Life Prediction of Bearing for the Drive Train of a Wind Turbine

Yun-Ho Seo[1], Sang-Ryul Kim[1], Bong-Ki Kim[1] and Pyung-Sik Ma[1]

[1]*Korea Institute of Machinery & Materials, Daejeon, 34103, Korea*
yhseo@kimm.re.kr

ABSTRACT

A wind turbine is a representative machine with varying rotational speed because unpredictable natural wind is a locomotive force of the rotation. Major mechanical components of the drive train such as bearings encounter varying and irregular loadings in accordance with the variation of the rotational speed. Therefore, the varying and irregular loadings are a critical factor to be considered for the life prediction of the bearings. The degradation processes for constant and varying loadings are measured in order to evaluate the characteristics. An efficient index to stand for the state of bearing is also suggested in the combination of measured vibration, temperature and torque. Then, two methods, which can be used with and without model information respectively, are proposed to predict the life in the case of varying loading. The proposed methods are validated for the several experimental results and expected for the practical application of condition monitoring.

1. INTRODUCTION

An essential element to realize the rotational motion for most of machines is a lubricating element such as a bearing, which minimizes the friction. Bearings can be divided into fluid lubricated bearings that utilize the dynamic pressure of the fluid, and rolling element bearings with direct friction of the machine elements. Among these, a rolling element bearing used at a relatively small load reduces frictions through rolling motion between the inner and outer races. Then, the rolling element bearing is exposed to various failures or fatigue because of the direct contact between the rolling element and the inner/outer rings. Therefore, in order to improve the cost effectiveness of maintenance, the rolling element bearings have been the top priority for the failure diagnosis and the life prediction among the machine parts.

In recent years, various studies have been proposed to predict the remaining useful life (RUL) in accordance with the results of real-time measurements. The first step in life prediction is to determine a state index that can quantitatively represent the state of the bearing (ISO, 2004). In recent researches, Boskoski (2015) used the root mean square (RMS) value of the bearing vibration as a state index. The well-known features such as kurtosis and fault frequency of bearing are also used for the prediction (Ali, 2015).

The prediction of the state index, which is the last stage of bearing life prediction, can be performed by a simple curve-fitting (Seo, 2017), using a filter (Xi, 2013), or obtaining a regression curve using various probability distribution models (Xi, 2011). Gebraeel (2005) proposed a method for predicting RUL, assuming model parameters of an exponential function as normal distributions. However, the above methods are only for the constant loading. Therefore, an additional method is necessary for the application of bearing in the wind turbine.

In this paper, the analysis of degradation characteristics is carried out on the basis of actual degradation tests and the determination of a state index is suggested. Then, the concept of data acquisition to apply two prediction methods to a wind turbine is explained. In order to validate the performance of the proposed methods, RUL is predicted and the RMS errors are evaluated.

2. CHARACTERIZATION OF DEGRADATION

The most important information for the prediction of life is characteristics of degradation with respect to time. The shape of degradation signal with respect to time, and effect of various loading and environmental conditions are the required knowledge in order to predict life time perfectly. As the first step, degradation tests of bearings up to failure with constant loading and rotational speed are performed. Then, alternating loading is also applied on degradation tests for the same bearing model.

2.1. Apparatus of Degradation Tests of Bearings

Degradation tests of bearings are performed in the laboratory by the many research teams (CWRU, 2017; NASA, 2017; KSPHM, 2018). In general, radial force is applied into bearing with the rotation of a shaft. At that time, some physical parameters such as vibration and temperature are measured. In this research, vibration, temperature and torque for the rotation are chosen as measured parameters. Radial and axial forces are made by feedback controlled hydraulic actuators. A pair of bearings as test specimens is located on the both ends of a rotating shaft. Another pair of bearings as support bearings is installed in the middle of the shaft so as to guarantee stable force exertion. If radial and axial actuators apply F_{r_act} and F_{a_act} in this layout, then each of test bearings is loaded by $F_r = 1/2F_{r\_act}$ and $F_a = F_{a\_act}$, respectively. The vibrations of two testing bearings are measured by accelerometers with respect to axial direction, respectively. Temperatures on the surface of the outer race and torque to rotate the shaft are also acquired. Figure 1 shows a conceptual diagram and locations of sensors for the degradation test. Detailed specifications of test bearing are summarized on the Table 1.

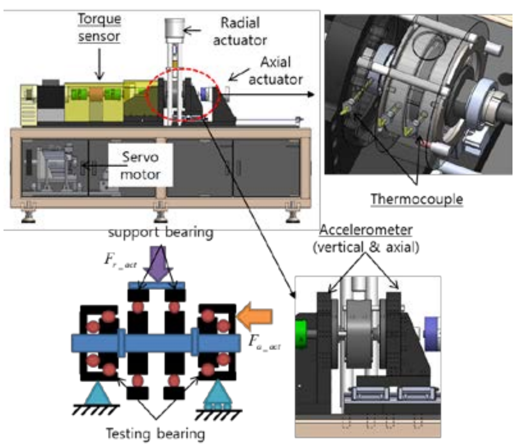

Figure 1 Apparatus of Degradation Tests of Bearings

Table 1 Specifications of test bearing

Inner diameter	30 mm
Outer diameter	72 mm
Width	20.75 mm
Static loading rate (ref. ISO 281)	60 kN
Dynamic loading rate (ref. ISO 281)	59.5 kN

2.2. Determination of State Index

Representative physical parameters, which show the state of bearing for prediction of life, are vibration, temperature, acoustic emission, ultrasonic, thermography and so on (Zhou, 2016). If simple diagnosis and prognosis are carried out, only one of the above parameters might be used as a single state index. But a combination of the above parameters is more effective to represent the accurate state. The uncertainties (or hidden characteristics) are complicated phenomenon and they are not easy to be identified analytically and experimentally. Therefore, utilization of various measurable parameters can guarantee to reduce various uncertainties which are originated from environmental condition, loading and measurement equipment (Sankararaman, 2015).

Figure 2 shows root mean square (RMS) of vibration with respect to time when constant forces are applied to bearings. As time goes by, magnitude of vibration becomes larger monotonically. However, the slope and change of increase are random and there are some peaks whose cause is not identified yet. Fault frequencies of bearing are good for diagnosis but RMS is simple and sufficient to represent amount of degradation. Figure 3 also shows operational data of bearing such as temperature and torque. In initial stage, the overshoots of temperature and torque exist before it becomes steady-state. After about 17 hours, temperature of bearing become increasing a little, and soar of temperature happens at the end of degradation test. Because vibration, temperature and torque show the degradation trend of a bearing, a combination of them can be used as a state index of the bearing.

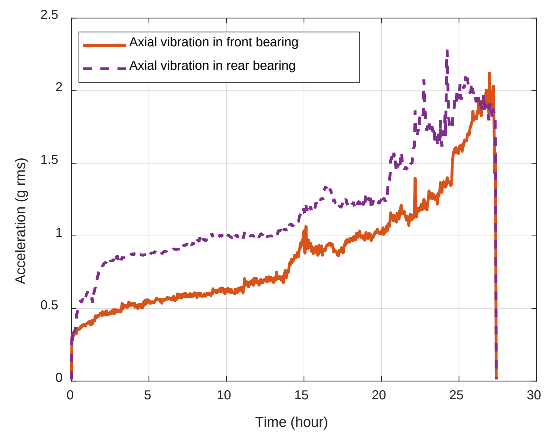

Figure 2 Root Mean Square (RMS) of Vibration

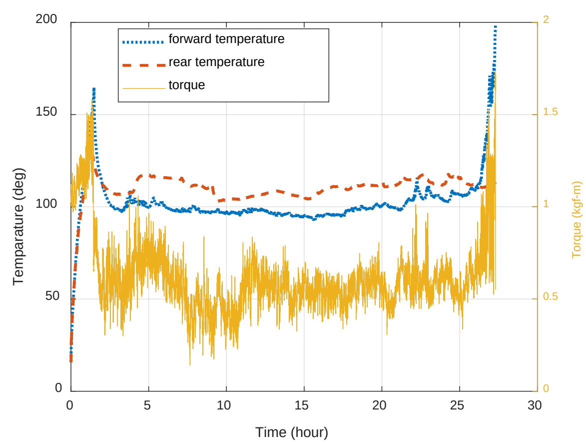

Figure 3 Operational Data of Bearing Degradation

An efficient method to consider all of vibration, temperature and torque is to use a weighted linear combination like below

$$SI = w_a \times V + w_b \times T + w_c \times Tor \quad , \tag{1}$$

where V , T and Tor are normalized RMS of vibration, temperature and torque, respectively. Since actual measured values have different units, it is necessary to normalize the measured value. If weighting factors (w_a , w_b and w_c) has, in addition, any values from 0 to 1, the state index (SI) can be assumed as less than 1. Then, a unity of SI can be defined as the end of life, which is a reference value to predict the life of bearing.

Before determining weighting factors (w_a , w_b and w_c), a degradation model has to be chosen. The degradation model is a mathematical model of a state index for the prediction of life. In this paper, an exponential function with respect to time is selected among the various degradation models because the exponential function is easy to be manipulated and applied in the case of the normal distribution. The exponential function is defined by

$$SI(t) = f(t) = ae^{bt+\varepsilon} + c \quad , \tag{2}$$

where a , b and c are model parameters which are expressed as probability distributions, and ε stands for measurement noise. ε is also defined as a probability distribution.

When the state index is assumed to be an exponential function, the weighting factors are determined by optimization, in which the state index has the highest correlation coefficient with the exponential function. The number of degradation tests is N , the life time of i^{th} test specimen is LT_i , and a measured state index, which is made by a weighting factor, during the degradation test can be represented by a vector form as

$$\mathbf{SI}_i = \left\{ SI_i(0) \quad SI_i(1) \quad \cdots \quad SI_i(LT_i) \right\}^T . \tag{3}$$

Each element of the above state index vector can also be expressed like Eq. (2) such as

$$f_i^{(SI)}(t) = a_i^{(SI)} \exp\left\{ b_i^{(SI)} t \right\} + c_i^{(SI)} . \tag{4}$$

Vector form of Eq. (4) from 0 to LT_i is

$$\mathbf{f}_i^{(\mathbf{SI})} = \left\{ f_i^{(SI)}(0) \quad f_i^{(SI)}(1) \quad \cdots \quad f_i^{(SI)}(LT_i) \right\} . \tag{5}$$

The correlation coefficient between Eqs. (3) and (5) is calculated by

$$r_i = \frac{\left| \mathbf{f}_i^{(\mathbf{SI})T} \cdot \mathbf{SI}_i \right|}{\left| \mathbf{f}_i^{(\mathbf{SI})T} \cdot \mathbf{f}_i^{(\mathbf{SI})} \right| \left| \mathbf{SI}_i^T \cdot \mathbf{SI}_i \right|} . \tag{6}$$

Optimization by the below equation for N degradation test results can be performed by various combinations in terms of w_a , w_b and w_c , and weighting factors(w_a , w_b and w_c) are determined.

$$\underset{0<w_a, w_b, w_c<1}{\arg} \max \sum_{i=1}^{N} r_i \tag{7}$$

3. LIFE PREDICTION OF BEARING IN WIND TURBINE

3.1. Concept of Bin for Condition Monitoring of Wind Turbine

Because a wind turbine is forced by natural wind, the rotational speed of the wind turbine, which is determined by wind speed, continues to vary. As damage detection methods of a rotating machine were generally developed for constant speed, an additional procedure to the condition monitoring and diagnosis is needed in order to apply it to the wind turbine. In this paper, the concept of bin is chosen as a tool to consider the characteristic of varying rotational speed. The bin was proposed by IEC 61400-25-6 to implement the efficient triggering for storing data of condition monitoring system (CMS) as it is shown in Figure 4.

Bin is a statistical term to represent a range of a variable. If a variable stays within a selected range, which is called as a bin, for a certain term, we can consider that the variable belongs to the bin. Similarly, if operational condition of a wind turbine stays within a range defined by operator for a certain term, the states of the wind turbine can be considered as being quasi-stationary although real operational conditions of the wind turbine continue to vary in accordance to the speed of wind. If the concept of bin is applied to the condition monitoring of a wind turbine, the condition monitoring is not always carried out for all the operational conditions. Instead, the condition monitoring is executed when an operational condition, which is exemplified by generated power of the wind turbine in Figure 4, stays in the bins for a certain term.

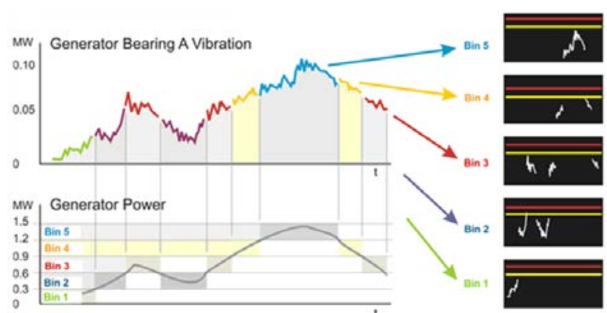

Figure 4 Concept of Power Bin (IEC 61400-25-6)

By using above the concept of bin, the prediction of life is realized as if wind turbine is a rotating machine with constant load and speed. Therefore, the techniques of life prediction in the case of constant load and speed are able to be applied to a rotational machine with variable speed.

3.2. Curve-fit Approach

One of the simplest way to predict the life of bearing is to make a fitting function instantly with most recent data (Seo, 2017). After a term of time for fitting is specified, curve-fitting with an exponential function as Eq. (2) is carried out. The fitted function from the curve-fitting reveals a possible trajectory of state index (SI) from current time to infinite time. Therefore, SI at the current time can be estimated and remaining useful life (RUL) is predicted by calculating the time that the fitted function is equal to a unit, which means the end of life.

In this method, the time term used in fitting should be specified. If the time duration is too short, prediction result becomes much sensitive to instant variation. If the time duration is too long, the prediction result do not change and measurements become meaningless. In this paper, the best time duration for fitting is chosen by trial and error. However, the development of a systematic method is needed for application of the proposed method in the future.

3.3. Bayesian Approach

There exist many methods to estimate a probabilistic variable (y) statistically. One of effective methods is Bayesian estimation by considering current measured data and prior information. This method calculates a maximum point of conditioned probability distribution with respect to measured data such as

$$y = \arg\max \Pr(y \mid x), \tag{8}$$

When prior distribution, $\Pr(y)$, of estimated variable exists, a posterior distribution, $\Pr(y \mid x)$, can be calculated by so-called Baye's rule like below

$$\Pr(y \mid x) = \frac{\Pr(x \mid y) \times \Pr(y)}{\Pr(x)} \tag{9}$$

If the intercept c in degradation model of Eq. (2) is assumed to be a known constant, logarithm of both sides of Eq. (2) can be written as (Gebraeel, 2005)

$$\begin{aligned} L &= \ln(y-c) = \ln a + bt + \varepsilon \\ &= \theta'(n) + b(n)t + c \end{aligned} \tag{10}$$

where $\theta'(n)$ and $b(n)$ are n^{th} time step(current) degradation model variables. It is assumed that $\theta'(n)$ and $b(n)$ have normal(Gaussian) distribution with mean values of $\mu_0(n)$ and $\mu_1(n)$, and standard deviations of $\sigma_0(n)$ and $\sigma_1(n)$, respectively. In this paper, $\mu_0(n)$, $\mu_1(n)$, $\sigma_0(n)$ and $\sigma_1(n)$ are expressed as μ_0, μ_1, σ_0 and σ_1 for simplicity, respectively.

On the other hands, if $\theta'(n)$ and $b(n)$ are partly dependent to each other, a joint probability density function is defined by

$$\pi(\theta', b) = \frac{1}{2\pi\sigma_0^2\sigma_1^2\sqrt{1-\rho_0^2}} \times \exp\left[-\frac{1}{2\left(1-\rho_0^2\right)} \left\{ \begin{array}{l} \dfrac{\left(\theta' - \mu_0\right)^2}{\sigma_0^2} - \\ \dfrac{2\rho_0^2\left(\theta' - \mu_0\right)\left(b-\mu_1\right)}{\sigma_0\sigma_1} + \\ \dfrac{\left(b-\mu_1\right)^2}{\sigma_1^2} \end{array} \right\} \right] \tag{11}$$

where ρ_0 is correlation coefficient of θ' and b. Similarly, it is assumed that ε in Eq. (2) has a normal distribution with zero(0) mean and standard deviation of σ like below

$$\varepsilon \sim l(L \mid \theta', b) = \frac{1}{2\pi\sigma^2} \exp\left[-\frac{1}{2}\left\{ \frac{\left(L - \theta' - bt\right)^2}{\sigma^2} \right\} \right]. \tag{12}$$

Eq. (11) is prior distribution of model parameters in Eq. (2), and then a posterior distribution can be obtained by manipulating Equation (12), which is a likelihood function, such as

$$p(\theta', b \mid L) \propto l(L \mid \theta', b) \times \pi(\theta', b). \tag{13}$$

If the posterior distribution like Eq. (13) is also a normal distribution, model parameters of the posterior distribution such as mean and standard deviation values are written as

$$\begin{aligned} \mu_{0p}(n) &= \frac{\mu_0\sigma^2\sigma_1\left(Y + M\rho_0\right) - \mu_1\sigma^2\sigma_0\left(Y\rho_0 + M\right)}{\sigma_1\left(XY - M^2\right)} \\ &+ \frac{\left(1-\rho_0^2\right)L\sigma_0\sigma_1\left(Y\sigma_0 - Mt\sigma_1\right)}{\sigma_1\left(XY - M^2\right)} \end{aligned} \tag{14}$$

$$\begin{aligned} \mu_{1p}(n) &= \frac{\mu_1\sigma^2\sigma_0\left(X + M\rho_0\right) - \mu_0\sigma^2\sigma_1\left(X\rho_0 + M\right)}{\sigma_0\left(XY - M^2\right)} \\ &+ \frac{\left(1-\rho_0^2\right)L\sigma_0\sigma_1\left(Xt\sigma_1 - M\sigma_0\right)}{\sigma_0\left(XY - M^2\right)} \end{aligned} \tag{15}$$

$$\sigma_{op}^2(n) = \frac{Y\left(1-\rho_0^2\right)\sigma^2\sigma_0}{XY - M} \tag{16}$$

$$\sigma_{1p}^2(n) = \frac{X\left(1-\rho_0^2\right)\sigma^2\sigma_1}{XY - M} \tag{17}$$

where

$$
\begin{aligned}
X &= \left(1-\rho_0^2\right)\sigma_0^2 + \sigma^2 \\
Y &= \left(1-\rho_0^2\right)t^2\sigma_1^2 + \sigma^2 \\
M &= \left(1-\rho_0^2\right)t\sigma_0\sigma_1 + \sigma^2
\end{aligned}
\tag{18}
$$

The new model parameters from Eqs. (14), (15), (16) and (17) are estimated and then predicted model variable $\theta'(n+1)$ and $b(n+1)$ are obtained by determining mean values as predicted values.

4. EXPERIMENTAL EXAMPLES

4.1. Degradation Tests with Constant Load and Speed

Degradation tests of 14 samples in the case of constant load and speed (Table 2) are performed and the life of each bearing is predicted by proposed methods in the previous sections. Although the conditions of constant load and rotating speed are not the same as those of a real wind turbine, the model parameters, which are acquired in the constant conditions, can be applied to the variable loading case if the monitoring for the wind turbine is executed by using the concept of bin.

Table 2 Condition of Degradation Test with constant load and speed

Axial load	Radial load	Rotating speed
15 kN	10 kN	1,000 rpm

Table 3 Terminal Condition of Degradation Test

Vibration RMS	Temperature	Torque
8 m/s^2	200 ℃	20 N-m

Terminal condition of degradation test, which is listed on Table 3, is set in order to protect the equipment and consider operational range of machine elements. Moreover, each of the terminal conditions is used as a reference value to normalize the measured value which are described in Eq. (1). Table 4 shows the weighting factors to consist of state index, which is determined by optimization in Eq. (7). Figure 5 shows state indexes of 14 samples with the weighting factors in Table 4. It is shown that each of state indexes has much difference because there are uncertainties (hidden characteristics) that originate from manufacturing tolerance, variation of environment, assembly error of test equipment and so on. Therefore, curve fitting and Bayesian approach are effective to predict the life of bearing.

Figure 6 and Figure 7 show histograms and fitted probability distributions of model parameter in Eq. (1) for 14 degradation samples. Even if scattering exists, their distributions are assumed to be normal distribution, and identified model parameters are shown in Table 5.

Table 4 Weighting Factors of State Index

w_a	w_b	w_c
1.0	0.1	0.1

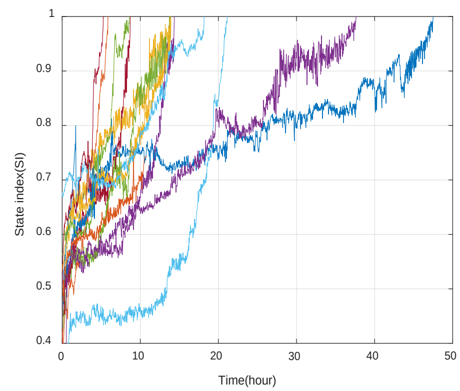

Figure 5 State Indexes with Constant Load and Speed

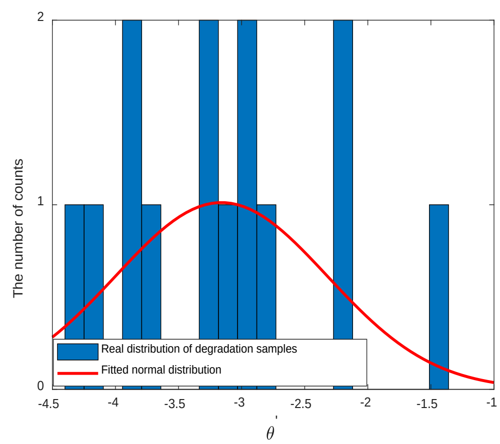

Figure 6 Distribution of Model Parameter(θ')

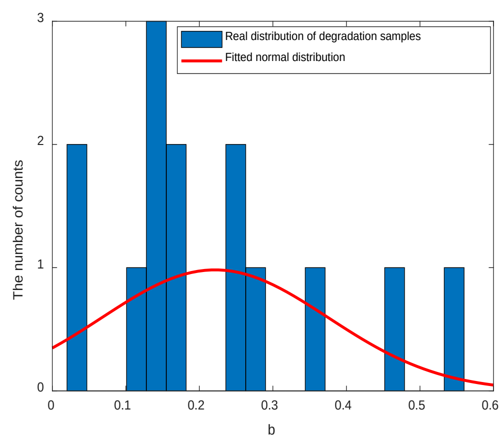

Figure 7 Distribution of Model Parameter(b)

Table 5 Statistical Model Parameters for Bayesian Approach

μ_{00}	-3.3	σ_{10}	0.02
μ_{10}	0.24	ρ_{00}	-0.2
σ_{00}	2	σ'	0.5

Figure 8 shows prediction results of a sample among 14 samples. In Figure 8, the results of curve-fitting approach is made when fitting term is 80 minutes (40 data points). Although the error of prediction is quite large, the error becomes smaller as operational time passes by. Since the curve–fitting approach is more sensitive to an instant variation, the prediction result has some rapid changes. If fitting term is elongated, the rapid changes would become smoother but insensitive to any external variation. If the external variation is an instantaneous fluctuation such as measurement noise, its influence on the life is insignificant, and the insensitivity (or robustness) of prediction method is better. On the other hands, if the variation causes a permanent effect, sensitive prediction is good for an accurate result. Therefore, the fitting term is a hyper parameter to be determined for the sake of proper prediction. But, any other information such as model parameters is not required for the curve-fitting approach. It is advantageous when a simple prediction method is needed or sufficient model information does not exist.

Figure 8, in addition, shows a prediction result by Bayesian approach for the same sample. While the RUL are underestimated, the prediction error becomes smaller like the curve-fitting approach. However, root mean square error between true RUL and predicted one is much smaller than that of curve-fitting approach. Because Bayesian approach demands more statistical model parameters such as Table 5 than curve-fitting approach, the accuracy is superior.

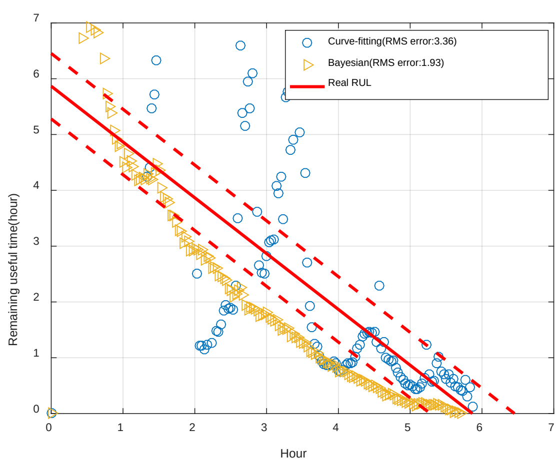

Figure 8 Prediction Results for Constant Load and Speed

4.2. Degradation tests with two-step variable load and speed

Because condition monitoring of a wind turbine is performed by using the concept of bin, degradation tests with two-step variable loading and speed are executed. Test conditions are shown in Table 6 and alternate time is 60 minutes. Degradation tests of 19 samples are carried out and Figure 9 shows one (sample No. 6) of 19 samples' state indexes which are calculated with weighting factors of Table 4. Because state indexes in both bins show increasing trend by degradation, curve-fitting approach can be applied to the prediction of life. Similarly, since test conditions in Bin I are the same as the loading and speed in the previous constant condition, the state index of Bin I is possible to predict the life by using the Bayesian approach with the model information in Table 5.

Table 6 Condition of Two-step Load and Speed

	Axial load	Radial load	Rotating speed
Step I (Bin I)	15 kN	10 kN	1,000 rpm
Step II (Bin II)	1 kN	1 kN	750 rpm

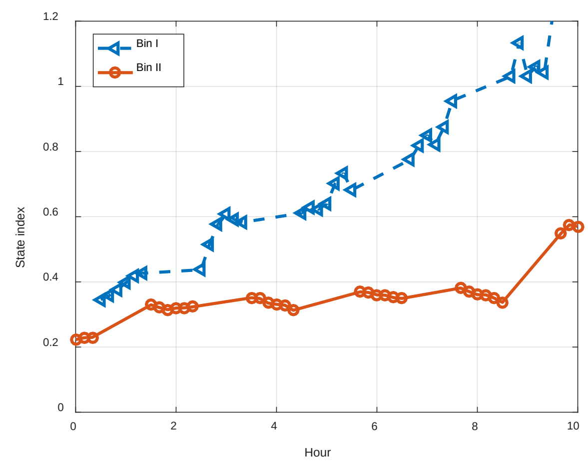

Figure 9 State Indexes of Degradation Tests with Two-step Load and Speed

Figure 10 is prediction results of both curve-fitting and Bayesian approaches for two-step load and speed. The predictions are carried out only for Step I load, which is equivalent to Bin I, in order to use the model parameters in Table 5. Even if the conditions of loading and speed alternate, both predictions show reasonable results because the life is influenced by cumulative loading. That is similar to famous Miner's rule in metal fatigue. Therefore, it is expected that the life prediction of a mechanical component for the random loading of a wind turbine is possible with the concept of bin in terms of data acquisition and analysis.

Life predictions of several samples for two-step loading condition are performed and their results are shown in Figure 11. Generally, the Bayesian approach is more advantageous with respect to the accuracy of the prediction because prior information is important for the prediction. But the complete predictions of all the cases are not possible. If the prior information is used without any updating, it is difficult to predict in the case of a bizarre sample. Therefore, a further study such as an effective updating method is needed to manipulate an outlier of the model.

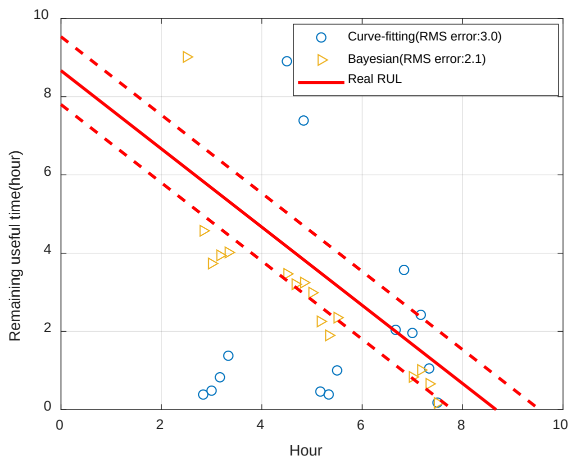

Figure 10 Prediction Results for Two-step Load and Speed

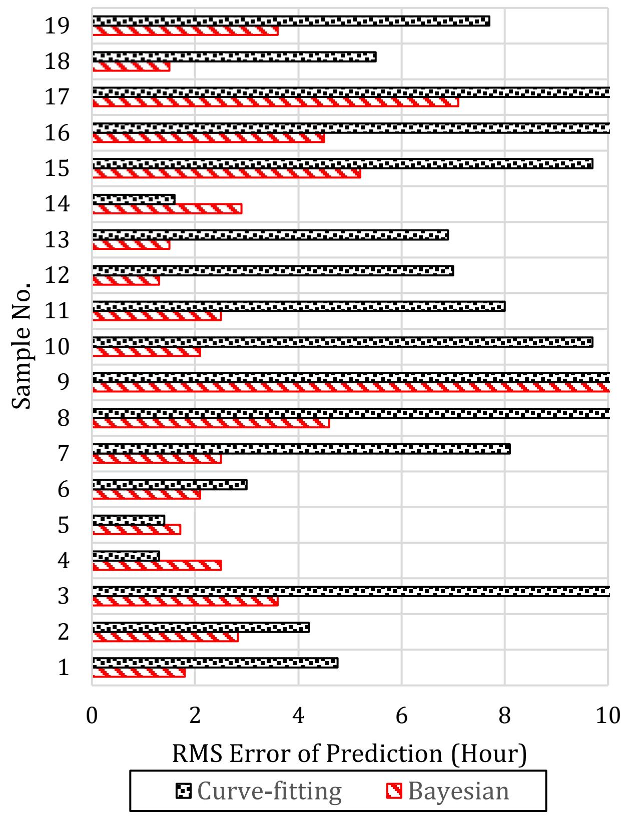

Figure 11 Performance of Prediction for Two-step Load and Speed

5. CONCLUSION

A wind turbine suffers various loadings and rotational speeds due to unpredictable natural wind. The life prediction of a bearing under the variable loading condition is worthy for condition-based operation and maintenance. In this paper, degradation characteristics of bearings for constant loading and speed in terms of time are analyzed, and an exponential function is used as a degradation model. A weighted linear combination of measured values is suggested as a state index to express the degradation model. Two methods such as curve-fitting and Bayesian prediction with the concept of a bin are proposed. While the curve-fitting is a simple method without any model information, the Bayesian prediction with model information shows more accurate results. Because both proposed methods are complementary, It is expected that the two methods are useful to predict the life of a bearing practically.

ACKNOWLEDGEMENT

This work was partially supported by the Korea Institute of Energy Technology Evaluation and Planning (KETEP) Grants No. 20163030024510(Development of a condition monitoring and diagnosis system for wind turbine generator system) funded by the Korean Ministry of Trade, Industry & Energy (MOTIE)

REFERENCES

Ali, J. B. (2015), Accurate bearing remaining useful life prediction based on Weibull distribution and artificial neural network, *Mechanical Systems and Signal Processing*, vol. 56-57, pp. 150~172.

Boskoski, P. (2015), Bearing fault prognostics using Renyi entropy based features and Gaussian process models, *Mechanical Systems and Signal Processing*, vol. 52-53, pp. 327-337.

CWRU Bearing Data Center, https://csegroups.case.edu/bearingdatacenter/pages/welcome-case-western-reserve-university-bearing-data-center-website, Accessed on December 16, 2017.

Gebraeel, N. (2005), Residual-life distributions from component degradation signals: A Bayesian approach, IIE Transactions, Vol. 37, pp. 543~557

International Electrotechnical Commission (IEC) (2016). Wind energy generation systems - Part 25-6: Communications for monitoring and control of wind power plants - Logical node classes and data classes for condition monitoring. Genève, Switzerland: International Electrotechnical Commission.

International Standards Organization (ISO) (2004). Condition Monitoring and Diagnostics of Machines - Prognostics part 1: General Guidelines. In ISO, *ISO13381-1:2004(e)*

Korean Society for Prognostics and Health Management (KSPHM) Data Repository for PHMAP 2017 Data Challenge, http://www.phm.or.kr/info/board.php, Accessed on April 11, 2018.

NASA Prognostics Data Repository, https://ti.arc.nasa.gov/tech/dash/groups/pcoe/prognostic-data-repository/, Accessed on December 16, 2017.

Sankararaman, S. (2015), Significance, interpretation, and quantification of uncertainty in prognostics and remaining useful life prediction, *Mechanical Systems and Signal Processing*, vol. 52-53, pp. 228~247.

Seo, Y. H. (2017), Prediction of bearing life by exponential curve fitting, *Proceedings of Asia Pacific Conference of the Prognostics and Health Management Society*, pp. 193~195

Si, X. (2011), Remaining useful life estimation – A review on the statistical data driven approaches, *European Journal of Operational Research*, Vol. 213, pp. 1~14

Si, X. (2013), A Wiener-process-based degradation model with a recursive filter algorithm for remaining useful life estimation, *European Journal of Operational Research*, vol. 226, pp. 53~66.

Zhou, H. (2016). Detection and diagnosis of bearing faults using shift-invariant dictionary learning and hidden Markov model, *Mechanical Systems and Signal Processing*, vol. 72-73, pp. 65-79.

BIOGRAPHIES

Yun Ho Seo received the B.S. degree from Yonsei University, Seoul, Korea, in 2003 and the Ph.D. Degree from KAIST, Daejeon, Korea, in 2009. Dr. Seo is a principal researcher in the Korea Institute of Machinery & Materials (KIMM) and a member of technical committee in Korea Certification Institute for Machine Diagnostics(KCI-MD). His current research topics are monitoring, diagnosis, and prognosis of machinery and dynamic analysis of structures.