Rolling Bearing Reliability Estimation Based on Logistic Regression Model

Hongkun Li, Yinhu Wang
School of Mechanical Engineering
Dalian University of Technology
Dalian, China
lihk@dlut.edu.cn

Abstract—**Rolling bearing (RB) has been broadly applied on mechanical systems. Its reliability is directly related to the performance of the whole mechanical system. RB reliability estimation technology is crucial for mechanical system. Logistic regression model (LRM) is constructed for RB reliability estimation in this paper. Vibration data acquisition and feature extraction are carried on for. Based on feature extraction investigation, root mean square and wavelet entropy are used to construct characteristics vector. Therefore, bearing degradation state information is determined by vibration information. Reliability estimation model based on LRM is constructed to estimate bearing performance. By using LRM, it has good performance on reliability estimation. It can be concluded that LRM is beneficial for RB life prediction.**

Keywords-rolling bearing; reliability estimation; logistic regression model; vibration; feature extraction

ACRONYM

RB	Rolling Bearing
LRM	Logistic Regression Model

I. INTRODUCTION

Rolling bearing (RB) condition is closely related with machine's high efficiency and production. According to RB development planning, it is one of the program for tackling key problems to provide RB reliability engineering technology. Traditional bearing reliability estimation method [1, [2]is based on the statistics analysis from great amount experiments. Statistics distribution models have been used on this area, such as normal distribution. This kind of method depends on plentiful of history data for relevance equipments. It has good performance when the data is enough. But small samples are not suitable for reliability analysis. As well, its defect is also typical as it is less of economic and not suitable for single bearing reliability estimation [3]. In practical working conditions, there are many conditions which cannot repeat again. But reliability is also important to estimate machine working condition. Therefore, further investigation should be carried on for small simples analysis.

Degradation is the main failure for RB. The key information of bearing life prediction can be determined from failure data. It can be used for reliability estimation. Logistic regression model (LRM) is a statistics method. It was firstly applied on people amount estimation and prediction [4]. It also applied on risk analysis for medicine [4], bank [5] and etc. In recent years, researchers apply LRM on machine reliability estimation and life prediction. Yan [6]constructs degradation model based on characteristic vector. As well, the probability distribution is constructed by using LRM. Auto-regressive moving averaging model is also used for life prediction and reliability estimation.

Li [7]applies LRM on rotating machine working condition life estimation. As well, the effectiveness of this method is verified on a bearing testing-rig. Chen [8] constructs cutting tool LRM by vibration characteristic vector. The result shows that this method can be used on cutting tool reliability estimation. At the same time, this method can also be used on machine tools failure estimation. RB history data is used to constructed LRM in this paper. This mode can be used others RB reliability estimation and life prediction. It is also verified the effectiveness of the method.

II. METHODOLOGY

A. Logistic Regreesive Model

LRM is a nonlinear regressive mode. It is usually used on two variables condition. LRM is to find the best suitable fitting model to describe two characteristics relation [9]. In a LRM, the output dependent variable is the probability of event. Therefore, the output is a discrete time series. It is between zero and one. The reliability estimation model can written as Eq.(1)

$$R(t) = P(y_t = 1 \mid X(t)) = e^{g[X(t)]} / \{1 + e^{g[X(t)]}\} \qquad (1)$$

The output $R(t)$ is the degree of reliability for RB with time variable t . When a machine is working in normal condition with $y = 1$, the result will one for Eq.(1). $X(t) = [x_1(t), x_2(t), \cdots, x_n(t)]$ is the corresponding covariant for input vector. It can be vibration signal time domain information or frequency information for RB. $g[X(t)]$ is the log transform for logistic function. It can be expressed as Eq.(2)

$$g[X(\mathrm{t})] = \ln\{\frac{P[y_t = 1 \mid X(t)]}{1 - P[y_t = 1 \mid X(t)]}\} = \alpha + \beta_1 x_1 + \ldots + \beta_n x_n \quad (2)$$

The occur ratio can be written as Eq.(3)

$$Odds = \frac{P[y_t = 1 \mid X(t)]}{1 - P[y_t = 1 \mid X(t)]} = e^{\alpha} \times e^{\beta_1 x_1} \times \ldots \times e^{\beta_n x_n} \tag{3}$$

In Eq.(3), $e^{\beta_i} > 1$ and the probability of event will increase with x_i when β_i is positive. On the contrary, $e^{\beta_i} < 1$ and the he probability of event will increase with x_i when β_i is negative. When β_i is equal to zero, $e^{\beta_i} = 1$ and the occur ratio will not change with x_i .

The parameters of LRM can be determined based on maximum likelihood estimation. Thus, LRM can be used on RB reliability estimation and life prediction.

B. Wavelet Entropy

Wavelet transform has good performance on time-frequency local attributes demonstration. It is suitable for non-stationary signal feature extraction. Wavelet packet analysis method[10] is the development of wavelet transform. It can decompose signal in the whole frequency band. Norm entropy [11] be used to estimate signal energy distribution. The norm entropy of the jth node in the signal $S=\{s(j), j = 1, 2, \cdots N\}$ is represented as Eq.(4).

$$E_n(j) = | s(j) |^p \tag{4}$$

where p is the power and must be such that $1 < p < 2$, In this research, we take $p = 1.1$. Then, norm entropy of the signal S is shown as Eq.(5).

$$E_n(S) = \sum_{j=1}^{N} E_n(j) \tag{5}$$

There are eight nodes for Signal S after three level decomposition based on one-dimensional wavelet packet analysis theory. $S_{3,i}$ is the wavelet packet coefficients of the node $[3, i]$. Therefore, the wavelet packet norm entropy can defined as Eq.(6).

$$WE_n(S_{3,i}) = \sum \left| S_{3,i}(j) \right|^p \tag{6}$$

III. Experiment

To verify the effectiveness of this method, experiment is carried on to testify the method. Experiment data [12] is from IEEE PHM 2012 prognostic challenge. Testing-rig is shown in Fig. 1. Vibration sensor, speed sensor, and force sensor are used to monitor RB condition and evaluate its condition. Testing-rig is from FEMTO-ST [13] institute design and manufacturing. This experiment is mainly about RB reliability analysis and life prediction.

RB degradation data of PRONOSTIA testing-rig is different from other reference testing-rig data. The data from PRONOSTIA testing-rig is with accelerated experiment and the working time is shorten. PRONOSTIA is composed with power, load and data acquisition. Data acquisition frequency is 25.6Hz. The data length is 2.56K. Data acquisition is carried on every ten seconds.

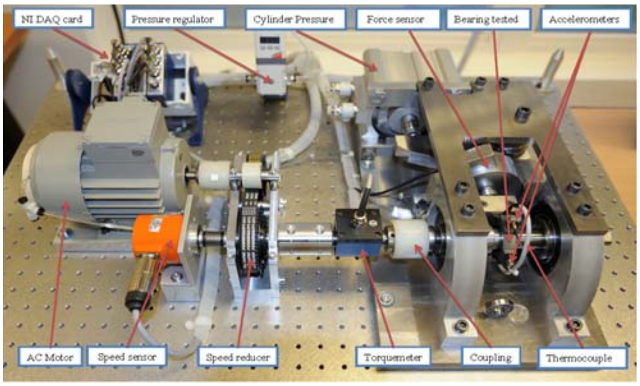
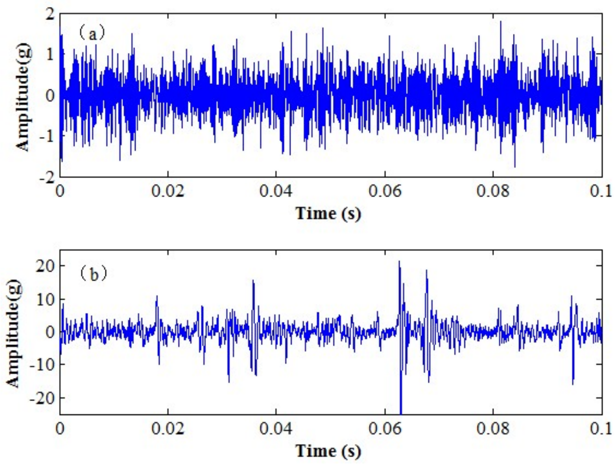


Figure 1. Overview of experimental platform.



(a) Normal condition; (b) Fault condition

Figure 2. Time domain waveform for rolling bearing.

Regarding the PHM challenge, data representing 3 different loads were considered, in this paper only the first group of bearing experiment data is used, and the first group data is with speed of 1800RPM and load 4000N. There are seven RBs in the first group experiment. Bearing 1-2 represents the second bearing of the first group, and so on. Table 1 summarizes the failure events in conditions 1. It is corresponding to the time domain waveform for RB with different condition. Fig. 2 (a) and (b) are corresponding to the normal condition and fault condition, respectively. For normal condition, time domain waveform is stationary and with less amplitude. On the contrary, there is typical impact information from fault RB. As well, its amplitude is bigger compared with normal condition shown in Fig. 2 (b). When RB is in serious wearing condition, its amplitude is almost ten times for normal working condition. Therefore, the vibration amplitude can be as characteristic parameter for reliability analysis.

TABLE I. Datasets of Conditions 1

Operating conditions 1	Bearing Test Results	
	Failed bearing	Censored bearing
Bearing Number	B1-1,B1-2	B1-3,B1-4 B1-5,B1-6 B1-7

IV. RELIABILITY ESTIMATION

A. Feature Extraction

Proper selection for RB degradation data is the key step for probability estimation and life prediction. It will contribute to the improvement of reliability estimation. root mean square (RMS) is determined as characteristic parameter in this research based on every RB vibration signal feature extraction in time domain. It also means that

$$Vib_1(t) = RMS(Y) \tag{7}$$

where, t , Y , and $Vib_1(t)$ stands for time, monitored vibration time series, and degradation data of RMS.

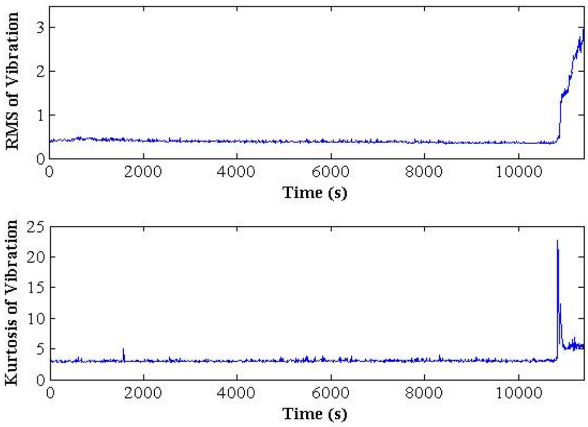


Figure 3. Vibration features of Bearing 1-4.

RMS demonstrates vibration signal energy. It is also the main estimation index for rotating machine vibration. Figure 3 shows the RMS and kurtosis change curve for 1-4 bearing. It is obvious that RMS increases with time. But kurtosis is different from RMS as the kurtosis reduce when the RB is almost broken. Kurtosis can provide information about fault occurs, but it cannot demonstrate bearing performance degradation. As there is not much kurtosis difference for normal condition and serious wearing condition of RB, it will lead to incorrect estimation for RB degradation. Otherwise, many parameters should be considered in reliability model construction. Although RMS is better than kurtosis, it increases very fast in end of the experiment. It is also not the best one for reliability model construction. In this research, it is just to verify the effectiveness of this method. Therefore, RMS is used to be one of the characteristic parameter for LRM.

Three level decomposition based on wavelet packets is carried on for rolling vibration signal. Norm entropy for the eight nodes are calculated based on wavelet packet coefficients. To eliminate the difference for different characteristic vector, logarithm is applied for the result. Wavelet entropy of the third node is selected as another parameter. It can be written as Eq.(9).

$$wentropy = \log[WE(S_{3,3})] \tag{8}$$

$$Vib_2(t) = wentropy(Y) \tag{9}$$

Fig. 4 provides the wavelet packet norm entropy comparison on normal and fault condition. Fig. 5 is the time series of wavelet packet norm entropy. Based on above analysis, the input vector for LRM analysis is $Vib = [Vib_1; Vib_2]$.

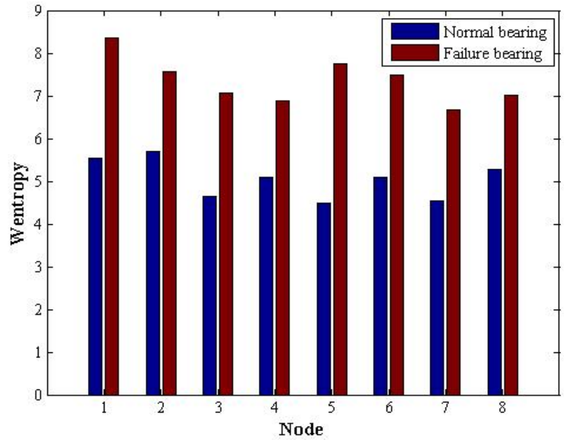


Figure 4. Wavelet packet norm entropy comparison on normal and failure condition.

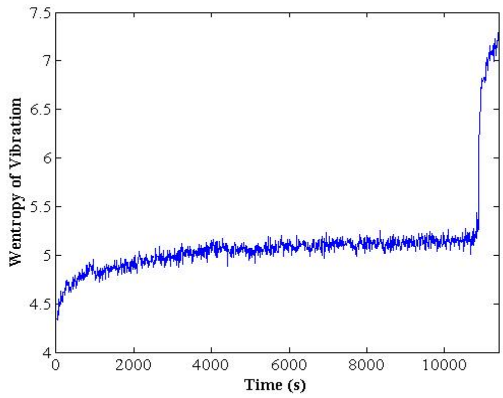


Figure 5. Wavele packets entropy of the third node for Bearing 1-4.

B. Reliability Modeling and Assessment

Characteristic vector Vib is as the independent input variable for the two failure bearings (1-1 and 1-2) together with four censored bearings (1-3, 1-5, 1-6, and 1-7). The reliability estimation model is constructed based on the variables. SAS software is used to construct LRM. The RB reliability estimation model can be demonstrated with Eq.(10).

$$\begin{aligned} R(t) &= \frac{\exp[\alpha + \beta_1 Vib_1(t) + \beta_2 Vib_2(t)]}{1 + \exp[\alpha + \beta_1 Vib_1(t) + \beta_2 Vib_2(t)]} \\ &= \frac{\exp[75.8245 - 14.5334 Vib_1(t) - 6.0858 Vib_2(t)]}{1 + \exp[75.8248 - 14.5334 Vib_1(t) - 6.0858 Vib_2(t)]} \end{aligned} \tag{10}$$

The regressive coefficients obtained by calculation is $\beta_1 = -14.5334$. Therefore, there is $e^{\beta_1} < 1$. It means that normal probability $P[y_1 = 1 | Vib(t)]$ divided by fault probability $P[y_1 = 0 | Vib(t)]$ decrease with RMS increment in time t. It demonstrates that the bigger RMS, the less reliability of RB. It also has the same result for wavelet entropy.

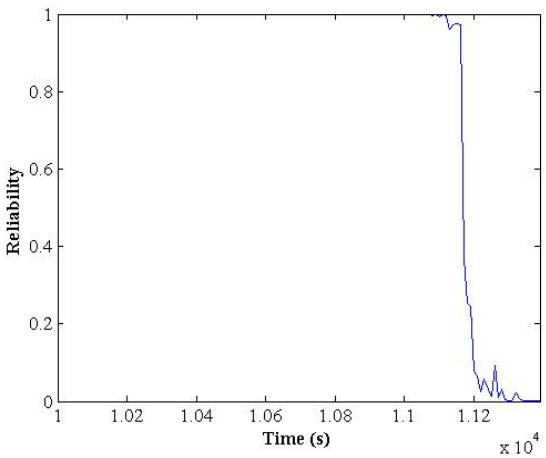


Figure 6. Reliability estimate for Bearing 1-4.

To test the validity of the model, The characteristic vector of RB 1-4 is input to Eq.(10). Then, the degree of reliability estimation for RB can be calculated shown in Figure6. The degree of reliability is designed with 0.5 based on reference [8]. The failure time for RB 1-4 is 11170s by using constructed reliability estimation model. Its failure time in the testing-rig is 11729s. The error is 4.77%. As well, prediction time is less than practical failure time is also reasonable. It can be helpful to make a decision for maintenance. As RMS and Wavelet packet norm entropy increase fast at the end of experiment, the degree of reliability reduce sharply. It can demonstrate the reliability process. But it is not suitable for practical application because there is not any time for preventative maintenance implementation. Therefore, further investigation should also be carried on.

V. CONCLUSIONS

RB performance estimation and reliability analysis are carried on in the research based on LRM. It can be concluded that LRM can be used to estimate RB reliability and failure time based on the experimental analysis for experimental data. It is also verified that RB vibration characteristic is closely with degradation process. The characteristic parameter can directly affect the reliability estimation performance. Therefore, characteristic vector is always the key step for reliability estimation and life prediction. It can be further investigated on reliability estimation and life prediction based on RB practical working condition.

ACKNOWLEDGMENT

The work was supported by the Natural Science Foundation of China under Grant No 51175057 and the National Basic Research Program of China under Grant No 2012CB026000.

REFERENCES

[1] A. Z. Keller, A. R. R. Kamath, and U. D. Perera, "Reliability analysis of CNC machine tools," Reliability Engineering, vol. 3, no. 6, pp. 449-473, 1982.

[2] A. Schömig and O. Rose, "On the suitability of the Weibull distribution for the approximation of machine failures," In Proceedings of he Industrial Engineering Research Conference, pp. 549-573, 2003.

[3] A. Heng, S. Zhang, A. C. Tan, and J. Mathew, "Rotating machinery prognostics: State of the art, challenges and opportunities," Mechanical Systems and Signal Processing, vol. 23 , no. 3, pp. 724-739, 2009.

[4] S. W. Menard, Applied logistic regression analysis. London: Sage, 2001.

[5] D. Martin, "Early warning of bank failure: A logit regression approach," Journal of Banking & Finance, vol. 1, no. 3, pp. 249-276,1977.

[6] J. H. Yan and L. Jay, "Degradation assessment and fault modes classification using logistic regression," Journal of Manufacturing Science and Engineering, vol. 127, no. 4 , pp. 912-914, 2005.

[7] F. F. Li, "Rearch on condition health assessment of machinery based on Logistic Regression," China Engineering Equipment, no. 5, pp. 20-23, 2009.

[8] B. J. Chen, X. F. Chen, B. Li, H. R. Cao, G. G. Cai, and Z. J. He, "Reliability estimation for cutting tool based on logistic regression model," Chinese Journal of Mechanical Engineering, vol. 47, no. 18, pp. 158-164, 2011.

[9] W. Caesarendra, A. Widodo, and B. S. Yang, "Application of relevance vector machine and logistic regression for machine degradation assessment," Mechanical Systems and Signal Processing, vol. 24, no. 4, pp. 1161-1171, 2010.

[10] M. V. Wickerhauser, "Lectures on wavelet packet algorithms," Lecture notes, 1991.

[11] E. Avci, "Comparison of wavelet families for texture classification by using wavelet packet entropy adaptive network based fuzzy inference system," Applied Soft Computing, vol. 8, no. 1, pp. 225-231, 2008.

[12] FEMTO-ST, IEEE PHM 2012 Data Challenge, available at: http://www.femto-st.fr/en/Research-departments/AS2M/Research-groups/PHM/IEEE-PHM-2012-Data-challenge.

[13] P. Nectoux, R. Gouriveau, K. Medjaher, E. Ramasso, B. Chebel-Morello, N. Zerhouni, and C. Varnier, "PRONOSTIA: An experimental platform for bearings accelerated degradation tests," In Proceedings of Prognostics and Health Management, pp. 1-8, 2012.