ESTIMATION OF REMAINING LIFE OF BEARINGS USING ROTATION FOREST AND RANDOM COMMITTEE CLASSIFICATION MODELS – A STATISTICAL LEARNING APPROACH

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ABSTRACT

Bearings are considered to be one of the critical elements in all rotating machineries. Bearings are in general used to reduce or minimize the friction in the rotating parts. Strengthening the predictive maintenance of bearings helps to improve the performance of the machines. Hence, bearing prognosis gains its importance in the recent times. This paper emphasis on estimation of remaining life of bearings using classification models through condition monitoring techniques. Vibration signals acquired from the experiments were used to assess the current state of the bearings while in operation. Statistical features were extracted from the signals and the best contributing features were selected for building a classification model with Random forest, Rotation forest and Random committee classifiers. The effectiveness of the classification model built by Random forest, Rotation forest and Random committee classifiers were analysed and compared through a statistical machine learning approach.

Keywords: Remaining Useful Life (RUL), Rotation Forest, Random Committee, Statistical Features, Vibration Signals

INTRODUCTION

Bearing plays an important role in many industrial and automotive applications. Bearings run continuously for many hours in machinery and its maintenance has to be scheduled well in advance to avoid loss of energy and further damages at later stages. Hence, an effective bearing prognosis method is required for flawless operations.

Palmgren (1924) and Anon (1990) have proposed a predictive model to assess the remaining lifetime of bearing using physics and experience based prognostic methods. The model was tested with distinct data points obtained from real-time data such as maintenance data and operational data like breakdown, scarp which are collected over a period of time. The experiment was carried out at rated load and speed conditions. The deployed functions were basic and simple to use. However, the results were precise compared to other methods.

The bearings wear over a period of time and its degradation affects the overall performance of machinery. In general, bearing studies can be grouped into two categories such as prognosis and diagnosis. Bearing diagnosis mainly focuses on the cause and effects of the failures and bearing prognosis deals with prediction and estimation of life of bearings under operations. Fault diagnosis on bearings was done under various techniques namely *viz* neural network wherein Gebraeel, et al., (2004) and Liu, et al., (2005) detailed the residual life predictions based on degradation models. Qui et al., (2003) and Zhao et al., (2004) proposed a degradation assessment method for assessing the current state of the rolling element bearings. Al-Ghamd et al., (2006) has detailed out a comparison study for bearing defect identification using vibration signals and acoustic emissions. Da Silva et al., (2001) and Artes et al., (2003) proposed a fault diagnosis model based on fuzzy logic and cluster analysis techniques.

I. EXPERIMENTAL SET-UP AND PROCEDURE

The main objective of this experiment is to assess the health state condition of the bearing tested at defined intervals. The experimentations were conducted with the carefully chosen bearings in a measured environment and run-to-failure test data is acquired to validate the effectiveness of the proposed model for predicting the remaining life of the bearing. In general, most of the bearing life tests would be done in accelerated conditions to cut short the test time. This paper is put up around to overcome the limitations set in the previous studies. The research on these bearings is continued at real time environments till the bearing degrades naturally. The comprehensive experimental setup used for data acquisition is shown in Fig. 1. This setup consists of a bearing, accelerometer, motor, DAQ card and LABVIEW (Fig. 2) software loaded into a computer to acquire the vibration signals.

Sample length: 1024; Sampling frequency: 24 kHz; Number of samples: 200 sample every 08 hrs. of running. The variations in signals, thus acquired from the bearings in various stages is shown in Fig. 3 (a), 3 (b), 3 (c), 3 (d) and 3 (e) respectively.

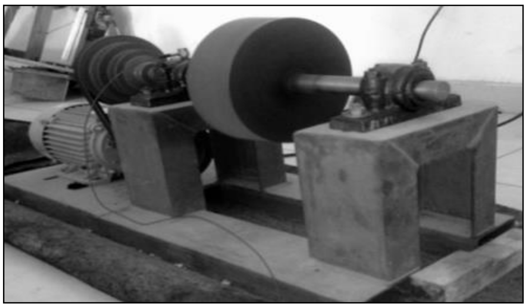

Fig. 1. Experimental Set-up

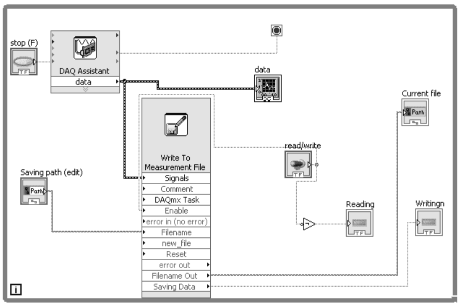

Fig. 2. LABView

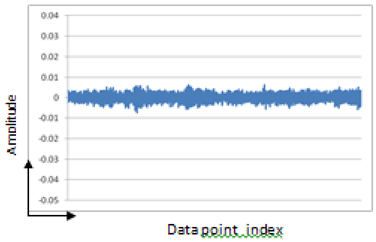

Fig. 3 (a) Satge-1: Vibration Signals at Start

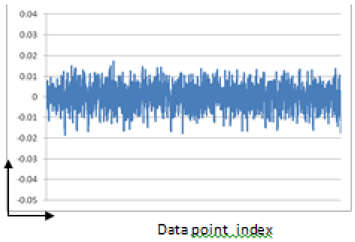

Fig. 3 (b) Satge-2: Vibration signals@1000 Hrs

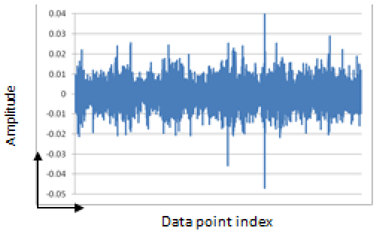

Fig. 3 (c) Stage-3: Vibration Signals@1250Hrs

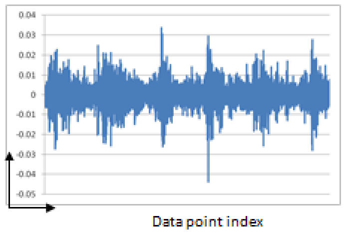

Fig. 3 (d) Stage-4: Vibration Signals@1500Hrs

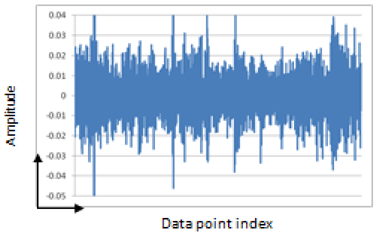

Fig. 3 (e) Stage-5: Vibration Signals @1800 Hrs.

II. FEATURE EXTRACTION AND FEATURE SELECTION

The signals acquired for the experiments will be too large for the algorithm to process and it is suspected to be redundant and hence, they are reduced to a set of features. This process is called as feature extraction. Descriptive statistical parameters such as standard deviation, mode, range, skewness, sample variance, mean, median, standard error, kurtosis, sum, maximum and minimum were computed to serve as features. They are named as 'statistical features' here. Brief descriptions of the extracted statistical features as detailed by Jegadeeshwaran and Sugumaran (2013 and 2015). Feature selection is the process of selecting well contributing features among the available features. In the present study 12 descriptive statistical features have been extracted and Out of 12 statistical features, it can be found that all parameters will not contribute equally towards classification accuracy and hence, the well contributing features have to be identified. A decision tree was used for feature selection (Satishkumar and Sugumaran 2015) detailed the feature selection process using J48 decision tree algorithm.

III. FEATURE CLASSIFICATION

In this paper, random forest, rotation forest and random committee classifiers are used for feature classification which is detailed in the below sections respectively.

A. *Random Forest:* Random forest is an ensemble method that uses decision trees as base classifiers (Fan Li, et.al.,2015). The idea of ensemble methods is to combine multiple weak classifiers into one strong classifier. The predictions by weak classifiers usually have high variance, which can be reduced significantly by majority voting or averaging of the results of the weak classifiers. The random forests algorithm followed is as detailed by (Andy Liaw, et.al.,2002).

B. ***Random Committee**:* Random committee is a diversified ensemble of random forest classifier. The classifier does the prediction by averaging the probability estimates made over the selected features. It should be noted that selected base classifier must be randomized in order to avoid the same results.

C. ***Rotation Forest:*** A rotation forest classifier builds a predictive model by choosing a random subset of input features and trains them by applying feature extraction technique using principal component analysis on every independent decision tree. Rotation forest can be used for both classification and regression. In this paper, random forest is used as a base classifier for random committee classification. The step by step process in building a rotation forest as detailed by Juan, et al., (2006) is followed.

IV. RESULTS AND DISCUSSIONS

The below sections details the results of predictive models built to diagnose the remaining useful lifetime of bearing. The models thus built are validated with the test data to ensure the effectiveness of the predictions.

A. ***Classification using Random Forest:*** The detailed accuracy by class and confusion matrix is the outcome of the classification model. Table 1 and Table 2 detail the results of the classification model built with Random forest. The classification accuracy of this model is 95.88% for the given data set.

Table 1: Detailed accuracy by class for Random Forest

	TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area	Class
	0.996	0	1	0.996	0.998	1	Stage-1
	0.908	0.026	0.899	0.908	0.903	0.99	Stage-2
	0.898	0.024	0.903	0.898	0.901	0.99	Stage-3
	1	1	1	1	1	1	Stage-4
	1	1	1	1	1	1	Stage-5
Weighted Average	0.96	0.01	0.96	0.96	0.96	0.996	

Stage-1: New; Stage-2:1000 hrs. ; Stage-3:1250 hrs ; Stage-4:1500 hrs ; Stage-5:1800 hrs

Table 2: Confusion Matrix for random forest

Category	a	b	c	d	e	
Stage-1	498	0	2	0	0	a=stage-1
Stage-2	0	453	47	0	0	b=stage-2
Stage-3	0	53	447	0	0	c=stage-3
Stage-4	0	0	0	500	0	d=stage-4
Stage-5	0	0	0	0	500	e=stage-5

B. ***Classification Using Random Committee:*** The detailed accuracy and confusion matrix of random committee classification model is presented in Table 3 and Table 4 respectively. From Table 3, TP rate denotes True Positive rate and FP rate denotes False Positive rate. It should be noted for an ideal system, a true positive rate which measures the proposition of positives that are correctly identified, should be '1' and false Positive rate which measures the proposition of positives that are incurrecttly identified, should be '0'. Classification did with the given dataset using random committee classifier results in TP rate close to '1' and FP rate close to '0' and which indicates that the model is accurate and precise. Table 4 details the results of the model in the confusion matrix. All the diagonal elements give the correctly classified data points. In the first row, the first element indicates that out of 500 instances, 498 data points are correctly classified as stage 1. In a similar way, leading diagonal elements gives the correctly classified data points. Confusion matrix helps in identifying the correctness of the predictive model built. The overall classification accuracy of this classifier for the given data set is 95.96%.

Table 3: Detailed accuracy by class for random committee

	TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area	Class
	0.996	0	1	0.996	0.998	1	Stage-1
	0.902	0.025	0.900	0.902	0.901	0.991	Stage-2
	0.900	0.026	0.898	0.900	0.899	0.990	Stage-3
	1	0	1	1	1	1	Stage-4
	1	0	1	1	1	1	Stage-5
Weighted Average	0.96	0.01	0.96	0.96	0.96	0.996	

Stage-1: New ; Stage-2:1000 hrs ; Stage-3:1250 hrs ; Stage-4:1500 hrs ; Stage-5:1800 hrs

Table 4: Confusion Matrix for random committee

Category	a	B	c	D	e	
a	498	0	2	0	0	a=stage-1
b	0	451	49	0	0	b=stage-2
c	0	50	450	0	0	c=stage-3
d	0	0	0	500	0	d=stage-4
e	0	0	0	0	500	e=stage-5

C. ***Classification Using Rotation Forest:*** Statistical features are extracted and a predictive model was built using rotation forest. Table 5 shows the detailed accuracy of rotation forest classifier. In addition to this, the precision value indicates the fraction of retrieved instances that are relevant and Recall value indicates the fraction of relevant instances that are retrieved. These values which are close to 1 indicate the classification model is precise. Hence, the system can be accepted for real-time applications. The overall classification accuracy of this classifier for the given data set is 96.20%.

Table 5: Detailed accuracy by class for rotation forest

	TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area	Class
	1	0	1	1	1	1	Stage-1
	0.900	0.023	0.909	0.900	0.905	0.990	Stage-2
	0.910	0.025	0.901	0.910	0.905	0.990	Stage-3
	1	0	1	1	1	1	Stage-4
	1	0	1	1	1	1	Stage-5
Weighted Average	0.962	0.01	0.962	0.962	0.962	0.996	

Stage-1: New; Stage-2:1000 hrs ; Stage-3:1250 hrs ; Stage-4:1500 hrs ; Stage-5:1800 hrs

Table 6: Confusion Matrix for rotation forest

Category	a	b	c	d	e	
a	500	0	0	0	0	a=stage-1
b	0	450	50	0	0	b=stage-2
c	0	45	455	0	0	c=stage-3
d	0	0	0	500	0	d=stage-4
e	0	0	0	0	500	e=stage-5

D. ***Comparative Study:*** Cross-validation was done to validate the feature selection process which is done with a J48 decision tree. Table 7 lists the classification models vs the resultant classification accuracy for the given data set. The classification was done using rotation forest yields the best accuracy of 96.20% when compared to other classification models. Random forest is used as a base classifier for classification done using random committee and rotation forest. The classification accuracy results compared in Table 8 clearly shows that the performance of random committee and rotation forest classifiers are enhanced by the base classifier. The role of Principal component analyser in rotation forest classification model proves out to be effective in retaining the appropriate datasets. Apart from classification accuracy, there are other performance metrics like kappa statistics, mean absolute error and root mean squared error to evaluate the classification models. Kappa statistics helps in measuring the diversity of data points present in the entire data set. The value close to 1 indicates less variance in the data set. Kappa statistics of rotation forest is 0.9525 is higher than the kappa statistics of random committee (0.9495) and random forest (0.9485) classifiers. Mean Absolute Error and Root Mean Squared Error are used in diagnosing the variation error present in the built model. Mean absolute error measures the variation between the estimates and the actual values whereas the Root means square error measures the average magnitude of the error. The difference between predicted value and the observed value are squared and then averaged over the sample. Root Mean Squared Error should be greater than or equal to Mean Absolute Error. The range of RMSE and MAE varies between 0 and ∞. The MAE value of rotation forest and random committee are 0.0352 and 0.028 respectively which is less than the RMSE value of the classifiers.

Table 7: Comparison Study

S. No.	Name of the Classifier	Classification Accuracy (%)
1	Random Forest	95.88
2	Random Committee	95.96
3	**Rotation Forest**	**96.20**

CONCLUSION

Estimation of remaining useful life of machine components is being widely accepted by industries in recent times because of its accuracy of prediction and its application to real-time environments. In this paper, an attempt has been made to predict the remaining life of the bearings using classification model. Vibration signals were acquired from the bearings in defined intervals running on an experimental set-up with rated conditions, simulating the real-time environment. The signals are then extracted into statistical features and further best features with more information gain are selected using a feature selection method. A predictive classification model is built with the selected features using random forest, random committee and rotation forest classifiers. This paper weights on the effectiveness of the classification models for the given data set. Classification model built using rotation forest yields best classification accuracy of 96.20% in comparison to the random forest and random committee classifiers. This result also shows that a model constructed using an ensemble classification approach proves out to be effective in terms of prediction accuracy. Hence, this model can be horizontally deployed for all other machine components in real time applications.

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