International Journal of Applied Engineering Research ISSN 0973-4562 Volume 10, Number 14 (2015) pp 34527-34531
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Remaining Useful Life Time Prediction of Bearing using Naïve Bayes and Bayes Net Classifiers

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Abstract- Bearings are critical components in rotatory machineries. Unexpected failure in the bearings causes huge impact in industries. Predicting the remaining useful life time of bearing helps in replacing them without any delay and allowing maintenance. Numerous research works have done in predicting the life time of bearings and many of the works were based on regression model. In the present work, classification approach was carried out and a predictive model was built to assess the remaining useful life time of bearings. Vibration signals will be acquired on continuous basis from bearings running in the experimental set-up. Vibration signals were used in the present study which was operated at rated speed and load conditions. A brand new bearing was taken for the experiment and the signals were acquired on daily basis till it fails naturally, meaning run to failure tests was carried out. In this paper, decision tree is used for feature selection and comparative study of Naïve Bayes and Bayes net classifiers in predicting remaining useful life time was carried out. The result shows that Bayes net classifier gives 89.64% classification accuracy with 5 features whereas Naïve Bayes classifier yields 77.16% accuracy.

Keywords- Bearings, Naïve Bayes classifier, Bayes net classifier, Vibration signals, Machine learning, Remaining useful life.

1. Introduction

Bearings play an important role in industrial applications. Failure in the bearings causes unplanned breakdowns and loss of time. Predicting the remaining life time of bearings helps in saving time and preventive measures can be taken to replace them at appropriate time. Numerous research works were done in fault diagnosis of bearing and the works were based on simulated fault (inner race faults, outer race faults, cage faults, etc.) and natural faults and thus estimating the life of bearings. Regression model were used by some researchers in the prediction of bearing life time. In the present study, predictive model is built using classification approach.

It is highly challenging to acquire data on regular intervals for a long time till the bearing fails on its own. Vibration signals were acquired from the brand new bearings from the experiments on daily basis till it fails naturally. The life time of bearings was divided into five different stages. Stage 1 includes the vibration signals from brand new bearing; stage 2 indicates that the signals were extracted after 1000 hours of running at rated speed and load conditions. Stage 3 and 4 indicates that signals were extracted after 1250 and 1500 hours of running the bearing respectively. Stage 5 indicates the damaged bearing condition at 1800 hours of running.

Out of 12 statistical features, five best contributing features were selected using decision tree. Structural information hidden in the data can be identified using decision tree and by merely looking at the tree, one can select the best feature. Best feature lies on the top of the tree and features that lie on the bottom of the tree can be ignored due to its least contribution. With the selected features the predictive model was built. The present study focuses on comparing the performance of Naïve Bayes and Bayes net classifiers in predicting the remaining life time of bearings. Bayes classifiers are built using conditional probability. The advantage in Bayes net classifier is that small erroneous data does not affect the whole predictive system because conditional probability does not vary too much due to small error. Since there is no parameters to be trained, Bayes classifiers does not require any skilled professionals for building the model.

2. Literature Survey

The standards for predicting the life time of the bearings with respect to the loads and speed of the application were dealt in the previous research papers [1-3]. Experience-based prognostic methods were deployed to predict the life time of bearing. In this method real time data were collected over period of time which includes maintenance data, operational work like scrap, breakdowns, *etc*. This method uses the basic reliability functions and it is simple to use. However, the results from this method were precise compared to other methods.

Bearing maintenance can be grouped into two categories diagnosis and prognosis. Diagnosis is mainly focused on identifying the state of bearing *i.e.* safe state or damaged state. Bearing diagnosis were done in three methods *viz* statistical study [4, 5], vibration analysis [6-8] and neural network [9, 10].

Prognosis is mainly focused on predicting the remaining life time of bearings. Prognosis is done in two ways direct approach for fracture mechanics [11-13] and statistical approach of vibration signals which is an indirect approach [14]. The primary research works were carried out in 90's. They built model to predict life time of bearings using recursive algorithm which was based on vibration analysis and fracture mechanics.

Stress based fatigue prognostic method [15] was developed in order to precisely predict the bearing life time. It is highly challenging to build a model because degradation phenomenons are not consistent over the period of time and complex environmental nature. Hence, Stress based fatigue prognostic method is very complex in real time applications.

Data driven method captures the signals with sensors, accelerometers, etc. These signals are converted into data which can be used in the study of degradation of systems. Various methods like Artificial Neural Network (ANN), statistical method, spall propagation model, *etc*. are used in prediction of remaining useful time of bearings.

Artificial Neural Network (ANN) based models [16, 17] were built to predict the bearing life time and bearing failures. The built model quickly responds to change the environments and accommodates to the variable conditions. Compared to other methods, data driven method are simple to use in real time applications. However, prognostic results from this method were precise and may not be suitable in all applications.

Numerous research works have been carried out in diagnosis and prognosis of bearing life time and still it is challenging to design a model which is reliable and remains stable under variable conditions. Many of the previous works were based on simulated faults and naturally acquired faults. The present study proposes a model that is based on classification approach and mainly focuses on comparing the performance of Naïve Bayes and Bayes net classifiers in estimating the remaining life time prediction of bearings. To extract meaningful features, statistical features like standard deviation, skewness and sum were used. The important features are selected using J48 decision tree algorithm. Classification is carried out with the selected features using Naïve Bayes and Bayes net classifier and results and discussions are presented.

3. Experimental Set-up and Procedure

The experiments were conducted with the bearings run-to-failure test data to validate the effectiveness of the proposed model for predicting the remaining life of the bearing. The entire experimental set-up used for data acquition is shown in Fig. 1. This set-up consists of a bearing, accelerometer, motor, DAQ card and lab VIEW software loaded into a computer to acquire the vibration signals.

Fig. 1 Experimental setup

The bearings are mounted on to a shaft with Housing and in-turn connected to a variable speed motor. Few major parameters like speed, load, temperature, lubrication, *etc*, are simulated at real time conditions. The brand new bearing (ball bearing 6205) are made to run to failure at rated speeds (1400 RPM)and rated axial loads (0.2 kN). The vibration signals from the bearings are collected through the accelerometers placed on the housings and acquired via DAQ card. These signals are processed in the lab view software which is connected to the computer. The experiment was run at real time conditions matching to the said bearing application. Adequate measures were taken to avoid bearing faults or damages due to fitments, misalignments etc. The experiments on each bearing was conducted till the bearing fails naturally. Of all the bearing monitoring data, vibration signal is more effective and suitable for reflecting bearing running condition. The amplitude of the vibration signals are monitored on daily basis for estimating the current health condition of the bearings. The vibration is found to be small when the bearing is in normal condition. And the occurrence of bearing defect can cause fluctuation of vibration. During the process of degradation, the amplitude of vibration increases obviously as shown in the Fig. 2. Thus vibration signal becomes the convenient variable to estimate the remaining useful life of the bearings. The variations in signals thus acquired for the bearings at various stages can be seen in Fig. 2(a), 2(b), 2(c), 2(d) and 2(e) respectively.

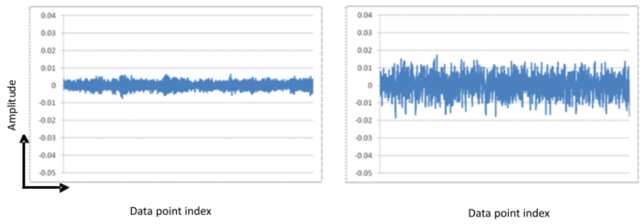

Fig. 2(a) Satge-1: Vibration Signals at Start
Fig. 2(b) Satge-2: Vibration signals@1000Hrs

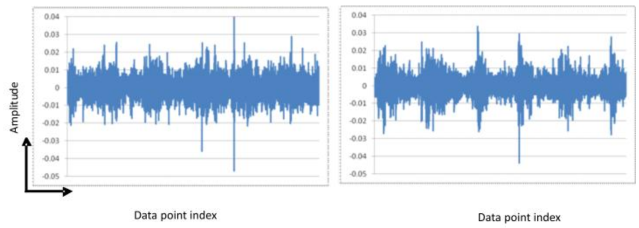

Fig. 2(c) Stage-3: Vibration Signals @1250Hrs
Fig. 2(d) Stage-4: Vibration Signals@1500Hrs

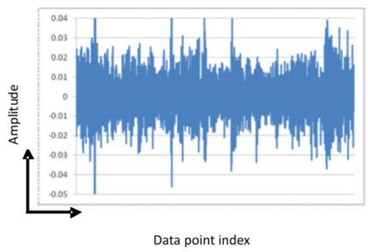

Fig. 2(e) Stage-5: Vibration Signals @1800 Hrs

4. Feature Description

Descriptive statistical parameters such as mean, median, mode, sample variance, kurtosis, skewness, standard error, standard deviation, minimum, maximum, sum, and range were computed to serve as features. They are named as 'statistical features' here. Brief descriptions about the extracted features are given below.

(a) Standard error: Standard error is a measure of the amount of error in the prediction of y for an individual x in the regression, where x and y are the sample means and *'n'* is the sample size.

$$\text{Standard error of the predicted, } Y = \sqrt{\frac{1}{n-2}\left[\sum (y-\bar{y})^2 - \frac{\left[\sum (x-\bar{x})(y-\bar{y})\right]^2}{(x-\bar{x})^2}\right]}$$

(b) Standard deviation: This is a measure of the effective energy or power content of the vibration signal. The following formula was used for computation of standard deviation.

$$\text{Standard Deviation} = \sqrt{\frac{\sum x^2 - \left(\sum x\right)^2}{n(n-1)}}$$

(c) Sample variance: It is variance of the signal points and the following formula was used for computation of sample variance.

$$\text{Sample Variance} = \frac{\sum x^2 - \left(\sum x\right)^2}{n(n-1)}$$

(d) Kurtosis: Kurtosis indicates the flatness or the spikiness of the signal. Its value is very low for normal condition of the bearing and high for faulty condition of the bearing a due to the spiky nature of the signal.

$$\text{Kurtosis} = \left\{\frac{n(n+1)}{(n-1)(n-2)(n-3)}\sum\left(\frac{x_i-\bar{x}}{s}\right)^4\right\} - \frac{3(n-1)^2}{(n-2)(n-3)}$$

where's' is the sample standard deviation.

(e) Skewness: Skewness characterizes the degree of asymmetry of a distribution around its mean. The following formula was used for computation of skewness.

$$\text{Skewness} = \frac{n}{n-1}\sum\left(\frac{x_i-\bar{x}}{s}\right)^3$$

(f) Range: It refers to the difference in maximum and minimum signal point values for a given signal.

(g) Minimum value: It refers to the minimum signal point value in a given signal. Therefore, it can be used to detect faulty signal condition.

(h) Maximum value: It refers to the maximum signal point value in a given signal.

(i) Sum: It is the sum of all feature values for each sample.

5. Classifiers

a) Bayes Net

Bayes netclassifier is built using conditional probabilities through directed acyclic graphical (DAG) model. The dependency and independent functions are represented through edges and nodes of directed acyclic graphical model respectively. Bayesian net drastically reduces the space for storing the values. As the number of data points increases the conditional probability will give better classification accuracy. Depth first algorithm is possible with Bayes net after the formation of directed acyclic graphical model. Probabilistic queries can also be answered through Bayes net. The joint probability is computed using the chain rule [18]. Fig. 3 shows simple Bayes net DAG

$P(X_i|parents\ (X_i))\ for\ each\ node\ X_i$

$$P(X_1, \ldots\ldots, X_n) = \pi_{i=1}^{n} P(X_i|\ X_1, \ldots\ldots, X_{i-1}) \tag{1}$$

$$= \pi_{i=1}^{n} P(X_i|parents\ (X_i)) \tag{2}$$

$For\ parents\ (X_i) \subseteq \{X_1, \ldots., X_{i-1}\}$

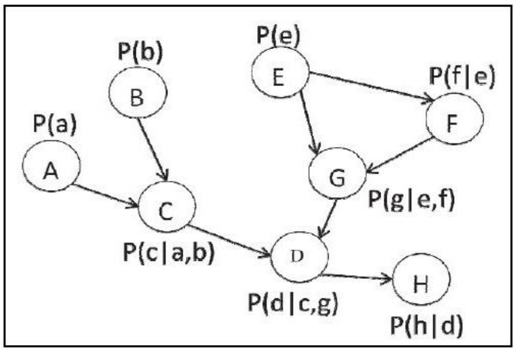

Fig. 3 Bayes Net DAG

b) Naïve Bayes

Naïve Bayes is a simple classifier which assumes that the value of particular attribute is independent of other attribute present in the class. Each attribute is assumed to contribute independently for the probability that it belongs. In a supervised learning setting, Naïve Bayes can be efficiently trained. The advantage of Naïve Bayes is that it requires only small amount of dataset for training. The detailed information for the conditional probability equations can be found in [18].

$$P(A_1, \ldots. A_n|\ B) = \pi_{i=1}^{n} P(A_i|B) \tag{3}$$

$$P(B = b_k|\ A_1 \ldots. A_n) = \frac{P(B=b_y)\ P(A_1 \ldots.. A_n|\ B=b_k)}{\sum_j P(B=b_j) P(A_1 \ldots\ldots A_n|\ B=b_j)} \tag{4}$$

$$P(B = b_k|\ A_1 \ldots. A_n) = \frac{P(B=b_y)\pi_i P(A_1|\ B=b_k)}{\sum_j P(B=b_j)\pi_i P(A_1|\ B=b_k)} \tag{5}$$

6. Results and Discussions

Vibration signals were acquired on continuous basis from bearings which are operated at rated speed and load conditions. Totally 2500 instances were taken for the experiment which are grouped into five different stages. Stage 1 has the signals that are acquired from brand new bearing. Stage 2 includes signals that are acquired after 1000 hours of running the bearing. Stage 3 and stage 4 includes the signals taken after 1250 and 1500 hours of running the bearing. Stage 5 includes the signals from damaged condition. Initially, a brand new bearing is taken for the experiment and the signals were acquired on continuous basis until it reaches the damaged condition (not suitable to use). The paper deals with building predictive model using data available. In the present study, Naïve Bayes and Bayes net classifiers are considered. The vibration signals that are acquired from bearings are used for training the prediction models. Initially 12 statistical features were taken for classification in both the classifiers. It is found using decision tree that all 12 features may not contribute equally towards the effective classification accuracy. Hence, features were optimized and only best performing features are selected for classification. Decision tree suggested the following five features namely standard deviation, maximum, sum, skewness and kurtosis. Only these features were considered for rest of the study.

a) Bayes net

Table 1 and Table 2 give detailed accuracy of Bayes net classifier and confusion matrix respectively. TP (True Positive) rate should be near to 1 and FP (False Positive) rate should be near to 0. In the present case, TP rate happens to be 0.896 and FP rate is 0.026 which can be accepted practically. It also shows the robustness of the model built.

Table 1 : Detail accuracy by class for Bayes net classifier

	TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area	Class
	1	0	1	1	1	1	Stage-1
	0.88	0.032	0.873	0.88	0.876	0.986	Stage-2
	0.874	0.03	0.879	0.874	0.877	0.986	Stage-3
	0.854	0.031	0.873	0.854	0.863	0.99	Stage-4
	0.874	0.037	0.857	0.874	0.865	0.99	Stage-5
Weighted average	0.896	0.026	0.896	0.896	0.896	0.991	

Table 2 : Confusion matrix for Bayes net classifier

a	b	c	d	e	Classified as
500	0	0	0	0	a = Stage–1
0	440	60	0	0	b = Stage-2
0	63	437	0	0	c = Stage-3
0	0	0	427	73	d = Stage-4
0	1	0	62	437	e = Stage-5

Confusion matrix identifies the correct and incorrect classifications. The interpretation of confusion matrix is as follows:

- The diagonal elements in the confusion matrix indicate the correctly classified features.
- In the first row, the first element shows number of data points that belong to 'stage -1' is correctly classified as 'stage -1'.

Similarly in all the rows, the diagonal elements represent correctly classified instances and the non-diagonal elements were interpreted as misclassified instances. In row 4 it can be found that 73 instances that belongs to stage 4 are misclassified as stage 5 (damaged stage). One should note that in row 5 out of 500 instances that belongs to stage 5(bearing is damaged), 63 instances were misclassified as stage 4(bearing is in critical stage). This situation is quite critical because already damaged bearings were misclassified as the stage about to breakdown. Hence, there is more chance of failure in industry which leads to loss of time, money and energy resources.

b) Naïve Bayes

Table 3 and Table 4 give detailed accuracy for Naïve Bayes classifier and confusion matrix respectively. TP rate and FP rate are interpreted as 0.772 and 0.057 respectively.

Table 3: Detail accuracy by class for Naïve Bayes classifier

	TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area	Class
	0.996	0.001	0.998	0.996	0.997	0.998	Stage-1
	0.944	0.137	0.634	0.944	0.758	0.972	Stage-2
	0.452	0.015	0.883	0.452	0.598	0.969	Stage-3
	0.798	0.083	0.706	0.798	0.749	0.953	Stage-4
	0.668	0.051	0.768	0.668	0.714	0.953	Stage-5
Weighted average	0.772	0.057	0.798	0.772	0.763	0.969	

Table 4: Confusion matrix for Naïve Bayes classifier

a	b	c	d	e	Classified as
498	0	2	0	0	a = Stage–1
0	472	28	0	0	b = Stage-2
1	273	225	0	0	c = Stage-3
0	0	0	399	101	d = Stage-4
0	0	0	166	334	e = Stage-5

The interpretation of confusion matrix remains same for Naive Bayes classifier also. The diagonal elements representing correctly classified features and non-diagonal elements representing incorrectly classified features.

- The diagonal elements in the confusion matrix indicate the correctly classified features.
- In the first row, the first element shows number of data points that belong to 'stage -1' is correctly classified as 'stage -1'.
- In the first row, the third element belongs to 'stage-1' is misclassified as 'stage -3'.

Similarly in all the rows, the diagonal elements represent correctly classified instances and the non-diagonal elements were interpreted as misclassified instances. In row 4, 101 instances that belongs to stage 4(bearing is in critical stage) was misclassified as stage 5(damaged stage). This situation is not critical because the bearing which is in critical stage (stage 4) was misclassified as stage 5(damaged stage). It results in replacing of bearing slightly at earlier stage. However, situation at row 5 was very critical because 166 damaged instances (stage 5) were misclassified as stage 4(bearing at critical stage) which in turn leads to loss of time, money and energy resources.

7. Conclusion

Role of bearings are inevitable in rotatory machineries which runs continuously for many hours. Predicting the remaining life time of bearing helps in replacing them before breakdowns. Numerous research works have done in diagnosis and prognosis of bearing life time and identifying bearing failures. This research work mainly focuses on comparing the performances of Naïve Bayes and Bayes net classifiers in predicting the remaining life time of bearings. Totally 12 statistical features were extracted out of which 5 best contributing features are selected using decision tree. A predictive model was built using the selected features. It can be found from results and discussions that Bayes net classifier gives 89.64% accuracy while Naïve Bayes classifier yields only 77.16%. It can also be found that more number of misclassifications were present in Naïve Bayes classifier. Hence, with selected five features Bayes net classifier performs well and inherently better. Thus, a practical system using Bayes net classifier will be efficient one in predicting remaining life time of bearings.

8. Reference

[1] Palmgren, Die Lebensdauer von Kugellagern (The Service Life of Ball Bearings), Zeitschrift des Vereines DeutscherIngenieure, vol. 68, no. 14, pp. 339-341,1924,.

[2] Anon, Load Ratings and Fatigue Life for Ball Bearings, ANSI/AFBMA 9-1990, The Anti-Friction Bearing Manufacturers Association, Washington, DC, 1990.

[3] Anon, Rolling Bearings-Dynamic Load Ratios and Rating Life, ISO 281:1990(E), International Organization for Standardization, 1990.

[4] Da Silva V., Fujimoto R. Y. Padovese L. R. Rolling Bearing Fault Diagnositic System Using Fuzzy Logic, 10 th International conference on Fuzzy Logic, vol. 3, no. 3, pp. 81-819, 2001.

[5] Artes M, Del Castillo L and Perez J, Failure Prevention and Diagnosis in Machine Elements using Cluster, Proceeding of the Tenth International Congress on Sound and Vibration. Pp. 119- 1203, 2003.

[6] Qui H., Lee J., yu G. Robust Performance Degradation Assessment Methods for Enhanced rolling Elements Bearing Prognostics, Advanced engineering informatics, vol. 17, no. 3-4, pp. 127-140, 2003.

[7] Zhao Y., Zhang G., Du J., Wang G., Vachsevanos G.: Development of distributed bearing Health Monitoring and Assessing System, 8th International Conference on Control, Automation, Robotics and Vision, pp. 474-478, 2004.

[8] Mba D., Al-Ghamd A.M.A comparative experimental study on the use of acoustic emission and vibration analysis for bearing defect identification and estimation of defect size, Journal of mechanical systems and signal processing, Vol. 20 No. 7, pp. 1537-1571, 2006.

[9] Gebraeel N., Lawley M., Liu R., Parmeshwaran V.Residual life predictions from vibration-based degradation signals: a neural network approach, IEEE Transactions on Industrial electronics, Vol. 51 No. 3, pp. 694-700, 2004.

[10] Liu T., Ordukhani F., Dipak J. Monitoring and diagnosis of roller bearing conditions using neural networks and soft computing, International journal of knowledge-based and intelligent engineering systems, Vol. 9 No. 2, pp. 149-157, 2005.

[11] Li Y., Billington S., Zhang C., Kurfess T., Danyluk S., Liang S.:Adaptive prognostics for rolling element bearing condition,Journal of mechanical systems and signal processing, Vol. 13 No. 1, pp. 103-113, 1999.

[12] Li Y., Billington S., Zhang C., Kurfess T., Danyluk S., Liang S.: Dynamic prognostic prediction of defect propagation on rolling element bearings, Tribology Transactions, Vol. 42 No. 2, pp. 385-392, 1999.

[13] Qiu J., Seth B. B., Liang S., Zhang C.Damage mechanics approach for bearing lifetime prognostics, Journal of mechanical systems and signal processing, Vol. 16 No. 5, pp. 817-829, 2002.

[14] Li Y., Kurfess T., Liang S. Stochastic prognostics for rollingelement bearings, Journal of mechanical systems and signal processing, Vol. 14 No. 5, pp. 747-762, 2000

[15] W.K. Yu and T.A. Harris, A new stress-based fatigue life model for ball bearings, Tribology Transactions, vol. 44, no. 1, pp.11-18, 2001.

[16] Y. Shao and K. Nezu, Prognosis of remaining bearing life using neural networks, Proc. Inst. Mech. Eng., J. Syst. Control Eng.,pt. 1, vol. 214, no. 3, pp. 217–230, 2000.

[17] N. Gebraeel, M. Lawley, R. Liu and V. Parmeshwaran, Residual Life Predictions From Vibration-Based Degradation Signals:A Neural Network Approach, IEEE Transactions On Industrial Electronics, vol. 51, no. 3, pp. 694-700, 2004.

[18] Vedant, V. Sugumaran, M. Amarnath and Hemantha kumar, Fault diagonosis of Helical Gear Box Using Sound Signal using Naïve Bayes and Bayes Net, International Journal of Engineering & Technology Research, vol. 1, issue-1, pp. 98-105, 2013.