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Research Article

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Posted Date: June 9th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-9795196/v1

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Version of Record: A version of this preprint was published at The International Journal of Advanced Manufacturing Technology on September 25th, 2026. See the published version at https://doi.org/10.1007/s00170-026-18653-x.

Kernel PCA Based Health Indicator Construction for Rolling Element Bearings Remaining Useful Life Estimation using ANFIS-DE

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Abstract

Rolling element bearings, key components within mechanical systems, are particularly susceptible to failure, and their condition is a primary determinant of overall system functionality. Hence, the accurate estimation of their remaining useful life is vital for effective condition-based maintenance, enhancing system reliability while potentially reducing maintenance costs. However, most remaining useful life estimation methodologies are often limited, leading to compromised prediction accuracy. In data driven methods, a robust health indicator is fundamental as it captures essential degradation signatures required for the core tasks of prognostics: starting with fault diagnosis and extending to accurate remaining useful life prediction. In this work, we propose an empirical hybrid framework for health indicator construction using feature engineering and kernel principal component analysis, for remaining useful life estimation using Adaptive Neuro-Fuzzy Inference System within it parameters optimized using Differential Evolution algorithm. The proposed framework was evaluated through experiments conducted on the XJTU-SY bearings dataset. Comparative analysis with other methods substantiated its effectiveness.

Keywords

Rolling element bearings, remaining useful life, kernel principal component analysis, health indicator, Adaptive Neuro-Fuzzy Inference System, Differential Evolution algorithm.

1 Introduction

Within Prognostics and Health Management (PHM), real-time prediction of equipment degradation is critical, as it enables the development of an effective Condition-Based Maintenance (CBM) strategies to avoid unexpected downtimes, aiming to maximize system's availability, reducing maintenance costs and improving system safety and reliability. Rolling element bearings,

considered as one of the basic components of rotating machinery, as it plays a crucial role in the safe operation of equipment [1], their health monitoring has become a high priority in PHM activities in several sectors such as aerospace, modern manufacturing, and renewable energy, as they operates in complex environments face variable conditions and stochastic degradation creating significant remaining useful life (RUL) prediction uncertainty [2]. Thus, accurately predicting RUL of bearings has become a challenging topic for maintenance decisions making in modern industries.

The main purpose of RUL estimation is the prediction of the remaining life of mechanical components until failure according its monitoring information. In this regard, for developing an accurate bearings RUL prediction model, researchers have pursued two methodological approaches: physics-based and data-driven techniques. Physics-based approaches for bearings RUL estimation are represented by physical laws such as the Paris crack growth [3], or by stochastic process such as: Wiener process [4] and Gaussian process [5], Its employs mathematical models and physics laws that reflects failure mechanisms to describe the degradation process [6] their prediction accuracy relies on the precision of the underlying mathematical model, and cannot be applied to complex systems with poorly defined failure mechanisms. Conversely, when system physics are well-characterized and the model accurately represents failure behavior, this approach yields reliable RUL estimation. Consequently, for RUL estimation without explicit knowledge of failure mechanisms, data-driven techniques has proven its effectiveness in PHM activities, these approaches are increasingly applied by learning the map between condition-monitoring data and system's degradation, these methods uses historical data to train a prediction model such as Support Vector Machine (SVM) [7], Transformers [8], Convolutional Neural Network [9] (CNN), Long Short Term Memory (LSTM) [10], or other models.

In data driven methods, developing a reliable health indicator (HI) is therefore critical for anomaly detection and RUL prediction, as it quantifies a system's real time health state, and it enables the forecasting of fault progression for an effective CBM implementation strategy. Based on their construction methodology, HIs are classified into two categories [11-12]: physical based HIs (PHIs), which reflects failure physics and computed from statistical features e.g., RMS, MAX, and virtual based HIs (VHIs), synthesized from fusing multiple physical based HIs using supervised methods, leveraging a labeled data to train the model to predict the new unlabeled data's output, or unsupervised methods including dimensionality reduction-based and reconstruction error-based [13], these VHIs represents degradation patterns without retaining physical significance. In this context, Wei et al. [14] uses a Sparse Autoencoder (SAE) to fuse sensitive features extracted from raw vibrations signals. Zhan et al. [15] employed attention mechanism to fuse time, frequency and time frequency domain features for bearings HI construction. Ni et al. [16] proposed a multi objective multi scale based feature fusing for HI construction. To handle the complex, non-stationary and non-Gaussian nature of vibration signals from degrading bearings, kernel principal component analysis (KPCA) is employed in this work, as it maps the extracted features into a high-dimensional space via a kernel function, uncovering non-linear relationships that linear

dimensionality reduction methods cannot capture, retaining essential degradation patterns while filtering redundant and noisy components. KPCA achieves efficient dimensionality reduction suitable for constructing HI, by selecting principal components that explain a high cumulative variance often above 90 %. Therefore, the motivation to use KPCA lies on its ability to integrate nonlinear feature fusion, noise resilience and features dimensionality reduction HI construction.

Regarding data driven based RUL prediction, numerous studies have been carried out using machine learning (ML) and deep learning (DL) methods, the process relies on extracting features from vibration data in time, frequency and time-frequency domains, these features are pre-processed to select the most meaningful ones, then used for HI construction that can describe bearing's degradation trend. Finally, these HIs are used as inputs to train a prediction model [17]. In existing literatures, a variety of RUL prediction model being explored: Qiu et al. [18] used a temporal convolutional network (TCN) as a prediction model, Sheng et al. [19] proposed a single gated recurrent neural network (RNN) model with a differential weighted information storage mechanism for RUL estimation. Zhang et al. [20] adopted four degradation functions to construct the HI of bearings and leveraged a novel two stage long short-term memory networks (LSTM) approach for RUL estimation. Jiang et al. [8] implemented a convolutional dual-channel Transformer network as a prediction model. Also, authors in [16] uses a gated recurrent unit (GRU) with optimized parameters for RUL estimation. Huang et al. [9] utilized 1D time series and 2D image (using Continuous wavelet transform CWT) as features, then a deep convolutional neural network (DCNN) as a prediction model, also, they proposed a bidirectional long short-term memory network (BiLSTM) based prognostic model for turbofan engines RUL estimation [10]. However, the previously cited ML and DL models typically requires a large labeled data for training, and operates as a non-interpretable systems "Black Boxes", making it difficult to understand their internal reasoning. To overcome this issue, an Adaptive Neuro-Fuzzy Inference System (ANFIS) uses the fuzzy logic (FL) with artificial neural network (ANN) to encode expert knowledge via human-readable fuzzy rules, providing a clear, linguistic explanations for the prediction results, which directly addressing the interpretability requirement. In safety-critical bearings maintenance, where is crucial to evaluate the results, ANFIS is particularly suitable due to its data efficiency for bearings RUL estimation when the model's transparency is required. Also, a hybrid implementation with Differential Evolution (DE) further optimize its parameters and reduce overfitting problems, enhancing accuracy in non-stationary operational environments. Consequently, we propose an ANFIS model within it parameters optimized using DE optimization as a prediction model, which provides a balanced choice between model complexity, adaptability, and explainability for industrial RUL prediction.

The main contributions of this work are summarized as follows:

1. Leveraging KPCA for unsupervised dimensionality reduction technique to synthesize a low dimensional unique HI for bearings degradation assessment, by combining multiple domain features.

2. A Sum of Squared Errors (SSE) minimization method for first degradation point (FDP) detection and bearings health stage division task.

3. Introduction of a hybrid ANFIS-DE prediction model for bearings continuous RUL value estimation.

4. Validation of the proposed approach using XJTU-SY bearings accelerated dataset under different environmental conditions, by evaluating the prediction error against relevant state-of-the-art models.

The organization of this work is as follows: related work, which include a comparison against prior KPCA-based HI methods, prior ANFIS-based bearing RUL methods and what is new beyond recombination in our work, preliminaries sections presenting the proposed approach and the adopted method for bearings health stage division, followed by three sections covering the basic knowledge of kernel PCA, Adaptive Neuro-Fuzzy Inference System and Differential Evolution Optimization. The experimental framework section explains a step by step, the HI construction method and the prediction model. The experiment section presents also the specific experimental results, analysis and discussion. Finally, in the last section is reserved for the conclusion and future work.

2 Related Work

In recent years, bearings RUL estimation has evolved significantly with substantial research dedicated for HI construction and RUL prediction. KPCA has been widely adopted for dimensionality reduction and feature fusion techniques to derive the HI that can reflect bearings degradation. For instance, Tai et al. [21] and Zou et al. [22] employed KPCA to fuse time domain, frequency domain and time-frequency domain features, then, the first principal component was selected as HI. Similarly, Wang et al. [23] used Pearson Correlation analysis to select features with low redundancy before feature fusion using KPCA. While these papers utilizes KPCA for dimensionality reduction, the lack of discussion about the kernel function choice is a significant gap. In parallel, the Adaptive Neuro-Fuzzy Inference System have gained popularity for RUL estimation for it interpretability and capacity for modeling nonlinear degradation process of bearings, In this regard, Lourari et al. [24] employed Wavelet Packet Decomposition (WPD) for data preprocessing, and Sequential Backward Selection (SBS) for feature selection, subsequently, the selected features are used as ANFIS's inputs for VHI prediction, ultimately, a reverse transformation from VHI to a continue value of RUL is performed. Similarly, the same process is employed in two other papers for VHI prediction using ANFIS model, and RUL calculation using the reverse transformation, using two different feature selection methods: a Recursive Feature Elimination in [25], and a systematic process of trial and error in [26]. However, a significant limitation of these methodologies lies in the "curse of dimensionality" inherent to the ANFIS, by using five features as the model's inputs with 3 membership function for each, the fuzzy rule base undergoes an exponential expansion which risks to overfit the training data.

The present work builds upon these foundations by proposing an empirical hybrid framework that combines KPCA for HI construction and ANFIS for RUL prediction. Unlike prior studies, our work uses KPCA for HI construction, by systematically exploring different kernel functions, including radial basis function (RBF), linear and sigmoïd across parameter spaces, subsequently, the selection of the raw HI is based on the calculation of the explained variance of the first two principal components. Regarding the prediction model, the constructed KPCA based HI is used as the ANFIS's input, ensuring a stable and interpretable mapping between bearings health state and it remaining useful life without any reverse transformation, furthermore, the model's parameters are tuned using a population based metaheuristic optimization using Differential Evolution (DE) algorithm.

3 Proposed approach

As Figure 1 presents the flowchart of the proposed prognostic methodology, this study investigates an integrated framework for bearings RUL estimation, by leveraging kernel principal component analysis for HI construction, and an Adaptive Neuro-Fuzzy Inference System optimized via Differential Evolution Algorithm for RUL prediction. First, horizontal vibrations signal is acquired under accelerated degradation conditions, these raw vibrations undergoes for feature extraction to capture bearing's degradation signatures. Subsequently, selecting the most informative features based on three common prognostic evaluation metrics that contribute significantly is vital task in RUL estimation, only sensitive ones are retained for fusion using kernel PCA to construct a monotonic HI for each bearing. Finally, the constructed HIs are split into training and testing data and fed to a prediction model, an ANFIS within its parameters are optimized using DE, minimizing root mean squared error as a cost function for RUL estimation using the HIs as inputs. Ultimately, the prediction results of the hybrid ANFIS-DE approach are validated using XJTU-SY bearings dataset.

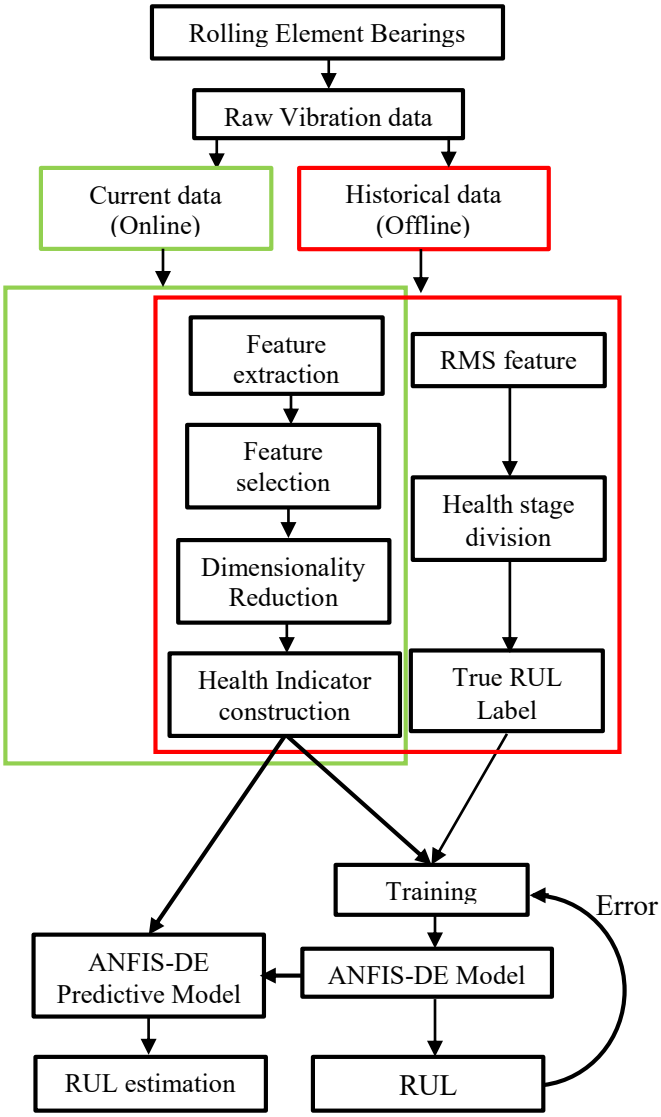


Fig. 1 The flowchart of the proposed approach

4 Health stage division

The accurate detection of the first degradation stage, also known as the first degradation point (FDP) is a cornerstone of an effective PHM activities in rotating machinery systems, serving as the initiator of the prognostic tasks to precisely identify the initial transition time from healthy state to degraded one. Consequently, a robust FDP detection is the preliminary step for the prognostic task, and a fundamental determinant for the prediction accuracy. For this specific task, advanced computational methods such as: statistical analysis [27], fuzzy methods [1] or deep learning techniques [28] are employed for FDP detection. According to the degradation process of bearings, its usually operates in a stable period in the earliest moment in time, after the FDP the degradation level becomes severe indicating that the component is in the fault stage. The health stage (HS) division task relies on dividing bearings degradation process into two stages, using statistical features to distinct the healthy stage and the faulty one for triggering the RUL prediction

process. In this work, we employed a linear regression model with Root Mean Square (RMS) feature for health stage (HS) division and FDP detection.

4.1 Sum of Squared Errors (SSE) minimization based method for first degradation point (FDP) detection

The main idea of sum of squared errors (SSE) minimization is to identify the optimal change point, by iteratively testing potential split locations in the sequential RMS feature of vibration signal. The process begins by identifying 10% of the RMS feature data to characterize the healthy stage, then dividing the data into two segments: pre-split data representing the bearing's healthy state and post-split, representing the faulty state. For each segments, we apply an independent linear regression model to capture their distinct patterns. An optimal change point is detected by minimizing the sum of squared errors between piecewise linear regression models fitted to sequential data segments, this identifies the transition index where the system's behavior deviates from baseline characteristics. Finally, the data are divided into healthy and faulty states, based on this change point, enabling a binary segmentation of the entire operational lifecycle. The approach provides a statistically rigorous method for HS division task.

4.2 Pseudo-code for SSE minimization method

```
Start of program
Initialization (RMS_feature, 0.1% baseline)
Baseline size
n0 ← Max(3, Round(baseline_pct × nbr_files))
mu0, sigma0 ← Mean(rms [1:n0]), Std(rms[1:n0])
optimal_cp ← n0 + 1
min_sse ← ∞
Change point detection
FOR cp ← n0+1 TO nbr_files-2:
    sse ← SSE(rms[1:cp-1]) + SSE(rms[cp:END])
    IF sse < min_sse THEN
    min_sse ← sse, optimal_cp ← cp
Stage division
segments ← [Healthy] × nbr_files
segments[optimal_cp:END] ← Degraded
End of program.
```

where:
n_0: Number of baseline points
mu_0: Mean of baseline RMS values
$sigma_0$: Standard deviation of baseline RMS values
cp: Candidate change point index during iteration
min_sse: Minimum sum of squared errors
sse: Sum of squared errors for candidate change point

5 Kernel principal component analysis

To avoid complicate subsequent processing stages, the use of dimensionality reduction methods is fundamental in feature engineering. Therefore, many works have been developed focusing on enhancing dimensionality reduction techniques. To deal with non-linear problem, an extension of standard Principal Component Analysis (PCA), Kernel Principal Component Analysis (KPCA), is a powerful technique to enable non-linear dimensionality reduction using the kernel trick, the basis it implementation is described below [29]:

Compute the Kernel Matrix: each element is defined as:

$$k_{ij} = k(x_i, x_j) \tag{1}$$

Center the Kernel Matrix to ensure zero mean in feature space

$$K_{centred} = K - 1_n K - K 1_n + 1_n K 1_n \tag{2}$$

Compute the Eigenvalues and Eigenvectors of the kernel matrix:

$$K_{centred}\, v_m = \lambda_m v_m, m = 1, 2, \ldots, n. \tag{3}$$

Where λ_m and v_m are the eigenvalues and eigenvectors, respectively.

Select the Principal Components: Select the top K eigenvectors by their eigenvalue magnitude to form the principal components in kernel space.

Project data into principal components:

$$T_i = \sum_{j=1}^{n} v_j k(x_i, x_j) \tag{4}$$

Where Ti is the i^{th} component of the projected data in the new space.

6 Adaptive Neuro Fuzzy Inference System

ANFIS combines the learning capability of Artificial Neural Networks (ANN) and the reasoning ability of fuzzy logic (FL) in one framework, it uses Takagi-Sugeno fuzzy model in multi-layers feed forward networks, turning both antecedent and consequence parameters via hybrid learning. As it shown in Figure 1, a typically ANFIS considering two inputs and one output is constructed with five layers, the functionality of each is as follow [30]:

Fuzzification layer: which transforms crisp inputs value into fuzzy sets using membership functions, the output are:

$$O_i^1 = \mu A_i(x), \; i = 1,2,..., n \tag{5}$$

$$O_i^1 = \mu B_i(y), \; i = 1,2,..., n \tag{6}$$

where μA_i and μB_i are the membership functions of the linguistic variables A and B, respectively.

Rule layer: which calculates the firing strength of each fuzzy rules, it is calculated by:

$$\text{if } x \text{ is } A_i \text{ and } y \text{ is } B_i \text{ then } f_i = p_i x + q_i y + r_i,\ i = 1,2,\ldots,n \tag{7}$$

where n is the number of rules,p_i, q_i and r_i are the parameters that are determined during the training phase. The output of this layer is obtained by:

$$O_i^2 = \omega_i = \mu A_i(x) \times \mu B_i(y),\ i = 1,2,\ldots,n \tag{8}$$

Normalization layer: which normalize the firing strength of all rules by the equation:

$$O_i^3 = \overline{\omega_i} = \frac{\omega_i}{\sum_{i=1}^{n} \omega_i},\ i = 1,2,\ldots,n \tag{9}$$

Defuzzification layer: which computes the weighted output of each rules by applying a linear function:

$$O_i^4 = \overline{\omega_i} f_i = \overline{\omega_i}(p_i x + q_i y + r_i),\ i = 1,2,\ldots,n \tag{10}$$

Output layer: which produce one final crisp output as a weighted sum of each rule's output:

$$O_i^5 = \sum_{i=1}^{n} \overline{\omega_i} f_i\ ,\ i = 1,2,\ldots,n \tag{11}$$

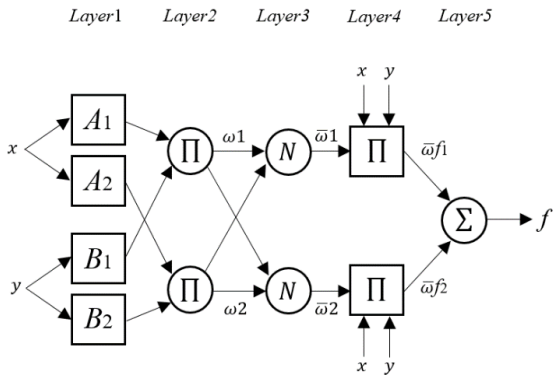


Fig. 2 ANFIS structure

However, during the classical ANFIS learning phase, the goal is to find the best set of antecedents and consequences parameters—using gradient descent and least squares respectively—by minimizing error metrics (typically RMSE or MAE between the real and the predicted output), this approach may struggle in local minima with complex, non-convex surfaces, furthermore, the hybrid learning optimizes these parameters separately, leading to sub-optimal convergence. To solve these issues, a population based global optimizer named by Differential Evolution (DE) is used to avoid local minima, also, optimizing both antecedents and consequents parameters simultaneously as single unified vector.

7 Differential Evolution

Differential Evolution is a population-based metaheuristic algorithm designed for solving continuous optimization problems, proposed by Storn and Price in 1995 [31], inspired by biological evolution by using mutation, crossover, and selection operations. However, the mutation

and the selection process differs from the other evolutionary algorithm [32]. Figure 3 shows the flowchart of DE algorithm, which can be summarized as follows:

Initialization: to establish the starting parameters of DE algorithm, aiming to identify a vector x and to optimize *f*(x):

Where x = $(x_1, x_2, x_3, \dots, x_D)$, *D* is the problem dimension.

Also, for each parameter *j*, we define the parameter upper and lower bounds, *Uj* and *Lj,* respectively.

$$X_{i,j} = L_j + rand_j(0,1) \times (U_j - L_j) \tag{12}$$

Mutation: generates the mutant vector $v_{i,g+1}$where:

$$v_{i,g+1} = x_{r1,g} + F(x_{r2,g} - x_{r3,g}) \tag{13}$$

F is mutation factor, r_1, r_2 and r_3 are randomly chosen, and pairwise different to each other and to *i.*

Crossover: DE executes crossover operation after mutation to create a hybrid trial vector U_i from $X_i$and V_i using binomial or uniform crossover as followed:

$$U_{i,j} = \begin{cases} V_{i,j}, if\ rand(j) \le Cr\ or\ j = j_{rand} \\ X_{i,j}, \quad otherwise \end{cases} \tag{14}$$

Where Cr is crossover rate, and j_{rand} is randomly selected within 1 and *D.*

Selection: is the final step to determine whether a newly generated trial vector U_i replaces the current vector X_i by comparing the objective function *f*(x) value of trial vector to the target vector:

$$U_i = \begin{cases} U_i, if\ f(U_i) \le f(x_i) \\ X_i, \quad otherwise \end{cases} \tag{15}$$

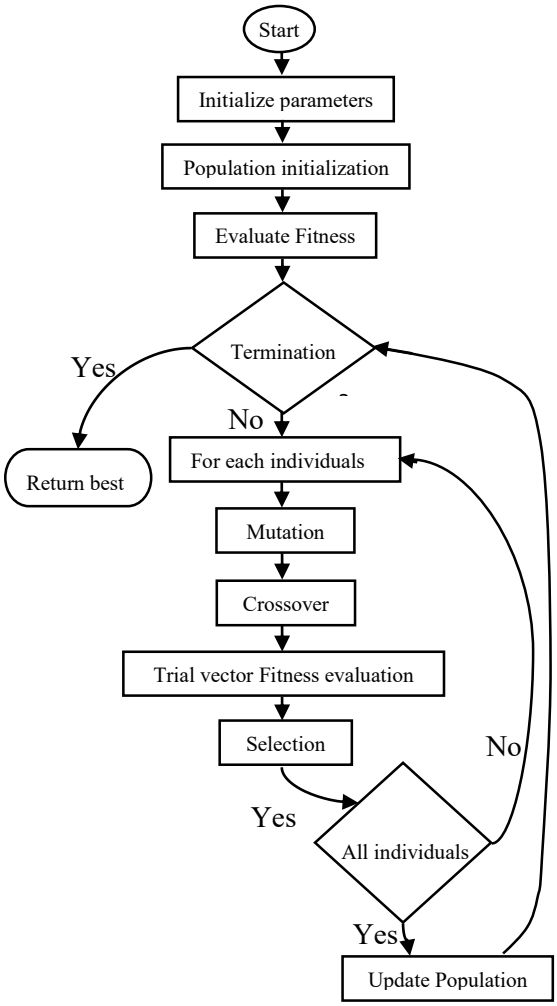


Fig. 3 Differential evolution optimization flowchart

8 EXPERIMENTAL ANALYSIS

8.1 Data description

In order to validate our proposed prognostic method, a publicly XJTU-SY dataset [33] provided by Xi'an Jiaotong University and Changxing Sumyoung Technology is used, where 15 LDK UER204 bearings were tested under three different conditions: Condition 1 (2100 r/min, 12 kN radial force), Condition 2 (2250 r/min, 11 kN), and Condition 3 (2400 r/min, 10 kN) until failure. Horizontal (as shown in Figure 4) and vertical vibration acceleration signals from the bearing housing were recorded every minute using two PCB 352C33 accelerometers, where each recording captured 1.28 seconds of data (32,768 points) at a 25.6 kHz sampling rate. Failure occurred when vibration amplitude reached 20 g. Dataset specifics are summarized in Table 1.

Table 1 XJTU-SY Dataset

Conditions	Rotation	Load	Datasets	Sample	Fault

	Speed			Number	Element
Condition1	2100rpm	12kN	Bearing1_1	123	Outer race
			Bearing1_2	161	Outer race
			Bearing1_3	158	Outer race
			Bearing1_4	122	Cage
			Bearing1_5	52	Inner race and outer race
Condition2	2250rpm	11kN	Bearing2_1	491	Inner race
			Bearing2_2	161	Outer race
			Bearing2_3	533	Cage
			Bearing2_4	42	Outer race
			Bearing2_5	339	Outer race
Condition3	2400rpm	10kN	Bearing3_1	2538	Outer race
			Bearing3_2	2496	Inner and outer race, ball and cage
			Bearing3_3	371	Inner race
			Bearing3_4	1515	Outer race
			Bearing3_5	114	

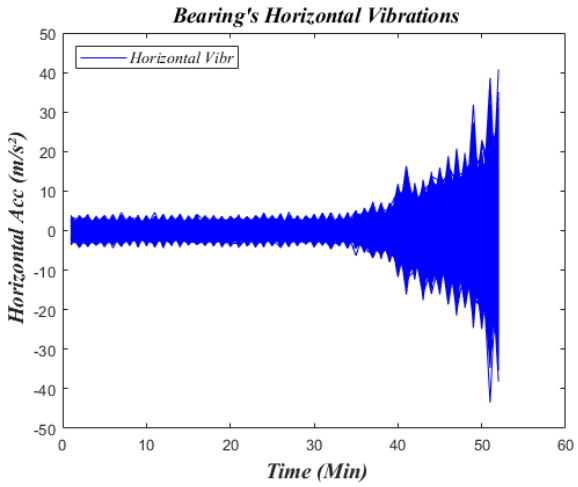


Fig. 4 Horizontal vibrations signal of bearing1_5

8.2 Feature extraction

A key task in data-driven RUL estimation is feature engineering, the process transforms raw data into meaningful features for enhancing the performance, interpretability, and efficiency of prediction models, also it complexity, and it involves extracting, transforming, selecting and creating features from raw data. Firstly, we compute 26 distinct features across three domains to characterize the degradation state of bearings using time domain (9 features), frequency domain (9 features) and time frequency domain (8 wavelet packet energy coefficients using db4 wavelets):

Time domain features: are used for their ability to identify bearing degradation stage and sensitivity to spiking behavior in vibration signals [34], the most common metrics are: RMS, peak

value, and skewness. These features are simple to compute, effective for initial fault detection and impulsive patterns that correlate with bearing's mechanical damage.

Frequency domain features: are effective features for revealing fault-specific signatures and identifying bearing's fault type. (e.g. ball pass frequency, inner/outer race fault frequencies) [35], computed via Fast Fourier transform (FFT) or envelope spectrum.

Time-frequency domain features: by creating a time-varying spectrum that illustrates frequency components variation over time, these features are vital due of the non-stationary nature of bearing vibrations (e.g change of load/speed) [36], these features are computed using Short-Time Fourier Transform (STFT), wavelet transforms or Empirical Mode Decomposition (EMD).

Time domain features	
$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2}$	$\sigma = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(x_i - \overline{x})^2}$
$\text{Max} = \max(x_i)$	$\text{Mean} = \frac{1}{N}\sum_{i=1}^{N} \mid x_i \mid$
$\text{Min} = \min(\mid x_i \mid)$	$\text{Energy} = \sum_{i=1}^{N} x_i^2$
$P2P = \max(x_i) - \min(x_i)$	$\sigma^2 = \frac{1}{N-1}\sum_{i=1}^{N}(x_i - \overline{x})^2$
$H = -\sum_{k=1}^{M} p_k log_2(p_k)$	

Table 2 Time domain features

Frequency domain features	
$P_{low} = \int_0^{Fe/4} S(f)df$	$Kurt = \frac{\frac{1}{M}\sum_{k=1}^{M}(A_k - \overline{A})^4}{\sigma_A^4}$
$P_{high} = \int_{Fe/4}^{Fe/2} S(f)df$	$Ske = \frac{\frac{1}{M}\sum_{k=1}^{M}(A_k - \overline{A})^3}{\sigma_A^3}$
$A_{max} = \max(\mid X(f) \mid)$	$H = -\sum_{k=1}^{M} q_k log_2(q_k)$
$\overline{A} = \frac{1}{M}\sum_{k=1}^{M} A_k$	$f_c = \frac{\sum_{k=1}^{M} f_k A_k}{\sum_{k=1}^{M} A_k}$
$\sigma_A = \sqrt{\frac{1}{M}\sum_{k=1}^{M}(A_k - \overline{A})^2}$	

Table 3 Frequency domain features

Table 4 Time-frequency domain features

Time-Frequency domain features
$WPE_j = \sum_{n\,1}^{Nj} \lvert c_j(n) \rvert^2$

where $x_i$the time series of vibration data, N is samples length. p_k is probability from histogram bins, M = 100 bins.

S(*f*) is the power spectral density, X(*f*) vibration signal fast Fourier transform A_k=|X(f_k)|.

$q_k = \frac{A_k^2}{\sum_{k=1}^{M} A_k^2}$ probability distribution (normalized power spectrum).

WPE_p is the wavelet packet energy using the db4 wavelet at level 3.

c_j is reconstructed wavelet coefficients for node *j*.

8.3 Feature evaluation

The combination of these domains form a multi-perspective degradation indicators for early fault detection and localization. However, in order to refine the feature set and retaining the most informative ones, feature selection based on three common metrics, is an important step in feature engineering for feature reduction and redundancy removal while discarding irrelevant ones, this

step significantly reduce complexity that can affect the prediction accuracy. Therefore, Monotonicity, the Pearson Correlation, and Spearman Rank Correlation are introduced to quantitatively evaluate the selected features.

Monotonicity: to reflect the irreversible deterioration trend of bearing degradation, a valid extracted feature must exhibit a consistent monotonic trend either increasing or decreasing, which is denoted as the following equation [1]:

$$M(X) = \frac{|\, nbr\ of\ \triangle(X) > 0 \ - \ nbr\ of\ \triangle\ (X) < 0\,|}{N-1} \tag{16}$$

Where $\triangle\,(X) \ = \ x_{N+1} - \ x_N$ the difference of the feature sequence, and N is the data length.

Pearson Correlation: named by correlation in [37], it is measured using the correlation coefficient between feature and time. As operating time increases, mechanical components undergo with progressive degradation, consequently, a feature that can describe bearing degradation should show a clear correlation with time, it is calculated according to Eq. (17):

$$P(X) = \frac{\sum_{i=1}^{N}(t_i - \ \bar{t})\,(x_i - \ \bar{x})}{\sqrt{\sum_{i=1}^{N}(t_i - \ \bar{t})^2 \ \sum_{i=1}^{N}(x_i - \ \bar{x})^2}} \tag{17}$$

where t_i and x_i are the values of the i^{th} time and feature, $\bar{t}$ and $\bar{x}$ are the averages of time and feature respectively.

Spearman Rank Correlation: also named Trendability by some scholars, **a**lthough standard correlation methods prioritize sensitivity to linear relationships, real-world machinery exhibits nonlinear degradations, consequently, the Spearman coefficient is widely adopted to evaluate the feature trendability for selection task, it is calculated by Eq. (18) [38]:

$$T(X) = \frac{K\left(\sum_{K=1}^{K}\widetilde{X_K}\ \widetilde{t_K}\right) - \left(\sum_{K=1}^{K}\widetilde{X_K}\right)\left(\sum_{K=1}^{K}\widetilde{t_K}\right)}{\sqrt{\left[K\sum_{K=1}^{K}\widetilde{X_K}^2 - \left(\sum_{K=1}^{K}\widetilde{X_K}\right)^2\right]\left[\,K\sum_{K=1}^{K}\widetilde{t_K}^2 - \left(\sum_{K=1}^{K}\widetilde{t_K}\right)^2\right]}} \tag{18}$$

where $\{\widetilde{X_K}\}_{K=1:K}$ and $\{\widetilde{t_K}\}_{K=1:K}$ are the rank sequence of the feature $\{X_k\}_{K=1:K}$, respectively.

8.4 Feature selection

Relying on a single metric for feature selection is often insufficient, as the prediction result typically requires features that satisfy multiple criteria evaluation simultaneously, a hybrid metric that integrate the three evaluation metrics into a single composite measure is proposed, enabling more robust and interpretable feature selection task. Consequently, we use a weighted combination with $\sum_{i=1}^{3}\alpha_i = 1$ for each feature as selection criteria as presented in Eq. (19):

$$C(X) = \alpha_1 M(X) + \alpha_2 P(X) + \alpha_3 T(X) \tag{19}$$

We calculate a composite score combining (0.5, 0.3 and 0.2 of weight value for monotonicity, spearman rank correlation and Pearson linear correlation, respectively) to quantify each feature's hybrid metric. The previous weights assign different levels of importance of the features and motivated by need to prioritize certain aspects for HI construction. The monotonicity weight ($\alpha_1 = 0.5$) is given the highest value indicating it's considered the most fundamental property, as it

measures the consistency of a feature as the system degrades. The trendability weight ($\alpha_2 = 0.3$) is given the second highest weight, the prognostability weight ($\alpha_3 = 0.2$) is given the lowest weight.

However, a fixed threshold can be a problematic due of the distribution of scores vary widely from dataset to another, in this work, we applied an adaptive threshold at the 70th percentile of the extracted features, to select the most performing features, ensuring a non-subjective method to select 30% most informative ones, and allowing the selection the top tier of features regardless of the absolute range of the hybrid metric scores. This method ensures our selection is tailored to the performance characteristics of each dataset. Each features exceeding the 70th percentile composite threshold are automatically selected for the next task as it presented in Figure 5, also, the selected features trajectory are shown in Figure 6.

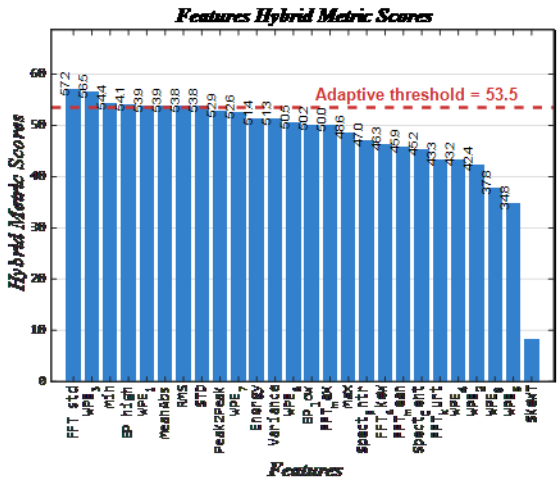


Fig. 5 Features hybrid metrics scores

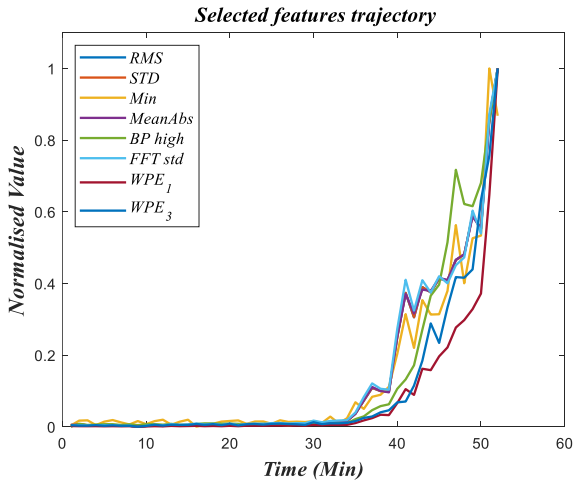


Fig. 6 Selected features trajectory of bearing1_5

8.5 HI construction and kernel function selection

Figure 7 presents a 2D scatter temporal evolution of bearing states, which summarizes the dominant variance directions, representing data observations projected onto first two principal components with color progression, indicating time progressing from earlier (blue) to later (red). The convex hull outlines the operational boundary, while the trajectory path reveals system evolution over time. The green circle and the red square markers highlight initial and final states, presenting directional drift in component space. This visualization allows qualitative evaluation of bearing's degradation patterns.

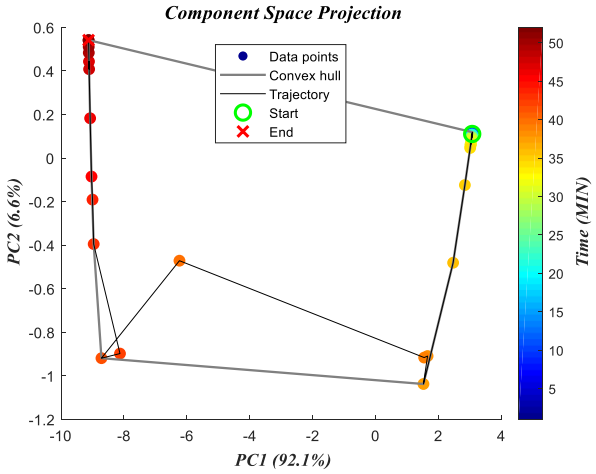
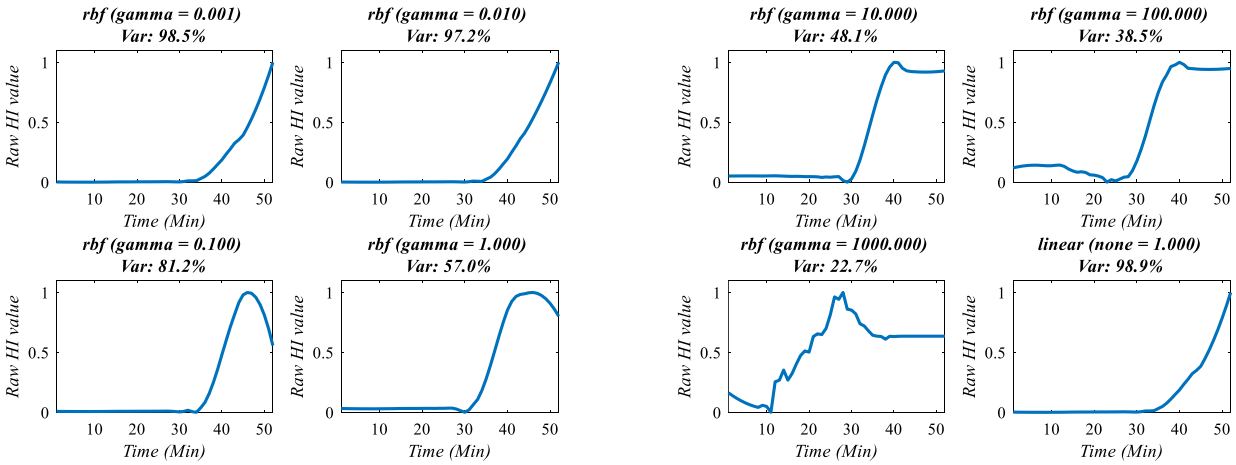


Fig. 7 Scatter plot of principal components of bearing1_5

For HI construction, KPCA is used to fuse the selected features, by systematically evaluating kernel functions and parameters. First, we normalize the selected features to ensure balanced kernel computations, then systematically explores radial basis function (RBF), linear and sigmoïd kernels across parameter spaces and extract dominant nonlinear components for each kernel parameter combination. The raw HI is constructed using a variance weighted fusion of the first two principal components ($\omega_1 PC_1 + \omega_2 PC_2$). This approach ensures a nonlinear feature interactions and maximizing the prognostic metric of the HI through kernel selection.

In this work, kernel selection prioritizes the explained variance to ensure degradation progression (Figure 8). Consequently, this pipeline transforms features data into a unified, monotonic HI suitable for RUL estimation as it shown in Figure 8.



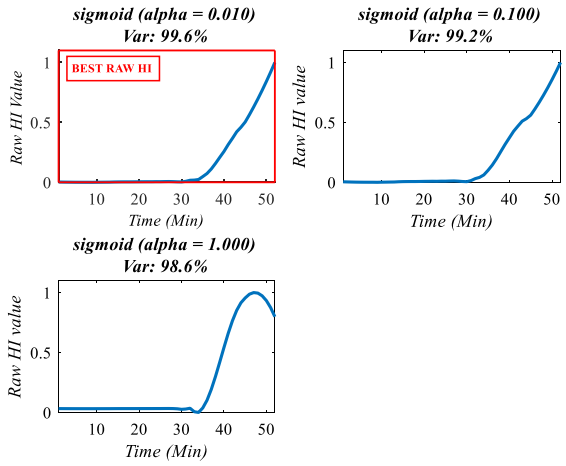


Fig. 8 Raw HI of bearing1_5 for different kernel functions

The raw HI undergoes with a post-processing step, starting with a smoothing process using Savitzky-Golay filter [39] within the parameter setting are summarized in Table 5, followed the application of a min-max normalization for [0,1] scaling. The final HI is presented in Figure 9.

Table 5 Savitzky-Golay filter parameters

Savitzky-Golay filter	
Parameters	**Value**
Polynomial order	2
Frame length	15

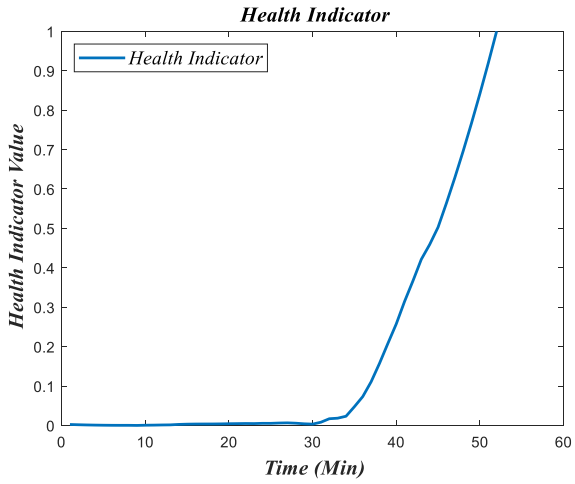


Fig. 9 Health indicator of bearing1_5

8.6 RUL labeling and FDP detection

As the true RUL label are not explicitly provided, it must be constructed from the run to failure data. In this work, the RUL label for supervised training were computed under piecewise linear degradation model using SSE-minimization method, to detect when a significant trend is found.

The piecewise linear degradation model is widely used for bearings RUL labeling, the concept of the approach acknowledges that the bearing operates in a healthy state in the early stage of operation, after which a linear degradation begins after the FDP is detected. The first sub-graph in Fig. 10 shows the temporal evolution RMS feature partitions: the blue shades represents a normal operating phase during bearing's healthy stage, while the red shades marks a potential degradation phase with higher amplitudes. After the FDP detection, the RUL label decreases linearly until failure, as it shown in Figure 10, which is calculated using Eq. (20) [40]:

$$RUL(t_i) = \begin{cases} 1 & , \quad t_i < t_j \\ (\frac{1}{t_j - t_n})t_i + (\frac{t_n}{t_n - t_j}), & t_i \geq t_j \end{cases} \tag{20}$$

Where t_j is initial degradation time, t_n is the full lifetime of bearing and t_i is the current time of bearing.

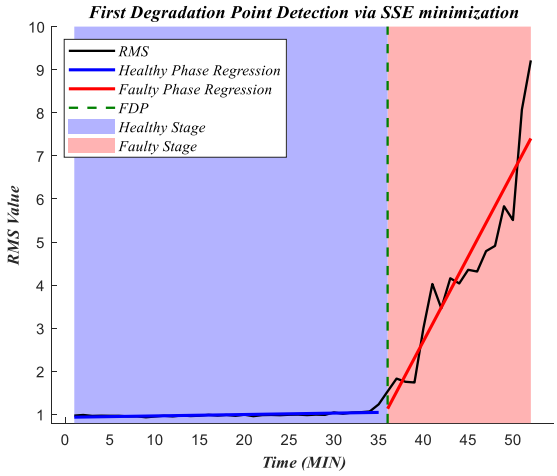


Fig. 10 FDP detection of bearing1_5

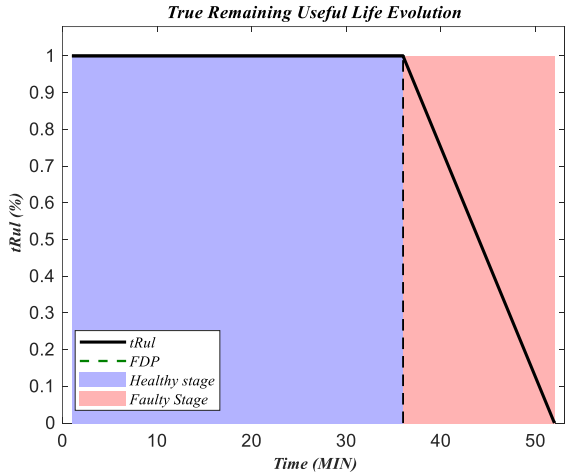


Fig. 11 True RUL label of bearing1_5

8.7 ANFIS-DE model for RUL prediction

This section explains how DE algorithm optimizes ANFIS parameters. First, the process starts with initialize FIS configuration by establishing it main structure, specifying the number of inputs, membership function count per input and its type (e.g., Gaussian, trapezoidal…). Secondly, DE initializes a population of candidate vectors representing ANFIS premise membership function parameters and consequent polynomial weights within a predefined search space, then, DE applies mutation strategies and crossover operations exploring the multi-dimensional parameter avoiding premature convergence. Fitness function evaluates prediction accuracy via objective function using RMSE. Then, Greedy selection mechanism preserves elite solutions, refining fuzzy rule structures and membership function geometries, driving the population toward globally optimal ANFIS configurations that enhance prediction performance. The parameter setting of ANFIS and DE are presented in Table 6, and Table 7:

Table 6 Parameter setting of ANFIS

Parameters	Value
Number of inputs	1
membership function	Gaussian curve
N° of Mf for each input	4

Table 7 Parameter setting of DE

Parameters	Value
Iteration	3000
Population size	24
Mutation scaling factor	0.8
Crossover rate	0.5

To replicate a realistic industrial scenario and demonstrate the prediction accuracy of our model, 15 bearings are used separately to construct HI for each, using the pipeline described from section 8.2 to section 8.5, these HIs are used as inputs in ANFIS-DE model. In this work, we employed the Leave-One-Out-Cross validation (LOOCV) method, for a robust RUL prediction results, to evaluate the generalizability of the prediction model, particularly when dealing with a limited run-to-failure data such as five bearings in each operational condition previously described in section 8.1. In each operational condition, the model is trained iteratively using four bearings for (offline RUL estimation), the remaining one bearing data is used as hold-out testing set, this unseen bearing is deployed for online RUL estimation. The proposed cyclical training and testing method yields distinct models offers several advantages such as maximizing the use of limited data as a training set, also, allowing the learn of different degradation patterns and failure modes of bearings, providing a high fidelity assessment of the model's generalization, which is important to evaluate and validate the model's accuracy, and the prognostic framework reliability across different operating conditions.

For prediction evaluation performance, two regression metrics are introduced: mean absolute error (MAE) and root mean squared error (RMSE) are computed using the following equations:

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|pred_{Rul} - tRul| \tag{21}$$

$$RMSE = \sqrt{\frac{1}{N}(pred_{Rul} - tRul)^2} \tag{22}$$

where $pred_{Rul}$ is the predicted RUL, $tRul$ is the grounded RUL and N is the data length.

8.8 Experimental results

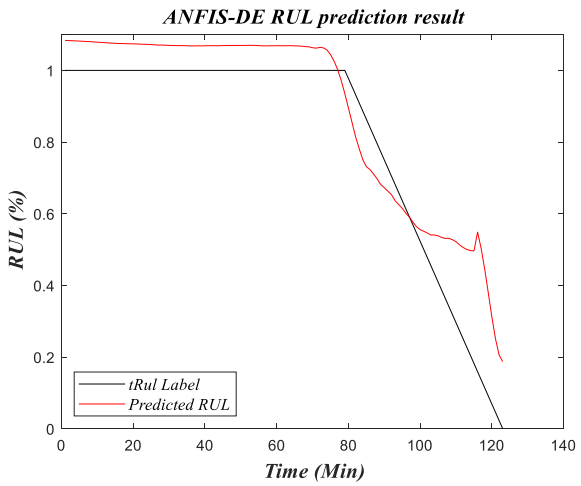
Also, the prediction results are benchmarked in Table 8, and compared against two previous works: The first is a dual network-based model, combining a DCNN and a MLP (DCNN-MLP) to process 1D time series and 2D image data, integrated into a Bootstrap framework for RUL prediction [9] The second work is a recursive exponential slow feature analysis, which extracts long term nonlinear degradation trends with a Bi-LSTM as a prediction model (RESFA-BiLSTM) [41].

Table 8 Performance comparison of different RUL estimation models

Bearings	**DCNN-MLP**		**RESFA-BiLSTM**		**ANFIS-DE**	
	RMSE	**MAE**	**RMSE**	**MAE**	**RMSE**	**MAE**
Bearing1_1	0.206	0.176	0.140	0.099	***0.120***	***0.071***
Bearing1_2	0.240	0.207	0.226	0.166	***0.157***	***0.102***
Bearing1_3	**0.178**	0.151	0.226	0.130	0.236	***0.110***
Bearing1_4	NA	NA	**NA**	**NA**	**NA**	NA
Bearing1_5	0.184	0.155	0.106	0.088	***0.084***	***0.013***
Bearing2_1	0.117	0.099	0.095	**0.020**	**0.088**	0.023
Bearing2_2	**0.122**	**0.102**	0.233	0.171	***0.227***	0.159
Bearing2_3	0.158	0.126	0.247	0.166	***0.123***	***0.054***
Bearing2_4	0.177	0.141	0.145	0.112	***0.134***	***0.071***
Bearing2_5	**0.091**	**0.075**	0.165	0.122	*0.213*	0.131
Bearing3_1	0.244	0.204	0.115	0.024	***0.087***	***0.018***
Bearing3_2	NA	NA	NA	NA	***0.097***	***0.025***
Bearing3_3	0.158	0.129	0.087	0.022	***0.085***	***0.007***
Bearing3_4	0.132	0.107	0. 109	0.031	***0.041***	***0.008***
Bearing3_5	0.266	0.219	0. 292	0.232	***0.185***	***0.120***

Table 9 Mean metrics comparison

	DCNN-MLP	**RESFA-BiLSTM**	**ANFIS-DE**
Mean RMSE	0.1748	0.1682	***0.1340***
Mean MAE	0.1455	0.1064	***0.0651***



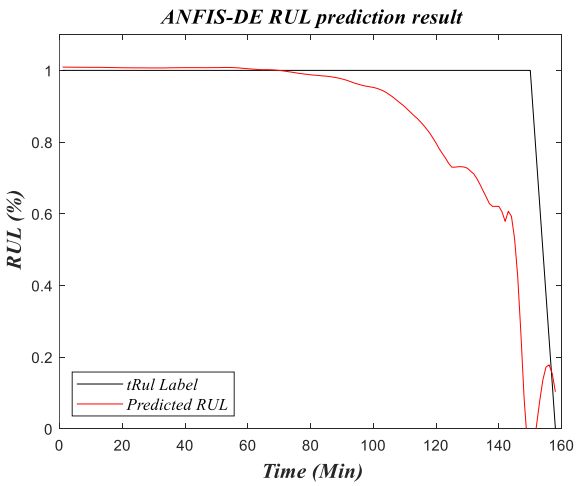


Fig. 12 Remaining useful life label of bearing1_1

Fig. 13 Remaining useful life label of bearing1_3

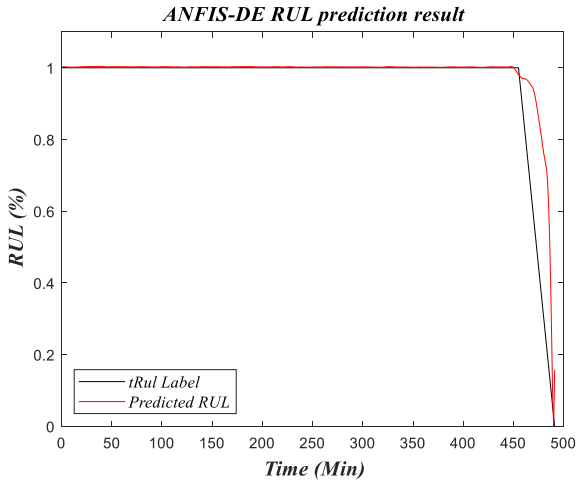


Fig. 14 Remaining useful life label of bearing2_1

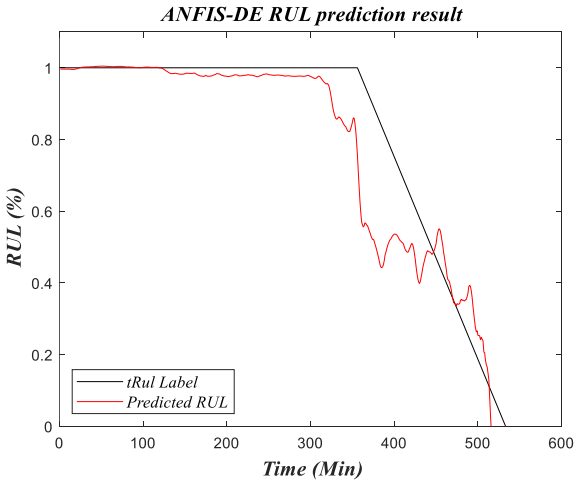


Fig. 15 Remaining useful life label of bearing2_3

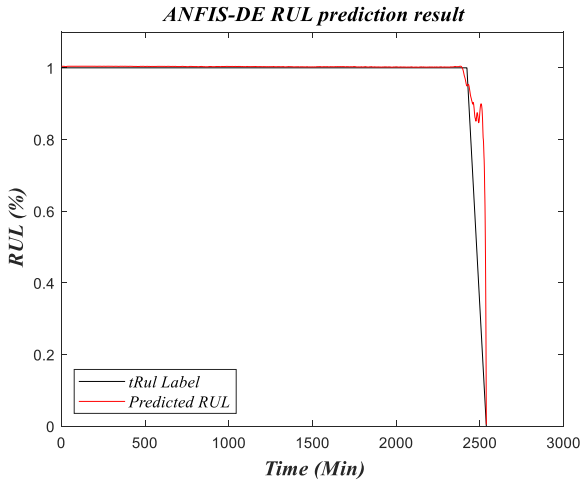


Fig. 16 Remaining useful life label of bearing3_1

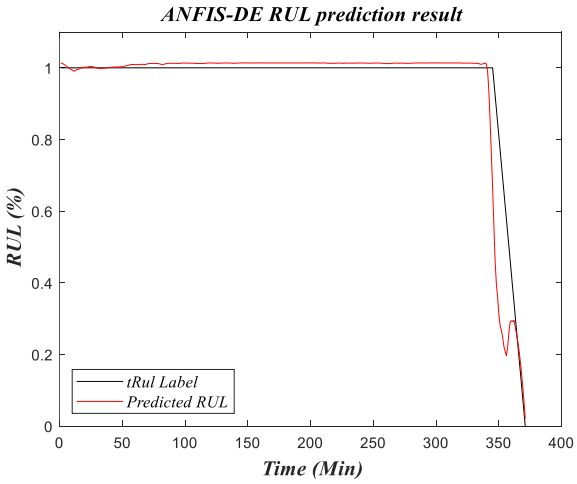


Fig. 17 Remaining useful life label of bearing3_5

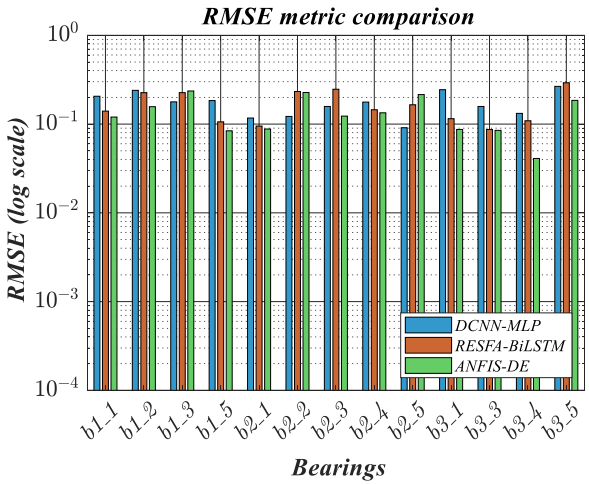


Fig. 18 RMSE metric comparison.

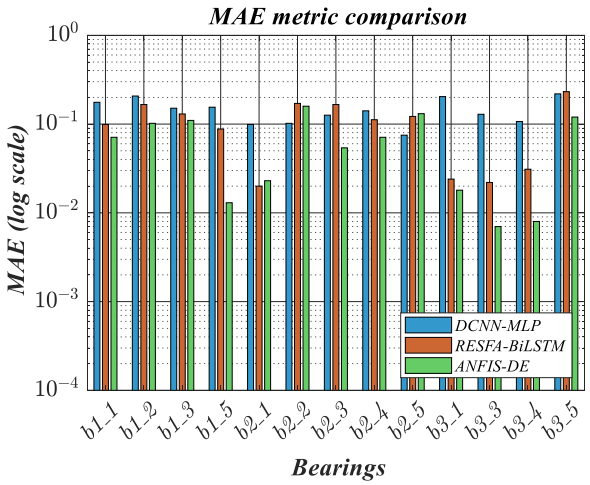


Fig. 19 MAE metric comparison

9 Discussion

This section compares the prediction performance of our work relative to alternative studies. The performance results for bearing1_4 were not included in the model evaluations due to it sudden failure. Table 8 indicates that our proposed approach yields the lowest RMSE and MAE scores for most of the tested bearings, also achieves a competitive accuracy in other bearings, these numerical results are summarized using bar charts as it shown in Figure 17 and Figure 18, achieving a mean RMSE of 0.1340 and mean MAE of 0.0651, compared to DCNN-MLP (0.1748 RMSE, 0.1455 MAE) and (0.1682 RMSE, 0.1064 MAE) for RESFA-BiLSTM as it shown in Table 9, demonstrating the superior accuracy in RUL prediction, making it ideal for applications where a high degree of agreement between the actual and predicted RUL is crucial. This superior performance demonstrates that ANFIS-DE model provides more reliable and accurate predictions, which are cornerstone for CBM in industrial systems. In addition of the statistical evaluation, Figures 12 to 17 represents a visual comparison of prediction results for bearing1_1 and bearing1_3 from operating condition1, bearing2_1 and bearing2_3 from operating condition2, bearing3_1 and bearing3_5 from the operating condition3, where the predicted RUL aligns closely with the actual RUL, even in regions where the RUL decreases rapidly, demonstrating the model's ability to track degradation process.

Several reasons explains the accuracy of the prediction results of our work: first, the use of a reliable HI method, which correlates with bearing's degradation trend as input, constructed using feature engineering, by selecting and fusing the most informative, non-redundant features using kernel PCA. Second, ANFIS flexibility, by leveraging the learning capabilities of neural networks and the interpretability of fuzzy logic to map the complex nonlinear interactions between bearing's HI and RUL. Also, the model requires a fewer parameters to adjust than ML models. Moreover, the use of DE optimization, performing a global exploration of ANFIS parameter space, finding the best configuration that minimizes prediction accuracy.

To ensure more transparency and enhance the study's credibility, our model did not achieve the best results for some bearings, the cause of the disparity may be attributed to: 1) Data variability between the tested bearing and the conditions shown in training dataset, due of the stochastic nature of bearings degradation process: bearings exhibits different fault initiation time (First degradation point), failure mode (gradual degradation, sudden failure) and fault type (inner-race, outer-race, ball, cage) even under identical load and speed conditions. 2) The generalization limits that characterizes ML models, which means a model that fits a run-to-failure bearing data, may overfit and fail a new data under the same condition monitoring, due to inner bearings variability (manufacturing tolerances and initial defect degradations). 3) The dataset may also be imbalanced (many healthy samples against few degraded ones, which is the case in bearing3_5), biasing the model toward non failure conditions, all the reasons mentioned above directly leads to less accurate RUL prediction in data driven approach.

Over all, the comparison results demonstrates that in most of the cases, ANFIS-DE model achieves the best prediction accuracy, which validates that our proposed model is considered as a promising solution for prognostic task.

10 Conclusion

This work introduced an empirical hybrid framework for constructing bearings Health Indicator using KPCA, and estimating its RUL using ANFIS-DE model. The method effectively captures nonlinear relationship between bearings HI and its RUL. Experimental results on the XJTU-SY datasets demonstrate that our model outperforms existing methods in terms of accuracy, achieving lower RMSE and MAE scores across various operating conditions. The integration of HI based KPCA, particularly for accurately capturing bearing degradation, with ANFIS-DE as a prediction model is a promising solution for Prognostics and Health Management deployments.

Future work should examine the use of deep learning models, such as Convolutional Neural Networks (CNN) or Long Short-Term Memory networks (LSTM) for feature extraction step, to model long-term temporal dependencies in the degradation sequence, and automatically extract features from raw vibrations data. Quantify the degree of uncertainty in each RUL prediction sequence, providing a prognostic confidence level using Bayesian deep learning. Also, examine a Cross-dataset validation of our proposed approach using more available data such as: FEMTO-ST (PRONOSTIA) dataset, KAIST Bearing Datasets, to validate it generalizability.

Author contributions: Islam Medjoudj: Conceptualization**,** Methodology, Validation, Formal analysis, Investigation, Writing original draft, Visualization; **Noreddine Bali:** Conceptualization, Methodology, Formal analysis, Visualization, Supervision; **Fouad Haouari:** Conceptualization, Methodology, Formal analysis, Visualization, Supervision.

Funding: No funding was received.

Declarations

Conflict of interest: The authors declare no competing interests.

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