Journal of Current Research in Engineering and Science
Bi-Annual Online Journal (ISSN : 2581 - 611X)

Volume 7- Issue 1, January 2024
Paper : 86

Bearing Remaining Useful Life Prediction Based on Hilbert–Huang Transform and Prophet Model

1st Pratik Ashok Chaudhari
Department of Computer Science and Engineering
Maulana Azad National Institue of Technology
Bhopal(M.P), India
pratikac127@gmail.com

2nd Rajesh Wadhvani
Department of Computer Science and Engineering Maulana Azad National Institue of Technology Bhopal(M.P), India
rajeshwadhvani@gmail.com

3rd Akhtar Rasool
Department of Computer Science and Engineering Maulana Azad National Institue of Technology Bhopal(M.P), India
akki262@gmail.com

4th Muktesh Gupta
Department of Computer Science and Engineering
Maulana Azad National Institue of Technology
Bhopal(M.P), India
mukteshgupta20@gmail.com

***Abstract*—The Remaining Useful Lifetime (RUL) is forecast using data-driven proposed simulation approaches based on the health indicator (HI). The HI monitors sensor data, like vibration signals, to determine the health of machinery or components. The Hilbert-Huang Transform (HHT) is utilized in the suggested strategy with some time domain features to extract new bearing health indicators that can monitor the deterioration of crucial bearing components are derived from stationary and nonstationary vibration signals. The extracted features are fused together to construct the HI. In the second module, a prophet algorithm is employed to predict the future trend of the HI until it reaches a predefined threshold. To determine the RUL, the prediction start time is subtracted from the prediction end time. Vibration data from tests on rolling element bearings with accelerated degradation are used to illustrate the suggested technique. The outcomes of the predictions support the effectiveness of the suggested method for predicting machinery's RUL.**

***Index Terms*—Remaining Useful Lifetime, Hilbert-Huang Transform, vibration signals, predefined threshold.**

I. Introduction

Bearings are a crucial component in machinery as they provide support for axial and radial loads on rotating shafts. Mechanical parts naturally deteriorate as they age, and the operating environment affects the behavior. Ball bearings are a component that is included in practically all rotating machinery in industrial workplaces and are frequently linked to premature failures. These parts' sudden failure can be critical sufficient to terminate a manufacturing system entirely. Because bearings are one of the most crucial components of rotating hardware, bearing diagnostics is an important field of signal processing. Statistics show that failures in bearings account for 30 % of all failures in rotating machinery. During system operation, a variety of rolling bearing problems may develop because of overload, inadequate lubrication, and poor installation. Establishing the performance degradation indication over the course of a bearing's life is crucial for preventing unexpected failures and implementing condition- based maintenance. The definition of RUL is the period of time starting from the current moment until a system or asset becomes inoperable. It is crucial to study conditional-based maintenance (CBM), health management, and prognosis to assess RUL accurately. Evaluating RUL is vital in making informed maintenance decisions to avoid disasters and save on maintenance costs. Predicting RUL is necessary to schedule maintenance activities in advance, extend life cycles, and pre- vent catastrophic events [1,2]. Due to this, there is a growing demand to enhance and develop RUL prediction techniques for bearings. [3-5]. Data-driven methods have been extensively studied for predicting the RUL of bearings, as reported in previous works [6,7]. The framework of these methods usually involves these steps: (a) data acquisition, (b) Generating HI, and (c) prognostics, which involves predicting the time until failure. the accuracy of the HIs plays a crucial role in deter- mining the forecasting accuracy of RUL [8]. Synthesized HIs have attracted a lot of interest recently, which are typically constructed using data fusion techniques. These techniques transform high dimensional statistical features, such as vari- ance, root mean square (RMS), kurtosis and others, into a one- dimensional HI [9,10]. The classical statistical features used for constructing HIs often have varying ranges, resulting in unequal contributions to the construction process. For instance, several deterioration characteristics and ranges are visible in statistical features recovered from vibration signals in the time domain [11,12], frequency domain [13], and time-frequency domain [14]. To address this issue, to translate the statistical information collected from vibration signals into a particular and equal interval, normalization techniques like "Min-Max scaling" are frequently used [15,16]. In their work, [17] author have shown the use of HHT and the ensemble empirical mode decomposition (EEMD) on vibration signals. instantaneous amplitude and instantaneous frequency at any time instant are calculated, EEMD was used to get a new signal from the original vibration signal that was made up of a group of selected intrinsic mode functions (IMFs). The HHT spectrum

Journal of Current Research in Engineering and Science
Bi-Annual Online Journal (ISSN : 2581 - 611X)

Volume 7- Issue 1, January 2024
Paper : 86

was then used to recognize the bearing fault. Similarly, Wu et al. [18] employed the extraction of HI from the data contained within the IMFs by using the HHT and EEMD to determine the amplitude modulation of various IMFs. The paper uses a combination of HHT and statistical features. In order to eliminate noise from the bearings' vibration, the Empirical Mode Decomposition (EMD) technique is utilized, which acts as an adaptive noise removal technique. The EMD decomposes the complex vibration signals into several IMFs, and the first three IMFs are selected for feature extraction. Eight statistical features are calculated from each IMF. The IMFs are then transformed into Hilbert spectrum using the Hilbert transformation, and two HHT features are extracted from the Hilbert spectrum. The most important fault features are found out using the correlation metrics. These selected features are then fused into a HI through Principal Component Analysis (PCA). By analyzing the training data from start to failure experiments, a threshold value for the HI is defined. When the HI value reaches the threshold, it is assumed that the bearing has failed. The time-to-failure prediction for each test bearing is made using a Prophet model. The RUL is calculated by subtracting the predicted end time with the predicted start time.

II. PROPOSED RUL ESTIMATION METHOD

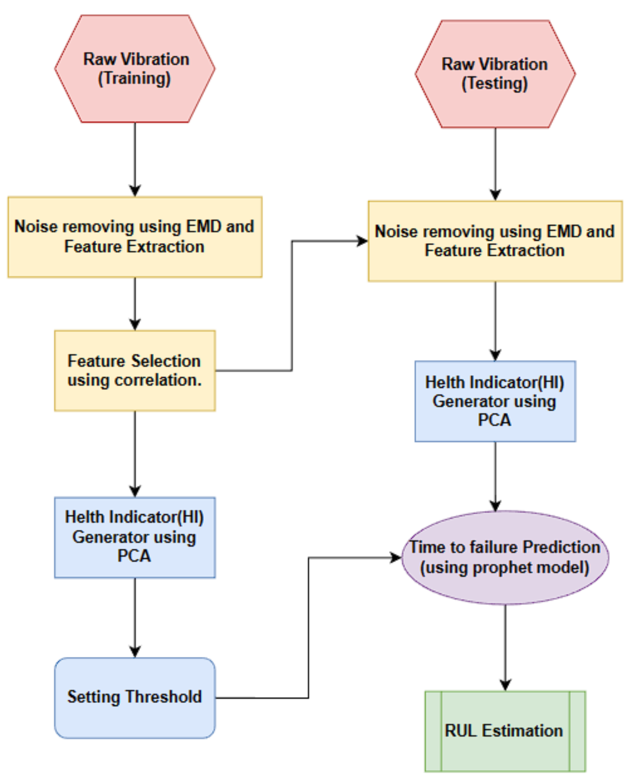


Fig. 1: Overview of the condition assessment method.

The proposed method as shown in Fig. 1 consists of the following steps: A. Feature extraction and selection, B. health indicator (HI) construction, C. setting a threshold and D. time to failure prediction and RUL estimation.

A. *Feature extraction and selection.*

Extracting significant properties from a reduced time-series signal facilitates proper training of RUL predictor models. The HHT is a new emerging technique of time–frequency signal processing designed to analyses nonstationary signals. It has been used in many applications, particularly in fault detection and diagnostic [19]. This technique decomposes a vibration signal x(t) into several IMFs representing the average trend of the signal. These IMFs, obtained because of the EMD [20], represent the input signal in specific frequency bands. EMD is a technique used for analyzing time series signals that are non- stationary and nonlinear in nature. Its core principle involves breaking down these signals into a set of IMFs and residues. IMFs are component signals that range from highest to lowest frequencies and have independent frequency bands, providing valuable physical information and enabling multiresolution analysis of the original signal. When added up, the IMFs and residual can re-create the original signal. An example of the IMFs obtained through EMD applied to a vibration signal is depicted in Fig. 2. To satisfy the EMD conditions, each IMF should have symmetric upper and lower envelops, and the number of zero-crossings and extremal points should be equal or differ by one. The EMD algorithm follows specific decomposition steps to obtain these IMFs from the original signal. To ensure compliance with EMD requirements, each IMF must meet two conditions: 1) the upper and lower envelopes must be symmetrical, and 2) the number of zero- crossings and the number of extremal points must be either equal or differ by one. These IMFs are obtained by following specific decomposition steps when given a time sequence x(t).

1) Identify all the maximum and minimum points of the raw sequence x(t) and then fit out the upper envelope Emax(t) and lower envelope Emin(t). The mean value of the upper envelope and the lower envelope can be expressed as

$$m(t) = \frac{E_{max}(t) + E_{min}(t)}{2} \qquad (1)$$

2) Compute the difference between the average envelope curve (m(t)) and the raw sequence (x(t)), represented by the symbol h(t)

$$h(t) = x(t) - m(t) \qquad (2)$$

3) See whether h(t) meets the constraint conditions of the IMF. In the event that h(t) is not an IMF, take h(t) as a new input sequence and step 1 and 2 are repeated until the aforementioned constrain requirement are satisfied. In the event where h(t) is an IMF, its is then become a first IMF component of x(t) and can be written as

$$c_1(t) = h(t) \qquad (3)$$

Journal of Current Research in Engineering and Science
Bi-Annual Online Journal (ISSN : 2581 - 611X)

Volume 7- Issue 1, January 2024
Paper : 86

4) To acquire the residual component r1(t), c1(t) is then removed from the original sequence x(t).

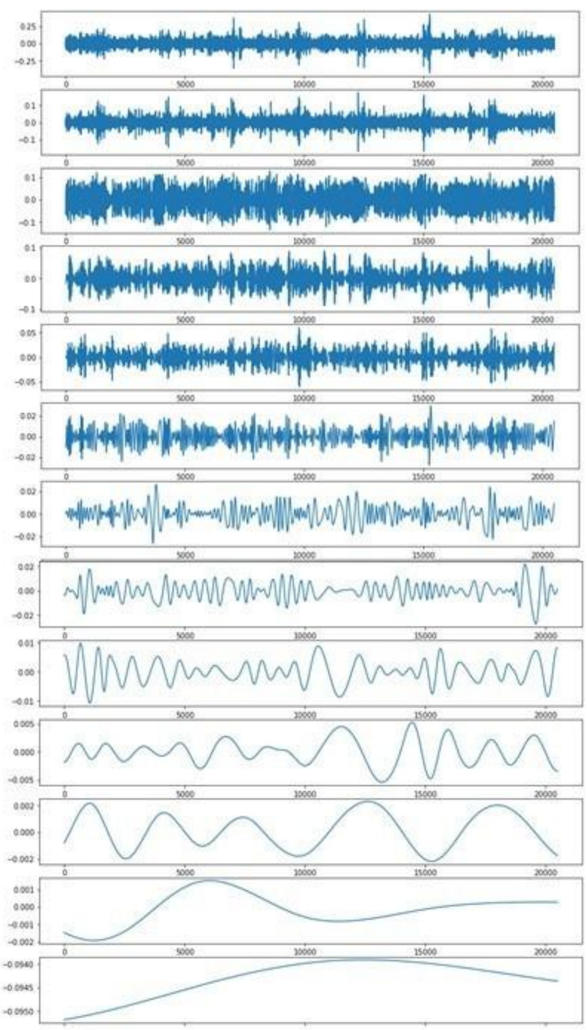
$$r_1(t) = x(t) - c_1(t) \tag{4}$$

5) The foregoing stabilizing procedures are then repeated until we get next IMF component c2(t). Thereafter, r1(t) is taken into consideration as a new sequence, and the procedures are repeated n times. The eventual outcome of EMD is best described as

$$E(t) = \sum_{i=1}^{n} c_i(t) + r_n(t) \tag{5}$$

where rn(t) is the residue reflecting the trend term of the initial sequence and ci(t) is the ith IMF, i.e.

$$x(t) = \sum_{i=1} IMFi + r_n(t) \tag{6}$$



$$c_iA(t) = c_i(t) + jc_iH(t) \tag{7}$$

$$c_iA(t) = a_i(t)e^{j\vartheta_i(t)} \tag{8}$$

where $c_iH_i(t)$ is the Hilbert transform of $c_i(t)$

$$H_i(t) = \frac{1}{\pi} P \int c_i(s) \frac{1}{t-s} ds \tag{9}$$

in which P denotes the Cauchy principal value.
It is possible to determine the instantaneous amplitude $a_i(t)$ and phase $\vartheta_i(t)$ using the polar coordinate from the analytical IMF $c_i(t)$. They are given as follows:

$$a_i(t) = \sqrt{c_i^2(t) + (c_i^H)^2} \tag{10}$$

$$\vartheta_i(t) = \tan^{-1} \frac{c^2}{c_i} \tag{11}$$

The formula below can be used to determine the instantaneous frequency $f_i(t)$ from the instantaneous phase $\vartheta_i(t)$.

$$f_i(t) = \frac{1}{2\pi} \frac{d\vartheta_i(t)}{dt} \tag{12}$$

The Marginal Hilbert Spectrum (MHS) calculated as fol- lows:

$$h_i(t) = \int h_i(f,t)\,df \tag{13}$$

Energy and entropy are the features which are extracted from Hilbert marginal spectrum. The MHS's energy can be determined using the formula below:

$$E = \int\int |h_i(f,t)|^2\, df\, dt \tag{14}$$

where P (f, t) is the normalized MHS at frequency f and time t. The entropy (MHS) provides a measure of the uncertainty or randomness of the signal's frequency content over time. Again, domain features are also calculated like:
Root Mean Square (RMS):

$$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2} \tag{15}$$

Fig. 2: Decomposed Vibration signals by EMD

Journal of Current Research in Engineering and Science
Bi-Annual Online Journal (ISSN : 2581 - 611X)

Where x^2 is the i-th sample of a signal and n is the number of samples.

i

Peak-to-Peak (P2P):

$$P2P = \max(x) - \min(x) \tag{16}$$

After EMD first 3 IMFs are selected for feature extraction. Here, The analytical form of an IMF ciA(t), is defined as

Crest Factor:

$$CF = \frac{\max(x)}{RMS} \tag{17}$$

Journal of Current Research in Engineering and Science
Bi-Annual Online Journal (ISSN : 2581 - 611X)

Volume 7- Issue 1, January 2024
Paper : 86

Kurtosis:

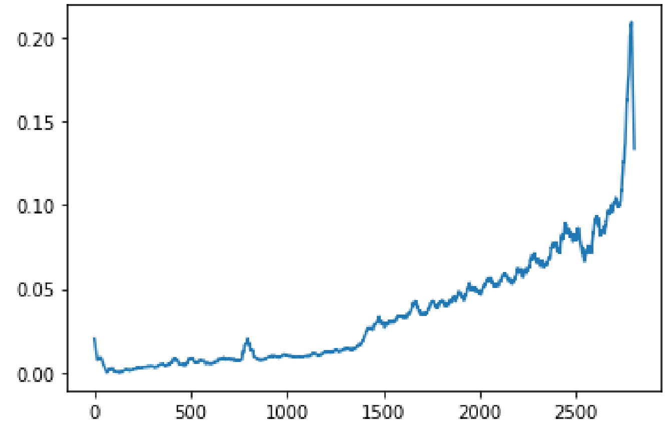
$$K = \frac{\frac{1}{n}\sum_{i=1}^{n}(x_i - \mathrm{mean}(x))^4}{\left(\frac{1}{n}\sum_{i=1}^{n}(x_i - \mathrm{mean}(x))^2\right)^2} \quad (18)$$

Skewness:

$$S = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{x_i - \mathrm{mean}(x)}{\mathrm{std}(x)}\right)^3 \quad (19)$$

Standard Deviation:

$$S_{td}(x) = \sqrt{\frac{\sum (x - \mathrm{median}(x))^2}{n}} \quad (20)$$



Journal of Current Research in Engineering and Science
Bi-Annual Online Journal (ISSN : 2581 - 611X)

Volume 7- Issue 1, January 2024
Paper : 86

Min, Max and Mean of a signal these are all features are extracted and the features having more than 0.5 as correlation coefficient are selected to construct HI.

Fig. 3: HI of bearing 1-1

B. health indicator (HI) construction

The method used in this study involves constructing a HI using PCA. To construct a HI using PCA for variable reduction. The first step in this process was to address the issue of variables measured on different scales, which can cause bias in the model fitting process. To mitigate this potential prob- lem, feature-wise normalization using Min-Max Scaling was applied before performing PCA. PCA seeks to minimize the feature's dimensionality while retaining most of the variability in the data. In other words, It seeks to reduce the original set of variables into a smaller set of main components, which are uncorrelated variables. This approach can help to identify the most important factors contributing to the variability in the data, making it easier to interpret and analyze. In this study, The characteristics derived from the training bearings were subjected to PCA. The resulting principal components accounted for most of the data variability, indicating that the transformation was successful in capturing most of the relevant information in the data as shown in figure 3. To obtain a smooth trend of HI, the researchers used a Moving Average (MA) smoothed method. This technique involves calculating the average of a subset of data points over a rolling window of fixed size, with the window moving forward one point at a time. This process helps to eliminate any short-term fluctuations in the data, revealing the underlying trend over time. By using MA smoothing, the researchers were able to obtain a clear and informative HI that accurately reflected the health status of the bearings.

C. Setting a threshold

The PRONOSTIA platform provides a feature that allows researchers to conduct run-to-failure experiments, where tests are terminated once the vibration signal amplitude surpasses a predetermined threshold of 20g [21]. Through the analysis of training data obtained from run-to-failure experiments, we observed that the bearings tended to fail at a HI value of approximately 0.2. Based on this observation, it is possible to establish the HI value of 0.2 as the threshold limit as shown in figure 4, beyond which the bearings are expected to fail. This threshold provides a reference point that can be used to monitor the health of the bearings and to identify potential failures before they occur. By continuously keeping the eye on the HI values of the bearings and comparing them to the established threshold, we can identify when the bearings are nearing failure and take necessary action to prevent a catas- trophic failure from occurring. Therefore, the establishment of a threshold limit helps in making decisions about maintenance and repair schedules, and it can also contribute to reducing the likelihood of unexpected equipment failure, thereby improving the overall efficiency and safety of the system.

Fig. 4: HI plot of bearing 1-1 with set threshold

D. Time to failure prediction and RUL estimation.

The Prophet model has remarkable accuracy in predicting the behavior of time series data [25]. In this particular scenario, the model was trained on a set of available data of the HI of a test bearing, with the endpoint of this data serving as the starting point for the prediction. The model was then deployed to forecast the future trend of the HI until it reached a fixed threshold value of 0.2. The Fb Prophet model is highly suitable for this application as it is specifically designed to handle time series data, accounting for trends, seasonality, and other effects that are often present in industrial systems. It provides a robust and efficient means of predicting the future behavior of such data. During the prediction phase, the model continually generated forecast values until the HI reached the fixed threshold value as shown in figure 5. At this point, the time was noted, which served as the endpoint of the prediction. The Predicted RUL was calculated by taking the difference between the starting point and endpoint of the prediction. The resulting RUL value is a crucial metric used in determining the remaining lifespan of the bearing, enabling timely maintenance or replacement to prevent catastrophic failure. Predicted RUL

Journal of Current Research in Engineering and Science
Bi-Annual Online Journal (ISSN : 2581 - 611X)

Volume 7- Issue 1, January 2024
Paper : 86

= Prediction end time - Prediction start time

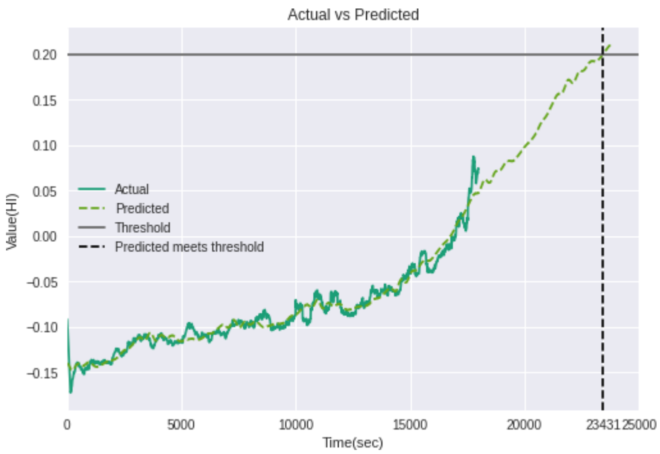


Fig. 5: Prediction Plot of bearing 1-3

III. EXPERIMENTAL SETUP AND RESULT DISCUSSION

A. Data Set

The experimental data used in the proposed approach was obtained from PRONOSTIA as part of the IEEE PHM 2012 Data Challenge [21]. The experiment platform, illustrated in

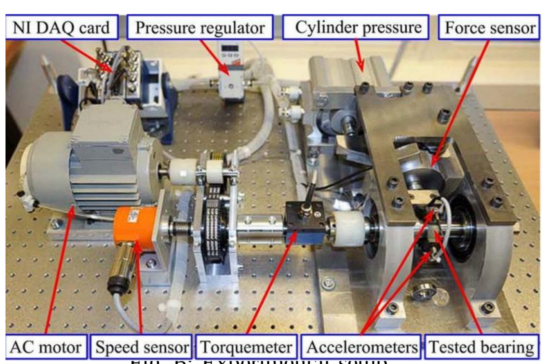
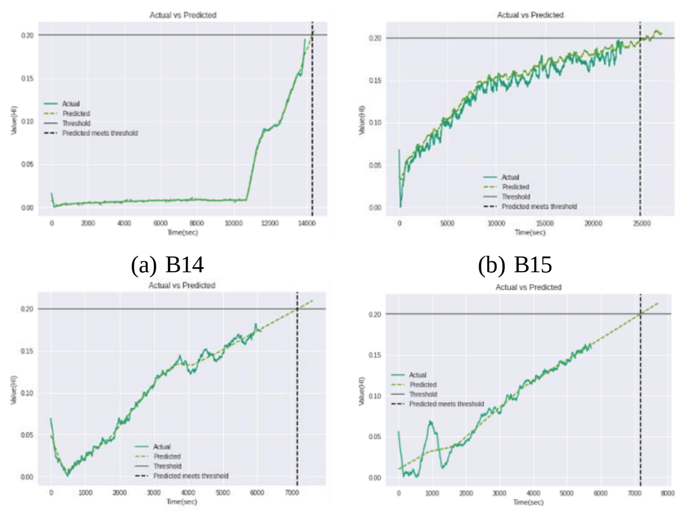


Fig. 6: Experimental setup

regulated shaft speed to quicken the bearing degeneration. On the test bearing, there are two accelerated sensors that are lateral to one another. The data is sampled at a frequency of 25600Hz, with each sample lasting for 0.1 seconds, resulting in 2560 data points per sample. The test is stopped whenever the amplitude of the captured signal exceeds a set threshold in order to prevent harm. The recording interval is 10 seconds.

B. Result on testing bearings.

In order to demonstrate the versatility of proposed frame- work for estimating RUL, tests on five additional bearings are conducted : bearing1-4, bearing-1-5, bearing2-4, bearing2-6, and bearing3-3 as shown in Figure 7.



(a) B14 (b) B15

(c) B24 (d) B26

Fig. 7: Prediction Plots of Testing bearings

C. Evaluation metrics

Two generally used metrics are employed to compare the review methodologies:

1) Relative Error (Er):

$$Er = 100 \times \frac{T_{failure} - \hat{T}_{failure}}{T_{failure}} \quad (21)$$

where Tfailure is the real RUL and Tˆfailure is predicted. A worse RUL prediction result is indicated by a higher absolute Er.

2) Exponential Transformed Accuracy (ETA): The preci- sion that was exponentially transformed and proposed in IEEE PHM 2012 [21]. ETA is an evaluation metric used to differen- tiate between major under- and over-predictions of RUL. To avoid more major harm to the bearing, underestimation (early warning) is better than overestimation (warning post damage). The equation is used to express the formula.

$$ETA = \begin{cases} e^{-\ln(0.5)\frac{Er}{5}}, & \text{if } Er \le 0 \end{cases} \quad (22)$$

Journal of Current Research in Engineering and Science
Bi-Annual Online Journal (ISSN : 2581 - 611X)

Volume 7- Issue 1, January 2024
Paper : 86

Figure 6, consists of three primary components: a rotating portion, a part for creating deterioration, and a part for collecting signals. A radial load force is delivered with a

$$S_{mean} = \frac{1}{\beta} \sum_{i=1} \mathrm{ETA}_i \tag{23}$$

β is Numbers of bearings

Mean absolute error (MAE),

$$MAE = \frac{1}{\beta} \sum_{i=1}^{\beta} T_{failure_i} - \hat{T}_{failure_i} \tag{24}$$

Normalized root means square error (NRMSE),

$$NRMSE = \frac{\sqrt{\frac{1}{\beta} \sum_{i=1}^{\beta} (T_{failure_i} - \hat{T}_{failure_i})^2}}{\frac{1}{\beta} \sum_{i=1}^{\beta} \hat{T}_{failure_i}} \tag{25}$$

D. Result comparison

To further validate the proposed approach, the predicted numerical errors of RULs generated by proposed method and three other methods are compared. These comparisons are listed in Table I and Table II compares the evaluation metrics like Smean,MAE and NRMS.

TABLE I: Error Comparison

Methods	Error					
	B13	***B14***	***B15***	***B24***	***B26***	***B33***
RNN [22]	-31.76	62.07	-22.98	-19.42	-13.95	3.66
LSTM [23]	54.73	38.69	-99.40	19.81	17.87	2.93
GPR [24]	-1.04	-20	-278	51.8	-20.8	-3.66
Our method	5.21	-15	-13	23	-13	32

TABLE II: Evaluation Metrics Comparison

Methods	Smean	MAE	NRMS
RNN [22]	0.21	990	0.74
LSTM [23]	0.39	900	0.96
GPR [24]	0.29	938	0.72
Our method	0.4	241	0.15

IV. CONCLUSION

$20,\quad$ if $E_r > 0$

A greater ETA value indicates a finer RUL prediction outcome. The range of the ETA value is 0 to 1. Three additional

assessment criteria are employed along with the two that test prediction accuracy for a particular bearing in order to conduct a thorough comparison of various approaches. These three metrics are: Average score Smean,CKNOWLEDGMENT

we are grateful to the FEMTO-ST Institute for their valu- able contribution to the development of PRONOSTIA. Their efforts in creating a comprehensive dataset through laboratory experiments are highly appreciated and will benefit researchers and practitioners in various fields.

References

[1] Y. Lei, J. Lin, M.J. Zuo, Z. He, Condition monitoring and fault diagnosis of planetary gearboxes: a review, Measurement 48 (2014) 292–305.

[2] A. Ghods, H.H. Lee, Probabilistic frequency-domain discrete wavelet transform for better detection of bearing faults in induction motors, Neurocomputing 188 (2016) 206–216.

[3] N. Li, Y. Lei, J. Lin, S.X. Ding, An improved exponential model for predicting remaining useful life of rolling element bearings, IEEE Trans. Ind. Electron. 62 (2015) 7762–7773.

[4] D. Pan, J.-B. Liu, J. Cao, Remaining useful life estimation using an inverse Gaussian degradation model, Neurocomputing 185 (2016) 64–72.

[5] A. Heng, S. Zhang, A.C. Tan, J. Mathew, Rotating machinery prognos- tics: state of the art, challenges and opportunities, Mech. Syst. Signal Process. 23 (2009) 724–739.

[6] J. Liu, W. Wang, F. Ma, Y.B. Yang, C.S. Yang, A data- model-fusion prognostic framework for dynamic system state forecasting, Eng. Appl.

The combination of feature extraction methods based on the HHT, and time domain features has been shown to be effective in reflecting the degradation of bearings and providing insights into the health of the equipment. The HI derived from PCA is able to be an effective approach for identifying the current degradation level. The suggested technique offers a practical tool for calculating the RUL of ball bearings, ultimately resulting in improved maintenance practices and equipment reliability. By incorporating these techniques, operators can better estimate when maintenance is needed, ultimately re- ducing downtime and preventing equipment failure

Volume 7- Issue 1, January 2024
Paper : 86

Artif. Intell. 25 (2012) 814–823.
[7] K. Javed, A Robust Reliable Data-Driven Prognostics Approach Based on Extreme Learning Machine and Fuzzy Clustering, Universite´ de Franche-Comte´, 2014.
[8] H. Qiu, J. Lee, J. Lin, G. Yu, Robust performance degradation assess- ment methods for enhanced rolling element bearing prognostics, Adv. Eng. Inform. 17 (2003) 127–140.
[9] D Wang, T Peter W, W Guo, et al., Support vector data description for fusion of multiple health indicators for enhancing gearbox fault diagnosis and prognosis, Meas. Sci. Technol. 22 (2) (2010) 025102.
[10] Y. Wang, Y. Peng, Y. Zi, X. Jin, K.-L. Tsui, A two-stage data-driven- based prognostic approach for bearing degradation problem, IEEE Trans. Ind. Inform. 12 (2016) 924–932.
[11] A. Widodo, B.-S. Yang, Machine health prognostics using survival probability and support vector machine, Expert Syst. Appl. 38 (2011) 8430–8437.
[12] F. Camci, K. Medjaher, N. Zerhouni, P. Nectoux, Feature evaluation for effective bearing prognostics, Qual. Reliab. Eng. Int. 29 (2013) 477–486.
[13] J. Yu, A hybrid feature selection scheme and self-organizing map model for machine health assessment, Appl. Soft Comput. 11 (2011) 4041–4054.
[14] H. Ocak, K.A. Loparo, F.M. Discenzo, Online tracking of bearing wear using wavelet packet decomposition and probabilistic modeling: a method for bearing prognostics, J. Sound Vib. 302 (2007) 951–961.
[15] L. Ren, W. Lv, Remaining useful life estimation of rolling bearings based on sparse representation, in: Proceedings of the 7th International Conference on Mechanical and Aerospace Engineering (ICMAE), IEEE, 2016, pp. 209–213.
[16] E. Sutrisno, H. Oh, A.S.S. Vasan, M. Pecht, Estimation of remaining useful life of ball bearings using data driven methodologies in: Proceed- ings of the IEEE Conference on Prognostics and Health Management (PHM), IEEE, 2012, pp. 1–7.
[17] H. Li, Y. Wang, and Y. Ma, "Ensemble empirical mode decomposition and Hilbert–Huang transform applied to bearing fault diagnosis," in Proc. 3rd Int. Congr. Image Signal Process. (CISP), Oct. 2010, pp. 3413–3417.
[18] T.-Y. Wu, C.-C. Wang, and Y.-L. Chung, "The bearing fault diagnosis of rotating machinery by using Hilbert–Huang transform," in Proc. Int. Conf. Electric Inform. Control Eng. (ICEICE), Apr. 2011, pp. 6238–6241.
[19] L. Hui, Z. Yuping, and Z. Haiqi, "Wear detection in gear systemusing Hilbert–Huang transform," J. Mech. Sci. Technol., vol. 20, no. 11,pp. 1781–1789, 2006.
[20] A.-O. Boudraa and J.-C. Cexus, "EMD-based signal filtering," IEEE Trans Instrum. Meas., vol. 56, no. 6, pp. 2196–2202, Jul. 2007.
[21] FEMTO-ST Institute UMR CNRS 6174 - UFC / ENSMM / UTBM 24
rue Alain Savary, 25000 Besanc¸on, France.

Volume 7- Issue 1, January 2024
Paper : 86

[22] Liang Guo, Naipeng Li, Feng Jia, Yaguo Lei, Jing Lin, A recurrent neural network based health indicator for remaining useful life predic- tion of bearings,Neurocomputing,Volume 240,2017,Pages 98-109,ISSN 0925-2312,

[23] A. Z. Hinchi and M. Tkiouat, “Rolling element bearing remaining useful life estimation based on a convolutional long-short-term memory network,” Procedia Computer Science, vol. 127, pp. 123–132, 2018.

[24] S. Hong, Z. Zhou, E. Zio, and K. Hong, “Condition assessment for the performance degradation of bearing based on a combinatorial feature extraction method,” Digital Signal Processing, vol. 27, pp. 159–166, 2014.

[25] Cho AD, Carrasco RA, Ruz GA. A RUL Estimation System from Clus- tered Run-to-Failure Degradation Signals. Sensors. 2022; 22(14):5323. https://doi.org/10.3390/s22145323