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Degradation assessment of bearing based on machine learning classification matrix

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Highlights

- Machine learning classification matrix is used to model the degraded behavior of bearing
- Prior state of art considers the various diagnostic and prognostic model of bearing
- Classification model is developed to assess the degradation of bearing.
- The analysis results show that the percentage of accuracy of different models

Abstract

In the broad framework of degradation assessment of bearing, the final objectives of bearing condition monitoring is to evaluate different degradation states and to estimate the quantitative analysis of degree of performance degradation. Machine learning classification matrices have been used to train models based on health data and real time feedback. Diagnostic and prognostic models based on data driven perspective have been used in the prior research work to improve the bearing degradation assessment. Industry 4.0 has required the research in advanced diagnostic and prognostic algorithm to enhance the accuracy of models. A classification model which is based on machine learning classification matrix to assess the degradation of bearing is proposed to improve the accuracy of classification model. Review work demonstrates the comparisons among the available state-of-the-art methods. In the end, unexplored research technical challenges and niches of opportunity for future researchers are discussed.

Keywords

degradation states, health condition indicator, machine learning, diagnostic model, prognostic model.

1. Introduction

Machine learning classification matrix is used to evaluate the degradation states of bearing over time due to variation in operating parameters and environmental conditions such as load, speed, high temperature, etc. Data driven machine learning model permits retrieving useful information from rotor bearing system using smart monitoring, multi-feature fusion, health condition indicator and advanced diagnostic and prognostic algorithms. Bearing condition monitoring is important for Industry 4.0 to reduce the economic loss and unscheduled downtime of mechanical systems caused by unexpected failures of bearing. Industry 4.0 is a paradigm shift in the modernization of industry propelled by the ever-growing computational capabilities, technological improvement, accuracy of prediction and recent advances in data driven model.

Diagnostics study the fault detection, fault isolation and fault identification in monitored mechanical machinery whereas prognostics deals with the prediction of fault before it occur. The fault detection is to observe the wrong functioning of machinery, where the fault isolation is to identify the components where fault takes place in complex system.

The fault identification is to indicate the nature of fault whereas the prediction of fault is to determine the evolution of fault in machinery before it reaches a critical stage. It has been observed that with the advancement of software technology, artificial intelligence methods are replacing the traditional diagnostics and prognostics systems to enhance the performance of health monitoring.

This paper has reviewed the publications from the science and engineering journals on bearing diagnostic and prognostic in the past 20 years. The published articles were retrieved mainly from Google Scholar using the search terms “bearing diagnostics and prognostics” and “bearing condition monitoring” and filtered by year, access, citations and relevancy. It is observed that there is an increasing trend in number of publications in this area of research after 2014. There are also some highly cited review papers from researchers at universities and industry experts in the past. A brief review of some of key papers is provided in chronological order. In the past few decades, development in diagnostics and prognostic of industrial systems had been reviewed. The multiple sensor and data fusion techniques used in condition based maintenance decision making [19]. Design methodology had been explored for converting data into prognostic information of rotary machinery system [28]. Prognostic techniques for non-stationary and non-linear rotating systems had been studied. The challenges in implementing prognostics technique in industrial system was discussed [23].

In recent years, some researchers started research in the domain of machine learning algorithm for diagnostic and prognostic. A review on spectral kurtosis theories namely; spectral kurtosis, kurtogram, and

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protrugram applicable for fault identification in bearing had been presented [52].Various aspects from data acquisition to remaining useful life prediction (RUL) in the field of machinery prognostic had been discussed. Authors divided the machinery prognostic program into various stages namely; data acquisition, development of health indicator, division of health stages [29].Generalized gamma distribution was used for the prediction of corrective maintenance of fleet vehicle [5]. Deep learning applications for system health management had demonstrated the benefits of deep learning for fault diagnosis and prognosis is [24]. Bearing diagnostics approaches were compared to consider the impulse behavior of vibration signal. The first approach was considered preprocessing the probabilistic component of the vibration signal by employing the minimum entropy de-convolution approach and the spectral kurtosis method. The second approach was considered the modeling of cyclo-stationarity based on spectral coherence and spectral frequency [1]. A comprehensive survey on recent development in vibration data fusion and application of deep learning tools in machinery prognosis and discussed the identification of research trend, unexplored challenges were provided[10].This paper gives a comprehensive review on bearing diagnostics and prognostics.

Hence, authors attempted to summarize a review for targeted journals published from 2000-2019. The literature search has been done among the electronic database i.e. Science Direct, IEEE explorer and Scopus. The published journals had been explored in the search engine with the following words: diagnosis, prognosis and condition monitoring, degradation model.

The main contributions of this paper are as following:

- The paper reviews the different health condition indicators used in the prior state of art for degradation assessment of bearing.
- The paper also reviews the diagnostic and prognostic models for the remaining useful life estimation of the bearing.
- The paper also discusses the case study of classification model to improve the accuracy of degradation assessment.

The remaining paper is organized as follows. In section 2, data acquisition and health condition indicator is explored for degradation assessment of bearing. Section 3 discusses the diagnostic models. Section 4 focuses on prognostic models for RUL prediction. Section 5 discusses the case study of classification model. Finally, Section 6 concludes the research challenge and provides directions for future research trends in the area of diagnostics and prognostics.

2. Data acquisition

Data acquisition is a procedure of acquiring and storing useful data from different sensors mounted on the machinery. Accelerometer sensor is installed to acquire monitoring data which reflects the degradation stages of bearing. Industry 4.0 has started using advanced sensor to capture monitored data for accurate maintenance decisions. Following obstacles i.e. interferences from operating conditions, noise, cost, time, service period and unexpected failure are main factors for decrease in the quality of the data. Data sources will be helpful to researchers to develop data driven diagnostic & prognostic models.

2.1. Experimental data

Experimental prognostic data set is acquired from accelerated degradation test. This paper has selected bearing prognostic datasets from the repository of NASA, Franche-Comte Electronics Thermal Science and Optics-Sciences and Technologies (FEMTO) and Case Western Reserve University (CWRU) bearing dataset.

Intelligent Maintenance system (IMS) bearing dataset**:** Bearing degradation data was generated by the center for intelligent maintenance system, university of Cincinnati with support from Rexnord corp. (www.imscenter.net). Four (Rexnord ZA-2115 double row) bearings were used in the experiment. All bearings used in the experiment are lubricated. Two accelerometers (PCB353B33 High sensitivity quartz ICP) are installed on the bearing housing to collect the horizontal and vertical vibration signals generated from the bearing respectively. Three run-to-failure tests are conducted to generate three data sets in different time periods. The test 2 consists of 984 files generated by recording data at every 10 minute with the help of NI DAQ card 6062E. The experiment is stopped when a significant amount of metal debris is found on the magnetic plug of the tested bearing. In this paper, test 2 data is utilized for the analysis of bearing degradation condition.

FEMTO bearing dataset**:** This dataset had been provided by FEMTO and was shared in the IEEE international conference (www.femto-st.fr/f/d/IEEEPHM2012- Challenge-Details.pdf). The data is collected from 17 run-to-failure data of rolling element bearing captured from accelerated degradation test in few hours. An accelerometer and a thermocouple were employed to acquire the vibration signals and the temperatures respectively. The healthy bearing was allowed to degrade naturally without introducing a fault. During experimentation, the frequency resolution and time length of each sample were maintained at 10 Hz and 0.1 s respectively. The bearing useful life is estimated at a threshold when vibration signal exceeds 20g.

Case Western Reserve University (CWRU): This data set had been provided publicly from a CWRU. In this data set, electro-discharge machining was used to create an artificial fault in deep groove roller bearing with fault depth of 0.1778 mm, 0.3556 mm, and 0.5334 mm. They acquired vibration data at a sampling frequency 12 kHz and each data sample containing 2048 points. This data set has been used in fault identification, signal processing and machine learning for bearing fault detection. The properties of experiments form two historical data sources are provided in Table 1.

Table 1. Properties- Experimental data

Data	Bearing	Rotor diameter	Load	Speed	Sampling frequency	Reference
IMS	Rexnord ZA-2115	0.331 inches	6000 lb	2000 RPM	20 kHz	www.imscenter.net
CWRU	6205-2RS	0.007 inches	0-3 hp	1797r/min	12kHz	http://csegroups.case.edu

The data source, parameter properties of the bearing has been provided to facilitate researchers for the development of degradation model of the bearing from experimental data.

2.2. Health condition indicator

Health condition indicator give information about the state of the machinery by analyzing the information contained in signal. This indicator is expected to quantify the degradation of machinery. A suitable health condition indicator is to follow the degradation trend for precise prediction results. This section provides the detailed information on the development of health condition indicator used in the evaluation of bearing performance.

Commonly, a health condition indicator is developed physically and virtual to serve as a quantitative description of bearing health condition. Confidence value was used to identify the current degradation state through self- organizing map[17]. Health assessment indicator had been developed based on negative log likelihood probability that measures bearing performance degradation[59]. Probability of degradation was discussed as health indicator[38]. Probability of different

Table 2. Health Condition Indicator

Health Indicator	Technique	Reference
Confidence Value	Self organising map	[17]
Health assessment Indication	Gaussian mixture model based negative log likelihood probability	[59]
Probability	Hidden Markov modeling	[38]
Generalized dimensionless bearing health indicator	upper and lower bounds non-central chi-square distribution	[53]
Monitoring Index	Self organising map	[29]
Virtual Health Index Current Tracking metric	Locally weighted linear regression method	[30]
Maximum likelihood ratio	Statistical methodology	[6]
Dimensionless health indicator	Linear rectification	[16]
Predication bandwidth	Multi scale convolutional neural network	[17]
Average spectral radius, the maximum eigen value, number of random point	Random matrix single ring machine learning	[18]
Moving average cross-correlation coefficient power spectral density	Measure the similarity of power spectral density of signal with adjacent signal	[19]

degradation states were calculated through Hidden Markov modeling. Dimensionless health indicator was presented to assess current health condition of the bearing [50]. They calculated mathematically upper and lower bound of the dimensionless health indicator by using non-central chi-square distribution. Condition monitoring index based on self-organizing map was developed to detect incipient bearing faults quickly [29].Virtual health index was introduced based on locally weighted linear regression method [30]. Statistical methodology based on maximum likelihood ratio was presented to design condition indicators [6]. These condition indicators had shown high potential to describe different phases of bearing degradation process. Dimensionless health indicator was developed through linear rectification technique [2]. They defined the indicator as the ratio of root mean square of the vibration acceleration signal at current time to the root mean square of the vibration acceleration signal for the baseline condition. New health condition indicator was developed based on combination of bathtub curve, multi scale convolutional neural network and inverse hyperbolic tangent function [55]. Three degradation indicators were proposed i.e. average spectral radius, the maximum eigen value and number of random points in inner ring by random matrix single ring machine learning. A data source matrix had been constructed from roller bearing full life failure experimental data through normalizing, singular value decomposition [37]. Health state was evaluated with moving average cross-correlation coefficient power spectral density of signal [56]. A new health index had been proposed on moving average cross-correlation of energy distribution of a signal in the frequency domain. It can also distinguished different health state by determining failure threshold for each case. Table 2 summarizes the health condition indicator (s) used in the published journals such as Mechanical system and signal processing, Journal of sound and vibration, Maintenance and reliability, Computer and Industrial engineering, Reliability Engineering and system safety, Microelectronics reliability and Digital Signal Processing A Review Journal.

This section focuses on the data acquisition and health condition indicators of the bearing vibration data. Then, different health condition indicators are described. This study will be helpful for researchers in the bearing diagnostic and prognostics.

3. Diagnostic model

Diagnostic model is vital to diagnose faults in machineries quickly and precisely. The model learns from the selected features obtained from the health condition of machinery. These models can be categorized in two class i.e. classification and regression based. There is a paradigm shift in research trends from traditional diagnostics approach to machine learning based diagnostics approach. This section investigates recent classification and regression based diagnostic models used in the health condition monitoring of machinery.

3.1. Classification and Regression model

The classification model gives an output in term of categorical variable using class labeled input data obtained from the fault feature extracted from machinery. Regression approach is used to explain the relationship between one continuous dependent variable and multiple independent variables. Regression model gives an output in terms of numeric variable. Model parameters are iteratively updated through optimization algorithm and classes are equally distributed to avoid bias and generalization capability. There are various intelligent classification model i.e. artificial neural network, support vector machine, fuzzy sets theory; fuzzy set theory based expert system used in the diagnosis of the bearing health condition. Artificial neural network on vibration signal data was used for bearing fault diagnosis[20].They trained the model to classify seven different bearing classes and classifier produce the high accuracy diagnosis of real bearing defects. Artificial neural network was discussed for fault diagnosis of rolling element bearing [21]. They trained the model through back propagation algorithm with a subset of experimental data obtained from machine condition. An approach based on dimensional exponent integrated with a surrogate data testing was suggested for bearing condition diagnosis [22].

Novel rough support vector data description method was designed for bearing performance degradation assessment based on one-class classifier [23]. They removed the problems like sensitive to outliers, over-fitting and invariability of model parameters with time. Orbit pattern recognition algorithm using the deep learning proposed for rotating machinery diagnostic [24]. They classified the fault modes of rotating machinery through orbit images. Improved support machine was developed for fault diagnosis based on multi classification of the condition [25]. They proposed an improved voting scheme in one-against-one support vector machine to improve the classification accuracy. Dynamic time warping in machine learning algorithm was proposed to bearing fault classification for mechanical fault detection [26]. They compared the accuracy with the traditional machine learning algorithm. Support matrix machine was developed for roller bearing condition monitoring using matrix as input. However, data was distinguished effectively by two parallel hyper planes and result showed that support matrix machine had better recognition performance as compare to support vector machine [27]. Multi-step support

Table 3. Diagnostic models

Category	Model	Major contributions	Reference
Classification & Regression	Artificial neural network	Back propagation algorithm	[44]
	Computational scheme	Surrogate data testing	[18]
	Rough support vector data	One-class classifier	[65]
	Deep learning	Orbit pattern recognition	[21]
	Improved support machine	Multi classification	[36]
	Machine learning algorithm	Dynamic time warping	[47]
	Support matrix machine	Distinguish the data with two Parallel hyper-planes	[41]
	Multi-step support	Update feature vector	[58]
Hybrid	Principal component analysis & Least square support vector machine	Multi-feature fusion technique	[11]
	Locality preserving projection & Gaussian mixture	Negative log likelihood	[8]
	Kernel principal component analysis, autoregressive & support vector machine	Fault location with recognition rate	[62]
	Weight sparse	Combined the sparse and kurtosis of the envelope spectrum	[61]
	Vibration Resonance	Resonance of main and auxiliary signal	[13]
	Fuzzy C-means and K-nearest neighbor	Using relatively amount of data	[12]
	SOM and PCA	Frequency analysis of residues produced by hybrid algorithm	[27]
	Linear discriminant analysis & Pattern recognition	Two dimensional visualization	[62]

vector regression was proposed method for fault diagnosis in the rotatory machinery [28].

3.2. Hybrid model

Hybrid model combined the advantages of different diagnostic models through their integration. This category contains limited number of publications. Bearing process degradation was studied using the principal component analysis and optimized least square support vector machine[29]. Original features were merged and new features were produced with the help of multi-features fusion technique, principal component analysis. Fault diagnosis had been analyzed by combining locality preserving projection and Gaussian mixture models [30].They developed negative log likelihood probability to quantify the bearing performance gradation using the Gaussian mixture model. Multi-feature fusion diagnosis approach was proposed based on the combination of Kernel principal component analysis, autoregressive model and particle swarm optimized support vector machine [31]. They identified the fault location with recognition rate, generalization capability in small training samples and degree of performance degradation of roller bearing.

Fault diagnosis of rolling element bearing was developed based on linear discriminant analysis and pattern recognition [32]. Two-dimensional visualization and classification accuracy of bearing data were showed to identifying different fault categories effectively. Weight sparse model was presented for bearing fault diagnosis [61]. The coefficient sequence of fault information i.e. sparse and kurtosis of the envelope spectrum were combined to develop weight sparse model. Two model gradient descent and Bayesian were combined to develop a hybrid algorithm. Vibration resonance method was developed on bearing fault diagnosis [13]. The experimental and simulated vibration signals were analyzed on bearing fault diagnosis. Fuzzy C-mean and optimized K-nearest neighbor method was combined to make accurate judgment of bearing fault [12]. The basic features were classified using small amount of fault data. Fault diagnosis of bearing was analyzed two dimensional with the help of linear discriminate analysis and pattern recognition [62].

Hybrid algorithm of SOM and PCA was developed to extract the bearing fault category [27]. The proposed algorithm had isolated the characteristic frequency of bearing fault from residue of data. Table 3 summarizes the different diagnostic models developed in the literature.

This section discusses the diagnostic models used in the bearing diagnosis. Review of the diagnostic models will help to researchers to solve industrial applications.

4. Prognostic model

The prognostic model is used to forecast the remaining useful life (RUL) of machinery before the machinery reach the failure stage based on the health condition information. The RUL of any system is defined as the time duration from present time to the functional failure of machine. Dynamic models were developed for the development of reliable prognostic algorithm [34]. Dynamic models were used to predict the changes in dynamic behavior reflecting the fault type and severity. Prognostic models are classified in to three broad category i.e. statistical data driven prognostic model, hybrid model and machine learning method.

4.1. Statistical data driven model

Statistical data driven prognostic model is based on empirical knowledge to estimate the remaining useful life of machinery. Statistical model is useful to study the uncertainties in the degradation process of machinery and its influence on the prediction of remaining useful life. Present work discusses the recent developments in the various traditional statistical prognostic models like Gaussian Hidden Markov, Gaussian process model, Wiener process model, inverse Gaussian process model and dynamic regression model. Statistically data driven approaches were reviewed for RUL estimation [45]. The pros and cons of the recent model developments and classification of RUL estimation model were discussed. Mixture of Gaussians Hidden Markov model was used for prognostics of bearing [48]. They generated the complex emission probability density function from the wavelet packet coefficients feature extracted from the raw vibration

Table 4. Pros and cons of prognostic model

Type of Prognostic model	Pros	Cons	References
Statistical data driven model	Dynamic calibration of model to adopt to evolving trend	Need for extremely large amount of data in numerous operating conditions Generalization capabilities are undefined	[45] [39] [7][40] [49][54][2] [45]
Hybrid model	Identify the nonlinear relationship between the variables	Unable to learn from clustering integration	[48][15][57][49] [50][51]
Machine Learning model	Solve the problem of gradient disappearance Construction of sample pair with advanced algorithm Consider the time cumulative effect of historical information on future information from a structural perspective.	Unable to learn long-time timing information	[42][9][25][60][14] [64][58]

signal. The parameters of model were estimated which best fit the degradation phenomenon. Switching Kalman filter approach was used for the prognostic of roller bearing [43]. This approach uses multiple dynamical models each describing a different degradation process.

Likelihood distribution obtained in the Gaussian process following Bayes' rule was used to estimate the RUL of bearing [7]. Inverse Gaussian process model with random effect was discussed to estimate the RUL of bearing [40]. Degradation model parameters were updated by Bayesian method which can capture the real condition of the system. Statistical model was developed for different stages of bearing degradation signal [51]. They considered the drift coefficient at current time in the likelihood function. Monte Carlo simulation was used to develop an RUL prediction approach [54] . Multiple change point wiener process model was developed as a degradation model. Recursively updated dynamic regression model was used to estimate the RUL of bearing [2]. They demonstrated experimentally that excellent prognostic performance of dynamic regression model due to its ability to determine time to start prediction and dynamic calibration of model.

4.2 Hybrid model

Hybrid prognostic model is an attempt to integrate the advantages of different prognostic models. There is limited literature available under this category. Principal component analysis and optimized least squares support vector machine based approach was proposed for bearing degradation prediction [11]. The original features were merged by principal component analysis and optimized the model parameters by particle swarm optimization. Remaining useful life prediction methodology that utilizes mechanistic modeling of vibration and self-training of parameter adaptation was suggested [31]. Prognostic approach utilizing fuzzy adaptive resonance theory map, neural network and Weibull distribution was proposed for RUL prediction [3]. The learned nonlinear time series and seven classes were defined for bearing degradation.

Hybrid prognostic model was developed for health monitoring using bond graph framework [22]. Variance adaption scheme with a statistical model was proposed for system parameter. The effective prediction of the RUL was produced with in confidence bounds. Grey Markov model was used to predict the RUL of roller bearing [35]. The fractal spectrum parameters were used to generate degradation trend and predict the RUL with higher prediction accuracy. Hybrid model of principal component analysis and internet of things with multi sensor was used to predict the bearing life [15]. Multi-dimensional feature predication algorithm had described the life information of rolling bearing from various angles as compare to single time domain feature predication. Hybrid model of support vector machine and degradation tracking model was presented to improve the accuracy of RUL [57]. Features were dimensionless and prognostic works solve the problem of time to start prediction and random fluctuation of measurement.

4.3. Machine Learning model

Machine learning prognostic models study the degradation trend of machinery using machine learning techniques i.e. artificial neural network, support vector machine, web semantic tool, long short-term memory and recurrent neural network. This paper considers only the recent research development in the field of machine learning techniques. Innovative prognostic model based on health state probability estimation was presented [25]. Health state probability was estimated by support vector machine for RUL prediction. Deep learning approach was discussed to predict the RUL of bearing based on deep auto encoder and deep neural networks [42]. They presented deep auto encoder joints features compression to retain effective information without increasing the scale. Recurrent neural network based on encoder-decoder framework with attention mechanism was proposed to predict automatic health indicator which were designed with the RUL values [9]. Features were extracted from five band-pass energy values of frequency spectrum. Proposed method was achieved lowest average percent error and highest average score as compare to traditional method. Accurate RUL prediction was depending on the use of long time-dependent information from the long-time sequence data effectively. Long short-term memory recurrent neural network was used to predict the RUL of bearing [60]. Degradation states were identified by giving input into long short-term memory recurrent network. Bearing performance degradation was studied using long short-term memory with multi-resolution singular value decomposition (MRSVD). The decomposition of vibration signal with MRSVD and reconstruction help to accurately identify the fault point in vibration signal [14]. New data driven transfer learning RUL prediction approach was proposed to solve the distribution discrepancy problem [64]. The fault occurrence time was detected by hidden Markov model. The domain discrepancy metrices and domain classifier were used to acquire domain invariant features through domain adaption module and condition recognition. New approach was presented to predict the RUL of industrial roller bearing based on state recognition and similarity analysis [16]. Life proportional adjustment function was constructed with the help of comprehensive similarity analysis between historical bearing data and monitoring bearing data. Life model was constructed by defining state matrix of different operation states of roller bearing. Result showed that proposed approach had better prediction accuracy and generalization as compare to hidden Markov model and grey model. Predicated fatigue life of radial cylindrical roller bearing subjected to radial and axial load was discussed [59]. Remaining useful life prediction was made via the combined use of support vector machine as a classification tool and autoregressive integrated moving average based identification. An expert tool was used for real time monitoring to prevent the potential failure of machines [26]. A novel model combines the importance of machine criticality assessment criteria with interaction between them was proposed [20]. Remaining useful life of a ball bearing was predicated using classification and regression techniques. Machine learning principles was

Table 5. Prognostic Models

Category of Prognostic model	Comments	Reference
Statistical data driven	Statistical data driven approach used for classification of degradation state	[45]
	Switching Kalman filter approach employed to identify unstable degradation state	[43]
	• Gaussian process applied to estimate posterior distribution of the bearing relative time • Probability density function was calculated for posterior distribution using Bayes rule • Gaussian process model used to evaluate likelihood	[7]
	• Inverse Gaussian model was employed with random effect to characterize the degradation process of the system • Parameters were updated by Bayesian method	[40]
	Statistical model was used to find analytical expression for posterior drift distribution	[49]
	• Monte Carlo simulation algorithm considered for multiple change-point • Wiener process employed to construct degradation model • Bayesian approach applied for parameters estimation • Exact recursive model was used for updation	[54]
	• Dynamic regression model used to forecast start time • Predication were made using alarm bound technique • Predicating future health indicator values by recursive updation • Remaining useful life estimation using time steps to fail threshold	[2][45]
Hybrid model	Mixture of Gaussians Hidden Markov models were used for better implementation and interpretability	[48]
	Hybrid model include internet of things with multi sensors was used for PCA	[15]
	Hybrid degradation tracking model (support vector machine and hybrid degradationtracking model)	[57]
Machine Learning	• Deep learning use of subset based deep auto encoder • Feature compression	[42]
	Novel deep learning use recurrent neural network based on Encoder-decoder framework with attention mechanism	[9]
	• Health state probability estimation using support vector machine • Prognostic model parameters were updated using historical knowledge	[25]
	Long short memory Recurrent neural network proposed for automatic detection and to identify fault occurrence	[60]
	Long short memory network with multi-resolution singular value decomposition technique used to detect accurate fault in vibration signals	[14]
	Training and testing data distribution discrepancy problem was solved by Transfer Learning based on multiple layer perceptron	[64]
	State recognition and similarity analysis used clustering algorithm and threshold correction to solve the problem of prediction accuracy and generalization	[16]

used to develop an algorithm to recognize underlying mapping function [46]. Table 4 summarizes the pros and cons of prognostic model. Table 5 summarizes the main features of prognostic models.

This section discusses the different prognostic models used in the bearing prognostics. The pros and cons of prognostic models are also discussed.

5. Case Study

Roller bearings have been degraded from normal condition to failure condition with the duration of time due to harsh industrial working conditions. However, rolling bearings have a low ability to withstand impact, so their service life is uncertain. This paper explores multi-stage categorization of bearing degradation. Table 6 summarizes the stages for bearing degradation criteria. Bearing degradation is categorized in one of the following three stages. The degradation states of bearing over time is shown in Fig.1.

- Stage I : Healthy stage
- Stage II : Degradation stage
- Stage III : Critical stage

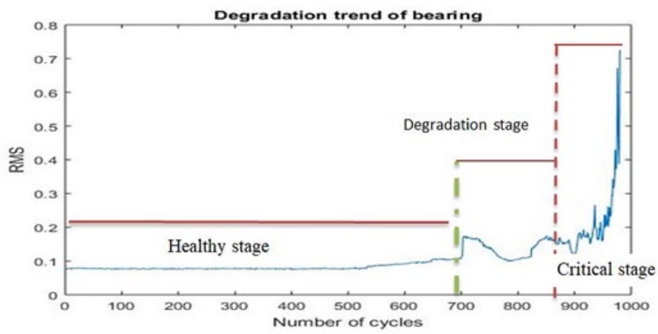

Fig. 1. Degradation states of bearing over time

5.1. Methodology

The health data used for bearing degradation assessment is the bearing vibration signal. Firstly, statistical features are extracted from the vibration signal data and features are selected from the values of correlation coefficient. Secondly collect the samples and divide the samples into the training samples and testing samples. Then the testing data used for input into a classification model for bearing degra-

Table 6. Stage for bearing degradation criteria

Stage	Criteria: Severity of impact in the bearing degradation
Catastrophic	Any impact which could potentially cause the loss of primary system functions resulting in significant damage to the mechanical system and cause the loss of life
Critical	Any impact which could potentially cause the loss of primary system functions resulting in significant damage to the mechanical system and negligible loss to life
Degradation	Any impact which degrades system performance functions without appreciable damage to either mechanical system or life
Healthy	Any event which could not cause degradation of system performance function(s) resulting in negligible damage to mechanical system

Fig. 2. Flowchart of proposed methodology

dation assessment. The flow chart of the bearing classification model proposed is shown in Fig. 2.

5.2. Experimental data

The bearing degradation data was generated by the center for intelligent maintenance system (IMS), university of Cincinnati with support from Rexnord corp. The used data set in this paper is downloaded from prognostics center of excellence through prognostic data repository. The bearing used in the experiment is Rexnord ZA-2115 double row bearing to support a rotating shaft. The bearing test rig and accelerometer sensor placement are shown in Fig. 3.

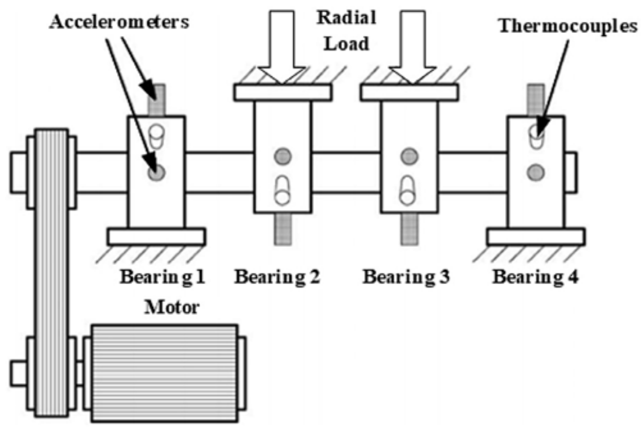

Fig. 3. Bearing Test rig [3]

The bearing test rig was designed to generate run-to-failure data from Feb.12, 2004 to Feb.19, 2004. Four bearings are used in this experiment. The rotating speed of the shaft is kept constant at 2000 rpm with the help of alternative current motor coupled to the shaft via rubber belts. The radial load of 6000 lb is applied onto the bearings by a spring mechanism. All bearings used in the experiment are lubricated. Two accelerometers (PCB353B33 High sensitivity quartz ICP) are installed on the bearing housing to collect the horizontal and vertical vibration signals generated from the bearing respectively. The data sampling frequency is 20 kHz. Three run-to-failure tests are conducted to generate three data sets in different time periods. The test 2 consists of 984 files that are 1-s vibration signal snapshots recorded at every 10 minute with the help of NI DAQ card 6062E. Each file stored of 20480 points with the sampling frequency set at 20 kHz. The failure in the bearing had occurred when the bearing cross the designed life time of the bearing which is more than 100 million revolutions. The experiment is stopped when a significant amount of metal debris is found on the magnetic plug of the tested bearing. In this paper, test 2 data are used to the time domain feature to monitor the bearing degradation condition.

5.3. Classification model

Classification based models have been used to develop a relationship between independent variables (i.e. features vectors) and dependent variables (i.e. response in term of predefined stages identified by labels). In this paper, we have feed the input feature vectors values (Predicators) and response corresponding with the bearing degradation system stages into classification learner tool in Matlab to obtain predicated label for future time period. The input feature vectors values are extracted from preprocessed time series of bearing vibration signals relevant to the degradation stages of the bearing. We have categorized the degradation of the bearing into three classes such as healthy stage, degradation stage and critical stage. This paper has considered 15 predicators such as kurtosis, peak, crest factor, standard deviation, variance, rms, mean, mode, median, range of values, mean and median absolute deviation, peak amplitude to rms ratio, interquartile range, root sum of square level and maximum to minimum difference. Three response classes are used to predict an output categorical variable using labeled input data. Predicators are independent to each other. In supervised machine learning methodology, the classification labels have been assigned to the feature vector values to which training instances belong. In this paper, we have found the accuracy of models in different classification algorithms. Table 7 shows the accuracy results of different classification algorithms.

Table 7. Comparison results on the testing accuracy

Classifier	Accuracy (%)
Decision tree	96.1 %
Linear discriminant analysis	92.9 %
SVM (Cubic SVM)	96.5 %
SVM (Medium Gaussian SVM)	96.2 %
Nearest neighbor classifiers (Weighted KNN)	93.5%
Ensemble classifiers (Bagged tree)	96.5 %

This section discusses the different classification models used for bearing health analysis. The accuracy of different classification algorithms are also discussed to study the degradation stages in bearing.

5.4. Bearing degradation failure

In the case study, the bearing degradation failure is discussed with machine learning classification matrix. Vertical axis and horizontal axis denote the actual and predicted label respectively. Elements in the main diagonal are the classification accuracies and others are the classification errors. Bearing degradations are divided into four categories i.e. healthy, degradation, critical and catastrophic. For each conditions, there are 1-second snapshots, each of which consists of

20,480 points. Each samples has 2000 data points. Totally, there are 1400 samples for the four health conditions. Random 50 % samples are for training and the remaining samples are for testing.

Graph theoretic model was considered the system structure explicitly and applied to model functions using matrix approach to examine the cause and effect. Result showed the reliability enhancement using step-by-step methodology [32]. Structural graph model for reliability at various hierarchical levels was developed by converting reliability graph into equivalent matrix [33]. System model was developed incorporating four states of degradation for each component [39].

6. Technical challenge

It has been observed that despite the positive outcomes from the existing state of art, there are many current research challenges need to be addressed. More research should be conducted on incorporation of uncertainty in diagnostic and prognostic model. The key idea of data acquisition is to transfer the knowledge gained from experimental data to improve the accuracy of predication model used in industry. It is emphasized to develop information fusion from multi-dimension data. The research problems pertinent in this field are design of health condition indicator and real time model to study the real time degradation of bearing. The big data provides research challenges to build robust diagnostic and prognostic model from machine learning technology. Further, research is required for dimensionless health indicator which is more sensitive to an incipient bearing defect. There is a paradigm shift in research direction from constant operating conditions to variable operating conditions. Thus, it is important to analyze uncertainties caused by time varying operation conditions. To address this change, future researchers need to redefine the failure threshold limit, health state division, degradation model and quantification of uncertainty according to the variable load, speed, etc. Research is needed to determine failure threshold limit for virtual dimensionless health indicator. This section discusses the unexplored technical challenges existing in the bearing health monitoring to match with variable operating condition and advanced machine learning algorithm.

7. Conclusions

In this paper, the prior state of art in the field of diagnosis and prognosis of bearing with emphasis on machine learning based techniques has been summarized. The review is focused on data acquisition, health condition indicator, diagnostic models and prognostic models. The advantage and disadvantage of models, algorithms are presented in this study. A case study is discussed based on machine learning classification matrix to improve the accuracy of degradation assessment. The future research challenges are moving from tradition algorithm to advanced machine learning algorithm to build accurate and robust prediction model. Further, there is a need to develop virtual dimensionless health indicator, failure threshold limit which can match the degradation trend of the bearing.

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