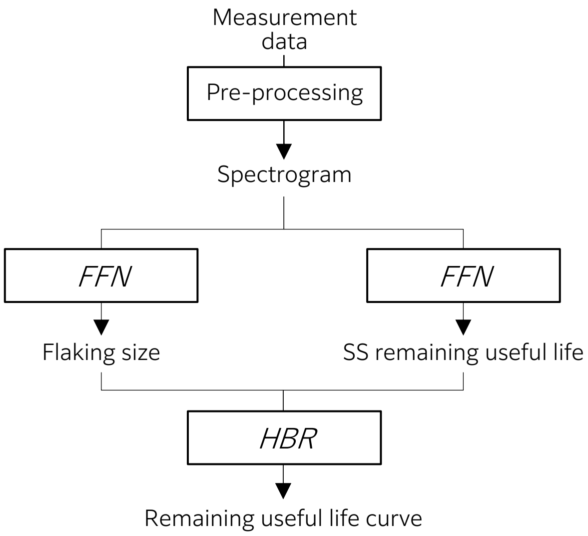

Fig. 2 Development model overview

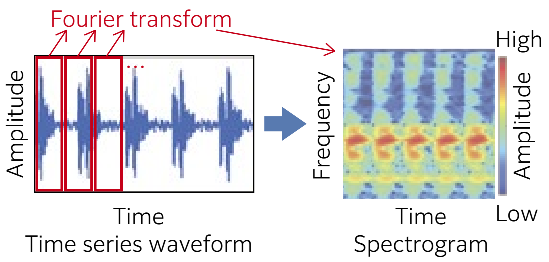

Fig. 3 Illustration of short time Fourier transform

4.2 Feature Fusion Network

FFN is a regression method based on a convolutional neural network (CNN)[11] in deep learning and is often used for image recognition. **Fig. 4** shows an illustration of FFN. Normal CNN directly predicts corresponding objective variables just from data input at the time of the measurement. FFN calculates a deterioration index (a normalized index in a range of 0 to 1 for the state of deterioration) at each point in time from data input from multiple times in the past. The deterioration index is then vectorized with a measured permutation to create a deterioration index vector, which is then used as an intermediate variable with the aim of improving the prediction accuracy of the objective variables (flaking size and SS remaining useful life).

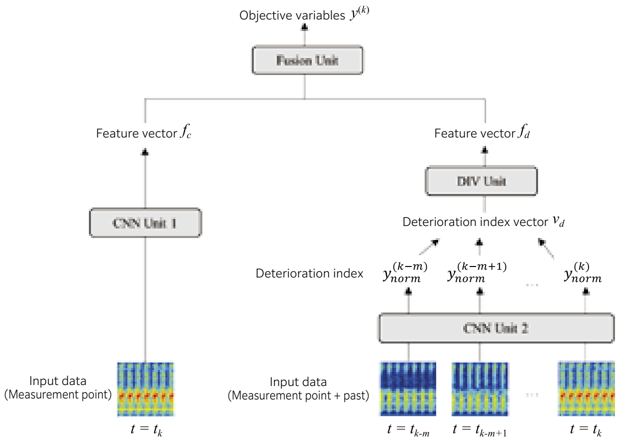

Fig. 4 Feature fusion network overview

4.3 Hierarchical Bayesian regression

Since the previously mentioned SS remaining useful life is predicted with a snapshot, the predicted value changes for each measurement time. In practical use, the regression curve for remaining useful life is defined by a monotonically decreasing function because it is preferable for the remaining useful life predicted value to monotonically decrease as operating time elapses. In addition to the above, HBR was used[7] as a method to consider variations between individual bearings during this development. HBR uses all past data before the measurement point to obtain the remaining useful life and regression curve. More specifically, differences in individual bearings are assumed to vary based on a probability distribution so that individual remaining useful life regression curves can be handled for each bearing. This enables relatively accurate predictions for remaining useful life output at the end, even for individual bearings whose SS remaining useful life greatly deviates from the average obtained from all learned data.

5. Evaluation test

5.1 Test equipment and measurement data

A schematic drawing for test equipment used to evaluate development technology is shown in **Fig. 5**, while test conditions are shown in **Table. 1**[7]. A cylindrical roller bearing (number NU224, bore diameter 120 mm, outer diameter 215 mm) was used as the test bearing. Operation continued until the bearing reached its limit of use after the initial flaking that occurred on the bearing raceway surface, and both vibration acceleration and flaking size were measured at regular intervals. Measurements were taken for a sample of 33 bearings. **Fig. 6** shows the relationship between the operating time and RMS from when the initial flaking occurred on each bearing sample until the bearing reached its limit of use. **Fig. 7** shows the relationship between the operating time and flaking size. At the end of flaking progress, RMS fluctuated significantly, and this made it difficult to accurately know the flaking conditions. Despite the fact that all 33 bearing samples were tested under the same operating conditions, the remaining useful life, up to when the bearing limit of use was reached, differed significantly among the bearing samples. Therefore, in order to improve the accuracy of predicting remaining useful life, it is necessary to consider fluctuations in feature quantities of vibration acceleration as well as individual differences in remaining useful life.

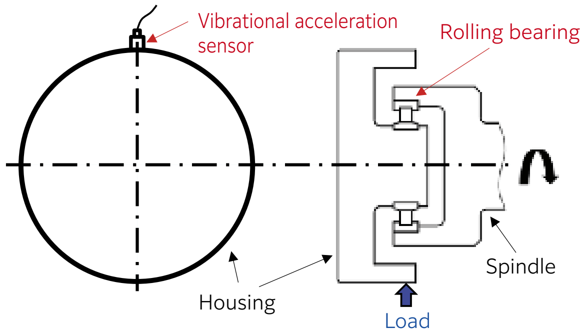

Fig. 5 Test equipment[7]

Table 1 Test conditions[7]

Rolling bearing	Cylindrical roller bearing (number: NU224)
Main shaft rotational speed	500 min^{-1}
Radial load	90 kN
Measurement data	Vibration acceleration (vertical direction)
Bearing sample quantity	33 pieces

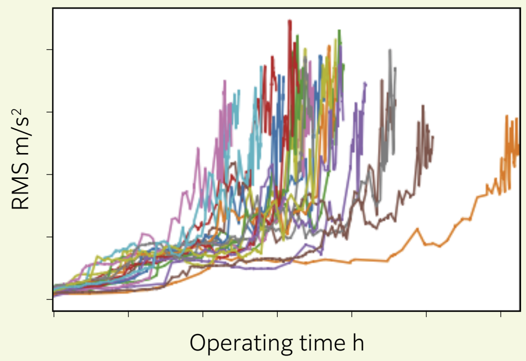

Fig. 6 Relationship between operating time and RMS

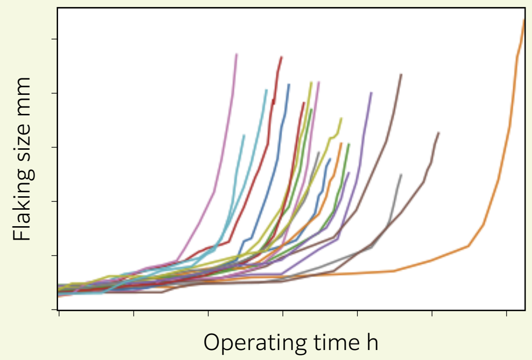

Fig. 7 Relationship between operating time and flaking size

5.2 Evaluation metrics

The coefficient of determination R^2 was used in the evaluation metrics of the development method. R^2 is an indicator of the degree to which a predicted value of the objective variables (flaking size or remaining useful life in this case) matches the actual value (hereafter, true value), and is shown in equation (1) below.

$$R^2 = 1 - \frac{\Sigma_{k=1}^{n}(y_k - \hat{y}_k)^2}{\Sigma_{k=1}^{n}(y_k - \bar{y})^2} \qquad (1)$$

Here, y_k and $\hat{y}_k$ denote the true value and predicted value of the objective variables at measurement time k, respectively. Furthermore, $\bar{y}$ denotes the true value average of the objective variables while n denotes the number of data. R^2 can be a value of 1 or less, and the larger the value (closer to 1), the higher the prediction accuracy. R^2 was calculated for each bearing sample, and both the average and variation of predicted values calculated using leave-one-out cross-validation[12] were evaluated. Furthermore, the whole range, from when flaking occurred until it was necessary to replace the bearing, was divided into two ranges which were the early stage and late stage. Both of these stages were evaluated. Here, the range in which flaking mostly progressed in the axial direction was taken to be the early stage, while the range in which flaking progressed along the circumference was taken to be the late stage.

5.3 Flaking size and SS remaining useful life prediction results using FFN

This section provides a comparison of FFN with the various regression methods and evaluates the accuracy of predicting flaking size and SS remaining useful life. Kernel Ridge (KR)[13], Random Forest (RF)[14], Support Vector Regression (SVR)[15], Neural Network (DNN)[16] with 4 hidden layers, and CNN were used as comparison methods. Similar to the development method, CNN inputs the vibration acceleration spectrogram and does not consider past data. Moreover, for KR, RF, SVR and DNN, statistics in the time domain, frequency domain and cepstral domain (RMS, maximum value, peak factor, kurtosis, skewness, RMS after envelope processing[17]) were used as inputs after various band pass filtering were applied to vibration acceleration. Hyper-parameters of the development method and comparison methods were then selected as optimal values using 5-fold cross-validation[12].

Fig. 8 shows a box plot of comparison results for the accuracy of predicting flaking size, while **Fig. 9** shows a box plot of comparison results for the accuracy of predicting SS remaining useful life.

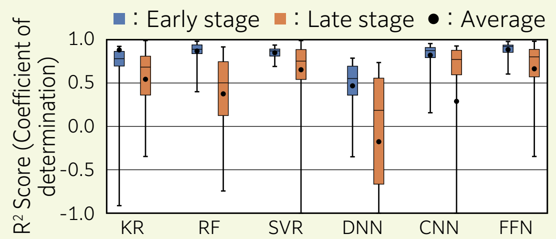

Fig. 8 Flaking size prediction accuracy (w/o HBR)[7), 17)]

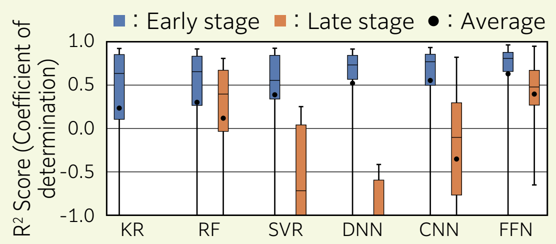

Fig. 9 SS remaining useful life prediction accuracy (w/o HBR)[7), 17)]

All four methods, excluding KR and DNN, had an average R^2 of 0.7 or higher for the flaking size prediction during the early stage of flaking progression. In particular, FFN prediction accuracy had the highest value. Additionally, the average R^2 for CNN and FFN was high during the late stage of flaking progression. However, because CNN prediction accuracy worsened for specific samples, on average CNN was significantly lower than FFN. Therefore, FFN has the highest prediction accuracy for predicting the flaking size.

The three methods DNN, CNN and FFN have a high R^2 for the SS remaining useful life prediction during the early stage of flaking progression compared with KR, RF and SVR. Among these three methods, FFN had the highest prediction accuracy. All methods had a lower prediction accuracy during the late stage of flaking progression compared with the early stage of flaking progression. However, RF and the development method maintained a comparatively high accuracy out of all the methods.

Based on these results, we can see that FFN maintains a high prediction accuracy for both flaking size and SS remaining useful life in comparison with the other general regression methods.

5.4 Remaining useful life curve using the development method

Fig. 10 shows the relationship for the median and prediction distribution of the remaining useful life curve and damage progression using HBR. In this figure, measured data in the range used for HBR learning is shown to the left of the red dotted line. Measured data in the prediction range is shown to the right of the red dotted line. The black line shows the prediction curve using HBR. Furthermore, the dark grey area shows a 50 % level of confidence range while the light grey area shows a 95 % level of confidence range. The three graphs in the figure show prediction results for remaining useful life at points where 10 %, 20 % and 50 % data was measured out of all measurement data for the bearing from the left, respectively. A dashed line is also shown in the figure to represent the limit of use (life criteria) as defined in chapter 3. The prediction curve approaches the true value and the range for the level of confidence became narrower as measurement data increased with the progression of damage. Therefore, the relationship between remaining useful life and damage progression using HBR can be expressed as a curve with a prediction distribution (reliability of predicted values). Furthermore, increasing measurement data improved the remaining useful life prediction accuracy and increased the reliability of the predicted value.

Fig. 11 shows a box plot of remaining useful life prediction accuracy due to the development method (the combination of FFN and HBR). For comparison, the figure shows the prediction results for RF and HBR combined, CNN and HBR combined, and FFN by itself. During the damage early stage, the development method has improved accuracy in comparison with the other methods. In particular, the interquartile range becomes smaller, confirming that variation in the bearing sample is smaller. This method also has a high prediction accuracy compared with the other methods during the damage late stage, with the only average R^2 exceeding 0.5. Therefore, using the development method can predict remaining useful life with high accuracy more than conventional methods.

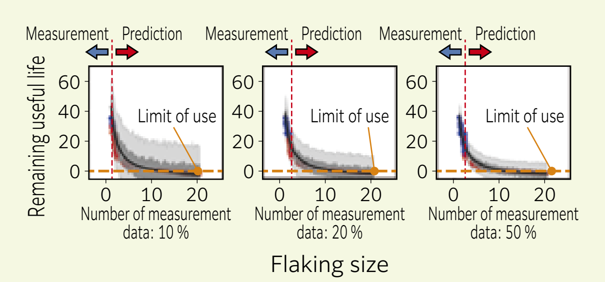

Fig. 10 Relationship between flaking progression and remaining useful life prediction distribution[7)]

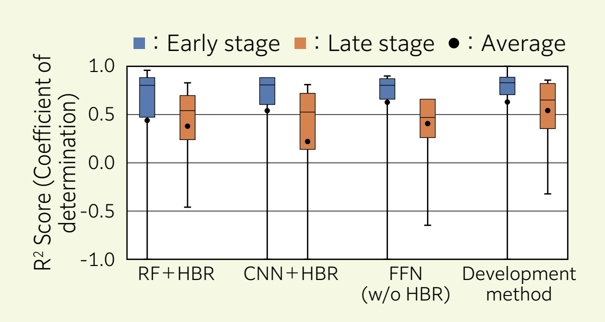

Fig. 11 Remaining useful life prediction accuracy[7)]

6. Summary

This paper compared and verified general machine learning methods and their performance for a remaining useful life prediction method developed to target rolling bearings after damage has occurred. It confirmed that using the development method can predict the remaining useful life with high accuracy until the time the rolling bearing needs to be replaced after damage has occurred. Therefore, use of this development method enables us to obtain a guideline for using rolling bearings in the range where the displacement between the inner and outer rings does not exceed the acceptable clearance for peripheral components even when operation is continued after flaking has occurred on a rolling bearing. Equipment such as pumps and fans used in special environments are an example of equipment that continue to be used even after the rolling bearings are damaged. In the future, **NTN** will continue working on increasing the versatility of this development technology while contributing to the reduction of maintenance costs on various equipment.

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