An ANFIS-based Framework for the Prediction of Bearing's Remaining Useful Life

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Abstract

Bearings are critical components extensively used in rotary machines, often being the leading cause of unexpected machine shutdowns. To mitigate system failures, it is crucial to implement effective maintenance strategies. This paper introduces a novel methodology for bearing prognostics, employing Wavelet Packet Decomposition (WPD) for data preprocessing, Sequential Backward Selection (SBS) for feature selection, and Adaptive Neuro-Fuzzy Inference System (ANFIS) networks for prognostic modeling. The proposed approach consists of two key steps. Firstly, the data undergoes preprocessing through Wavelet Packet Decomposition, enhancing the quality and extracting relevant features. Subsequently, the Remaining Useful Life (RUL) of the bearing is predicted using a degradation model. The accuracy of the proposed method is evaluated using a bearing life dataset obtained from a run-to-failure test (IMS dataset). The results demonstrate the remarkable capability of the ANFIS model to learn and accurately estimate the system's RUL. By leveraging the combined power of WPD, SBS, and ANFIS, this methodology showcases its potential as an effective prognostic tool for bearing health assessment and proactive maintenance planning.

Keywords: Wavelet Packet Decomposition (WPD), fault Prognosis, Sequential Backward Selection (SBS), Adaptive Neuro Fuzzy Inference System (ANFIS), Data preprocessing, Maintenance.

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1. Introduction

Bearings are vital components extensively employed in rotating machinery, serving as key elements for transmitting loads and facilitating smooth operation, including manufacturing, transportation, and energy production (Y. Wang, Xu, Zhang, Liu, & Jiang, 2015; Soualhi, Lamraoui, Elyousfi, & Razik, 2022; Lourari, Soualhi, Medjaher, & Benkedjouh, 2024). Their reliable performance is crucial for ensuring the overall efficiency, productivity, and safety of various industrial processes(Lei, Lin, Zuo, & He, 2014; Ghods & Lee, 2016; Liu, Wang, & Golnaraghi, 2009; Jia, Lei, Lin, Zhou, & Lu, 2016). However, bearing failures can lead to unexpected machine breakdowns, resulting in significant financial losses, production delays, and potential safety hazards(Heng, Zhang, Tan, & Mathew, 2009; Soualhi, Yousfi, Lamraoui, & Medjaher, 2022).

Prognostics and health management literature encompasses three distinct fields, each offering unique methodologies for predictive analysis. Model-based techniques rely on mathematical models and theoretical frameworks to predict future behavior, necessitating a thorough understanding of the system's characteristics. Data-driven approaches, on the other hand, leverage vast datasets to identify patterns and trends without explicit models, making them well-suited for complex systems. However, these methods may suffer from overfitting and limited generalizability. In response, hybrid techniques emerge as a fusion of model-based and data-driven strategies, aiming to capitalize on the strengths of both paradigms to achieve more accurate and robust predictions. A comprehensive analysis and comparison of these three fields are crucial to uncover their respective advantages and drawbacks, paving the way for advancements in Prognostics and health management methodologies. Among the mentioned methods, the data-driven approach is frequently preferred due to its capacity for real-time insights(Medjaher, Zerhouni, & Gouriveau, 2016; Habbouche, Benkedjouh, & Zerhouni, 2021), predictive maintenance, and operational efficiency improvements through data analysis and pattern recognition. To effectively manage the health and performance of bearings, it is essential to monitor and analyze various health indicators that provide insights into their condition. Health indicators are measurable quantities derived from sensor data such as electrical(Satish & Sarma, 2005; Schoen, Habetler, Kamran, & Bartfield, 1995; Abdenour, Kamal, François, et al., 2022), acoustic(Elforjani & Shanbr, 2017), and vibration sensor data(K. Zhou & Tang, 2023), reflecting the degradation and fault development in bearings.

In bearing prognosis, the utilization of vibration signals plays a crucial role and holds significant importance among the various signals used for analysis(Gohari, Tahmasebi, & Ghorbani, 2023). Vibration signals capture the mechanical behavior and dynamic characteristics of bearings(Lv, Zhao, Zhao, Li, & Ng, 2022), providing valuable insights into their health condition. Vibration analysis enables the extraction of essential features related to bearing faults(Buchaiah & Shakya, 2022), such as amplitude variations, frequency components, and changes in signal patterns. The distinctive advantage of vibration signals lies in their sensitivity to early-stage degradation, making them highly effective for detecting and monitoring the progression of bearing faults. In fact, bearings generate vibration signatures during their normal operation. These signatures are processed to detect changes in the bearing condition. This procedure is called signal processing. There exist three signal processing techniques:

(i) **Time Domain Analysis:**
Time domain analysis is a powerful technique that involves analyzing the vibration signal's time waveform to identify trends, amplitudes, and frequencies. This analysis method proves particularly valuable in the identification of specific fault frequencies associated with various bearing faults. By scrutinizing the time domain characteristics, such as changes in signal amplitude and frequency, bearing fault types such as inner and outer race defects, rolling element defects, and cage defects can be effectively identified. The ability to pinpoint fault-specific frequencies enables accurate fault diagnosis and facilitates timely maintenance interventions to prevent unexpected machine breakdowns(Fu, Liu, Xu, & Liu, 2016).

(ii) **Frequency Domain Analysis:**
Frequency domain analysis is a crucial technique used in bearing fault diagnosis. This approach involves transforming the time-domain vibration signal into its frequency components using methods such as the Fourier Transform. By analyzing the frequency domain, valuable information about the spectral content of the vibration signal is obtained, enabling the identification of specific frequencies associated with bearing faults. Fault-related frequencies, such as those resulting from inner and outer race defects, rolling element defects, and cage defects, can be effectively detected and isolated. The application of frequency domain analysis enhances the accuracy and sensitivity of bearing fault diagnosis, contributing to timely maintenance actions and the prevention of costly machine breakdowns(L. Zhou, Duan, Mba, Wang, & Ojolo, 2018).

(iii) **Time-frequency analysis:**
Time-frequency analysis is a valuable technique that provides a detailed understanding of both time and frequency characteristics of a vibration signal, surpassing the limitations of frequency domain analysis. By breaking down the signal into shorter time intervals and examining the frequency content within each interval, time-frequency analysis generates a time-varying spectrum that captures how the frequency components change over time. This approach enables the detection of evolving frequency components and transient features associated with bearing faults. The ability to observe the temporal variations of frequency components enhances the accuracy of fault detection and diagnosis, enabling proactive maintenance strategies. Overall, time-frequency analysis offers a comprehensive analysis of the signal's behavior and facilitates effective bearing prognostics(Medjaher et al., 2016).

Time-frequency techniques combine both time and frequency information to capture the dynamic behavior and transient changes in bearing signals. Methods like the Continuous Wavelet Transform (CWT)(Niu, Liu, Wang, & Zhang, 2023) and the Short-Time Fourier Transform (STFT)(Hamid, Ibrahim, Abdelgeliel, & Desouki, 2023) enable the representation of signals in the time-frequency domain. These techniques are particularly useful for detecting transient faults, bearing damage initiation, and the identification of fault development patterns. Among the various time-frequency techniques, Wavelet Packet Decomposition (WPD) stands out as an effective approach for feature extraction from bearing signals(Habbouche et al., 2021). WPD provides a multi-resolution representation of the signal, enabling the extraction of detailed information at different scales and frequency bands. This decomposition technique offers superior adaptability and flexibility for capturing fault-related features in bearing signals. In the field of prognostics for bearing health assessment, machine learning algorithms have gained significant attention due to their ability to learn complex patterns and make accurate predictions. Different techniques such as artificial neural networks, support vector machines, and fuzzy logic systems have been applied to develop prognostic models for estimating the Remaining Useful Life (RUL) of bearings. These models utilize the extracted health indicators as input features to predict the future degradation and remaining lifespan of the bearings. The overall procedure of the proposed methodology is illustrated in Figure 1.

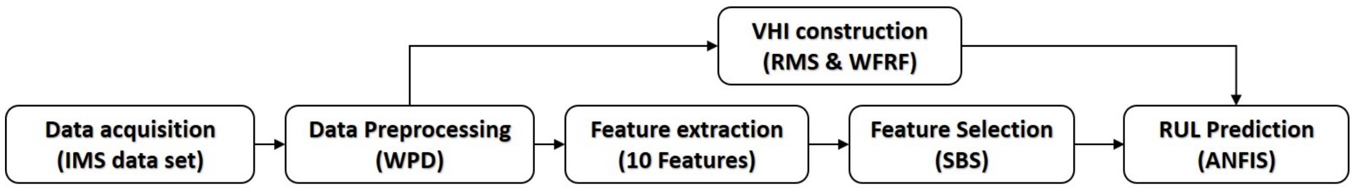

Figure 1. Overall framework of the proposed method.

The rest of this article is organized as follows: Section 2 presents the proposed methodology, which combines Wavelet Packet Decomposition (WPD), Sequential Backward Selection (SBS), and the Adaptive Neuro Fuzzy Inference System (ANFIS) for bearing prognostics. Section 3 discusses the results and provides a comprehensive analysis of the experimental findings. Section 4 concludes the study, highlighting the key contributions and discussing future perspectives in the field of bearing prognostics and maintenance management.

2. METHODOLOGY AND PROGNOSTIC APPROACH

The proposed methodology represents a crucial aspect of Prognostics and Health Management (PHM) activities, focusing on Rolling Element Bearing (REB) health monitoring, Remaining Useful Life (RUL) estimation, and decision support. This data-driven approach relies on the integration of WPD and ANFIS techniques, requiring expertise in signal processing, statistics, machine learning, and mechanical engineering. The implementation of the methodology is carried out using the MATLAB platform for network development and training.

The field of maintenance has witnessed significant advancements in recent years, particularly in the field of PHM based on machine learning techniques. Nonetheless, certain challenges persist in practice. Firstly, automatic detection of the onset of degradation before its spread remains a gap. Secondly, the development of a robust health indicator capable of monitoring degradation over time is crucial. Lastly, an algorithm that effectively utilizes historical REB data to estimate the severity of defects is needed (Zhang, Zhang, & Li, 2019).

To tackle these challenges, we present a comprehensive framework for predicting the remaining life of bearings, as depicted in Figure 2. This framework comprises four key steps: data pre-processing, construction of a virtual health indicator (VHI), extraction and selection of features, and learning the prediction model. In the data pre-processing stage, we employ the Wavelet Packet Decomposition (WPD) algorithm to extract different levels, enabling us to pinpoint the most pertinent level for prognostic purposes. Subsequently, we construct a virtual health indicator by fitting the Root Mean Square (RMS) value using the Weibull Failure Rate Function (WFRF) algorithm. This step allows us to precisely capture and track the degradation state of the studied bearing. After determining the optimal WPD level, we calculate a set of time-domain and frequency-domain features. The Sequential Backward Selection (SBS) algorithm is then applied to choose the most relevant indicators for training the prediction model. Finally, the Adaptive Neuro Fuzzy Inference System (ANFIS) model is adopted to map the selected features, which serve as the input, to the corresponding VHI value at each instant. This VHI value, representing the degradation state, is the output of the ANFIS model, providing a comprehensive approach to bearing life prognostics.

2.1. Data Pre-Processing using the Wavelet Packet Decomposition

Various time-frequency analysis techniques have been developed, including the Short-Time Fourier Transform (STFT) (Attoui, Fergani, Boutasseta, Oudjani, & Deliou, 2017), Empirical Mode Decomposition (EMD) (Motahari-Nezhad & Jafari, 2020), Variational Mode Decomposition (VMD) (Motahari-Nezhad & Jafari, 2020), and Wavelet Packet Decomposition (WPD). Among these techniques, WPD has gained significant attention in the prognostics field as an effective tool for degradation monitoring (Belmiloud, Benkedjouh, Lachi, Laggoun, & Dron, 2018). WPD provides high resolution in both the time and frequency domains (J. Wang & Liao, 2005). The process involves iterative decomposition using a pair of filters, resulting in approximation and detail signals (Tobon-Mejia, Medjaher, Zerhouni, & Tripot, 2011), as illustrated in Figure 3 (Medjaher et al., 2016). To perform signal analysis using WPD, it is essential to define the decomposition levels and select the appropriate filtering waveforms (such as db1, db2, db4, haar, etc.) for extracting detail and approximation coefficients at each level (Dastourian, Dastourian, Dastourian, & Mahnaie, 2014). Once the signal analysis is completed, the data organization phase begins in preparation for the prediction model. The input data for the model consists of decomposed signals obtained from the WPD, represented as $X = \{x_t, x_{t-1}, x_{t-2}, \ldots, x_{t-n}\}$. These signals correspond to the measurements recorded at different time points $(t, t-1, t-2, \ldots, t-n)$. The target vector for the model is the Health Indicator (HI) labeled from 0 to 1, representing the entire degradation process.

2.2. Virtual Health Indicator Construction

Monitoring the health status of REBs traditionally involves periodic inspections, which can be cumbersome, leading to

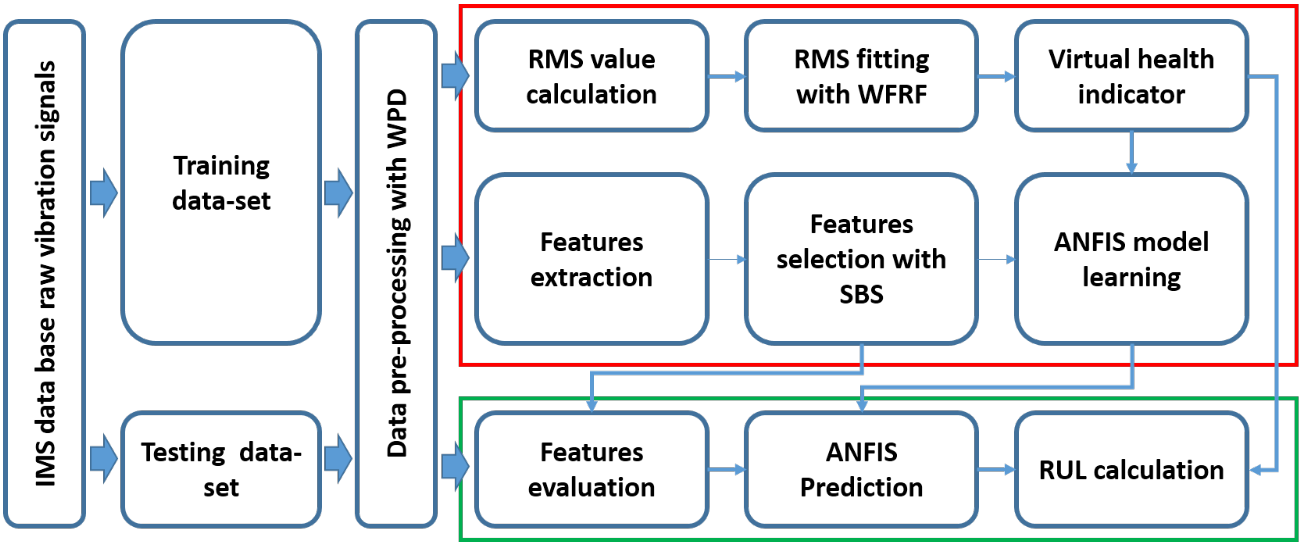

Figure 2. Architecture of the proposed bearing fault prognostic methodology.

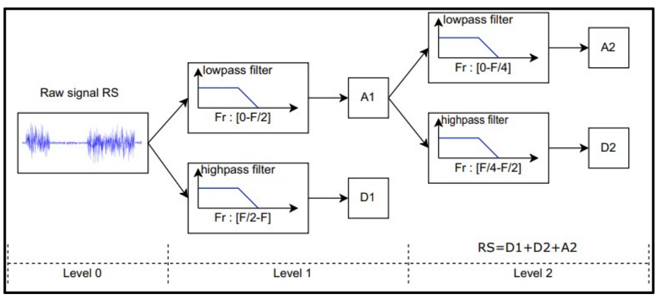

Figure 3. Illustration of wavelet packet decomposition of second order.

production disruptions. Moreover, detecting defects such as cracks often necessitates sophisticated means. Real-time tracking using sensors like accelerometers and microphones proves valuable in this regard. However, the acquired sensor signal contains both useful information and noise, making it necessary to employ a Health Indicator (HI) to extract relevant information (Lei et al., 2018). The chosen HI should accurately represent the health state while exhibiting a monotonous behavior (Zhang et al., 2019).

The Root Mean Square (RMS) is one of the most commonly feature used for the monitoring of bearing degradation (Cheng, Cheng, Lei, & Tsai, 2020). Among the reasons that made us select RMS as good HI in this investigation is that it reflects the state of the monitored bearing (Ahmad, Khan, & Kim, 2017) and have a proportional relation with the energy of the vibration signals (Lei et al., 2018).

In this case, the utilization of a fitting feature with a model that closely represents the degradation phenomenon becomes essential. Two commonly employed models in the literature are the Weibull Failure Rate Function (WFRF) and the Exponential Degradation Model (EDM) (Yan, Wang, Wang, Chang, & Muhammad, 2020). In this paper, a modified version of the WFRF (Wu, Li, Qiu, et al., 2017) is utilized to fit the RMS for irreversible degradation. The formulation of this modified WFRF requires the identification of specific model parameters, namely Y,K,β and η:

$$\vartheta\left(t\right) = Y + K\frac{\beta}{\eta^{\beta}}t^{\beta-1} \tag{1}$$

One of the key advantages of the Health Indicator (HI) is its ability to eliminate the need for continuous monitoring of machines throughout their entire operational lifespan, which is often unnecessary in practice. The HI's evolution over the life of the Rolling Element Bearing allows for the division of its lifespan into multiple health stages (HS). This division enables a better understanding of the REB's health condition and facilitates the identification and assessment of different levels of degradation severity. By monitoring the HI, the severity of degradation can be effectively assessed, leading to improved maintenance strategies and enhanced overall system performance.

2.3. Features Extraction & Selection

Signal processing plays a pivotal role in the domain of Prognostics and Health Management (PHM) activities. It serves as a crucial step in extracting pertinent features from the acquired data to enable effective analysis and decision-making. In this context, various techniques are employed to accomplish the task of feature extraction. Among these techniques, time-frequency methods hold significant prominence due to their ability to capture both temporal and spectral information concurrently.

In this study, health indicators play a pivotal role in characterizing the condition of the system under investigation. Health indicators encapsulate crucial information derived from the underlying signals, enabling a comprehensive assessment of the system's state. The calculation of health indicators involves intricate processing techniques that extract pertinent features from the raw signals. These techniques are designed to capture various aspects of the signal's behavior, providing valuable insights into the system's health status. The chosen indicators are meticulously tailored to highlight specific trends, anomalies, or degradation patterns that might otherwise remain concealed within the raw data. This methodological approach empowers us to transform complex signals into quantifiable metrics, facilitating robust decision-making in maintenance and prognostics.

Table 1 summarizes the ten distinct health indicators employed in this study, each capturing distinct facets of the system's health. These indicators are meticulously calculated through a combination of advanced signal processing techniques, including wavelet packet decomposition, statistical analysis, and feature extraction methods. The selected indicators span a range of characteristics, including amplitude variations, frequency content, energy distribution, and temporal behavior. By combining these indicators, a comprehensive understanding of the system's health can be achieved, enabling accurate assessments and informed maintenance strategies.

Table 1. Health Indicators and Mathematical Descriptions

INDICATOR	Mathematical Description
Crest	$\frac{\max(\lvert x(t)\rvert)}{\text{RMS}(\lvert x(t)\rvert)}$
Skewness	$\frac{E[x(t)^3]}{(\text{RMS}[x(t)])^3}$
Mean	$\frac{1}{N}\sum_{i=1}^{N} x_i$
Energy	$\sum_{i=1}^{N} x_i^2$
Kurtosis	$\frac{E[x(t)^4]}{(\text{RMS}[x(t)])^4}$
Variance	$E[(x(t)-\mu)^2]$
Maximum Amplitude	$\max(\lvert x(t)\rvert)$
Maximum FFT Value	$\max(\lvert \text{FFT}(x(t))\rvert)$
Peak-to-Peak Value	$\max(x(t)) - \min(x(t))$
Waveform Factor	$\frac{\text{RMS}[x(t)]}{\text{Mean}[x(t)]}$

Where $x(t)$ represents the time-domain signal under investigation, x_i represents the individual data points at time index i where i varies from 1 to N, μ corresponds to the mean value of the signal $x(t)$ and N stands for the total number of data points in the dataset $x(t)$.

1. **Sequential Backward Selection**
The SBS technique, commonly applied in statistical modeling and machine learning, serves as a feature selection method. Rather than exhaustively evaluating all conceivable combinations of indicators, this approach aims to identify and eliminate the least relevant indicators based on a computed Criterion Quality (QC). This QC metric is contingent on the discriminative power and compactness of the classes under investigation. Its fundamental purpose is to assess the significance of the selected indicator. A higher QC value is indicative of lower intra-class dispersion (Disp-intra) and higher inter-class dispersion (Disp-inter). Both of these properties are formulated as follows:

$$\text{Disp-intra} = \frac{1}{C}\sum_{i=1}^{C}\frac{1}{N}\sum_{j=1}^{N}(S_{ij}-g_i)\cdot(S_{ij}-g_i)^T \tag{2}$$

$$\text{Disp-inter} = \frac{1}{C}\sum_{i=1}^{C}(g_i-g)\cdot(g_i-g)^T \tag{3}$$

The Criterion Quality (QC) is then calculated as follow:

$$\text{QC}=\frac{\text{Disp-inter}}{\text{Disp-intra}} \tag{4}$$

In the context of the SBS technique, let Sij represent the j-th sample belonging to the class Ci. To illustrate, each class Ci is depicted as a matrix where each row j corresponds to a sample represented by a vector. The total number of samples per indicator is denoted as N, and the number of classes is represented by C. Additionally, gi denotes the gravity center of class C_i, while g signifies the gravity center of all samples. The formulas for computing these gravity centers are given as follows:

$$g = \frac{1}{C}\sum_{i=1}^{C} g_i \tag{5}$$

$$g_i = \frac{1}{N}\sum_{j=1}^{N} S_{ij} \tag{6}$$

As demonstrated in Figure 4, the SBS technique proves valuable in selecting indicators for different operating modes, offering an effective means to reduce data dimensionality and enhance model efficiency and interpretability.

2.4. Adaptive Neuro Fuzzy Inference System

ANFIS networks leverage the capacity of neural networks to learn from training datasets and the uncertainty modeling of fuzzy logic. In contrast to traditional binary logic, fuzzy logic quantifies failure degrees using different distributions of membership functions. This ability aids in defining the severity of bearing defects at any stage of degradation. A typical

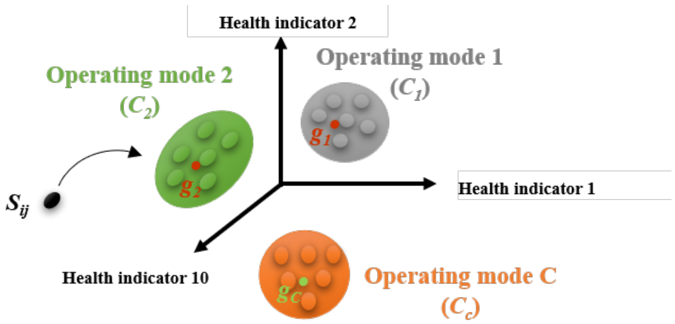

Figure 4. Representation of good health indicators selection with the SBS.

ANFIS architecture is illustrated in Figure 5. The ANFIS model comprises five distinct layers, each serving a specific role and composed of a certain number of nodes.

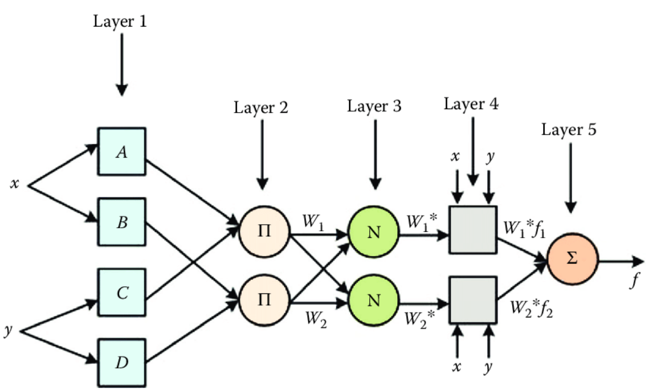

Figure 5. ANFIS architecture.

For a simple ANFIS network, as shown in Figure 5, the operating principle of each layer is as follows:

1. **Fuzzification layer:**
In this first layer, the degrees of membership for inputs are determined using the chosen membership function. By default, the adopted function is the Gaussian membership function.

$$A\left(X\right) = e^{-\left(\frac{X-\mu_1}{\sigma_1}\right)^2} \quad (7)$$

Where A is the membership function, μ_i and σ_i $(i = 1, ..., 4)$ are called the premise parameters.

2. **Inference layer:**
The outputs of this layer are calculated by the product of the membership degrees defined in the fuzzification layer.

$$W_1 = A\left(X\right) \cdot C\left(Y\right), W_2 = B\left(X\right) \cdot D\left(Y\right) \quad (8)$$

3. **Normalization layer:**
In this layer, the weights calculated in the subsequent layer are normalized as follows:

$$W_1{}^* = \frac{w_1}{w_1 + w_2}, W_2{}^* = \frac{w_2}{w_1 + w_2} \quad (9)$$

4. **Aggregation layer:**
In this layer, we will use the consequent parameters with the model inputs to determine the outputs of this layer.

$$f_1 = p_1X + q_1Y + r_1, f_2 = p_2X + q_2Y + r_2 \quad (10)$$

p_i, q_i and r_i $(i = 1, 2)$ are the consequent parameters.

5. **Defuzzification layer:**
In this layer we calculate the final score as follows:

$$f = W_1{}^* \cdot f_1 + W_2{}^* \cdot f_2 \quad (11)$$

The prediction of the RUL is defined as the time remaining between the current moment and the failure threshold. This definition has been interpreted in previous works as the intersection of the HI with the FT. In essence, RUL estimation entails estimating the remaining lifespan of a machine by monitoring the HI, even if it does not reach the end-of-life threshold. This provides a decision-making interval, enabling proactive maintenance actions to be taken (Lei et al., 2018). Problems in PHM can be approached through two different methods: classification or regression. In the classification approach, the life of a REB is divided into several stages based on the behavior of the health indicator. On the other hand, regression techniques, as illustrated in Figure 6, in this figure, tc represents the current time, ti corresponds to the instance of incipient threshold and tf signifies the time associated with the failure threshold. This limits allow for a smooth tracking of the machine's life or a sequential observation of various health stages. However, the use of machine learning algorithms in regression models often leads to local fluctuations that can influence the accuracy of RUL prediction.

To mitigate this issue, a smoothing technique such as the moving average filter can be employed for denoising the data (Sarih, Tchangani, Medjaher, & Péré, 2019). Subsequently, a reverse transformation from the Health Indicator (HI) to RUL is performed using the equation (Habbouche et al., 2021):

$$RUL(t) = t_{EOL} - HI^{-1}(t) \quad (12)$$

Metrics serve as a means of evaluation and facilitate the exchange of standardized information among scientists, thereby providing opportunities for improving proposed techniques to meet the requirements of PHM activities (Saxena, Celaya, Saha, Saha, & Goebel, 2010). In this study, the employed metrics include root mean squared error (RMSE), mean absolute error (MAE), mean squared error (MSE) (Du & Wang, 2019), and accuracy (Siswipraptini, Aziza, Sangadji, & In-

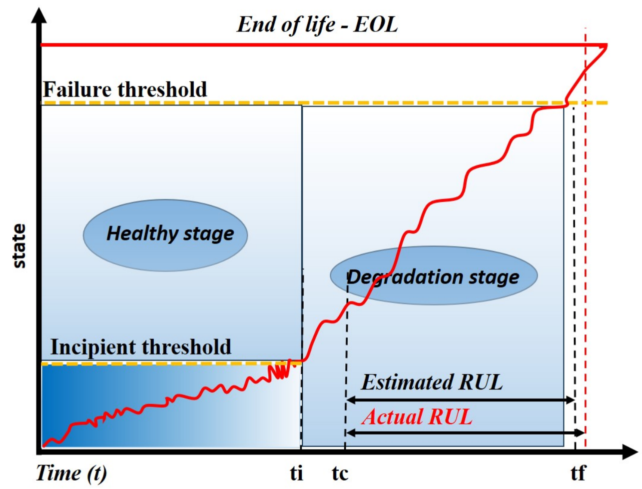

Figure 6. Illustration of prognostic process.

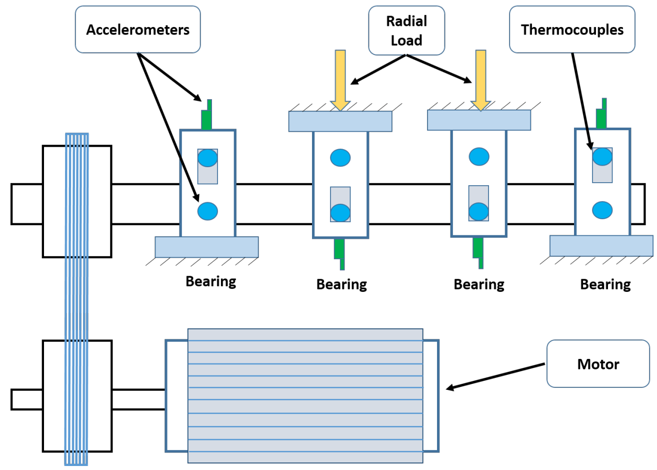

Figure 7. bearing prognosis bench.

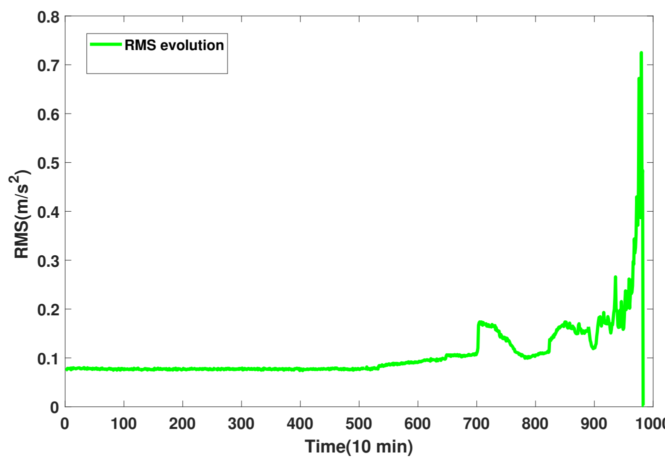

Figure 8. RMS measurement.

drianto, 2020), which is directly related to the mean absolute percentage error (MAPE) through the equation Accuracy = 100% - MAPE. To ensure reliable comparisons, these metrics are estimated using random sub-sampling cross-validation, enhancing the credibility of the results.

3. RESULTS AND DISCUSSION

3.1. Experimental setup

The proposed method was evaluated and tested using the IMS vibration dataset (Eker, Camci, & Jennions, 2012), which comprises three experiment tests, each test involves running one or more bearings to failure. The data was collected at a frequency of 1 record per second, with a sampling frequency of 20 kHz, and recorded every 10 minutes using the NI DAQ 6062E. The test was conducted on a Rexnord ZA-2115 double-row bearing, depicted in Figure 7, with a radial load of 6000 lbs. The rotation speed was maintained at 2000 RPM, and force lubrication was employed to ensure the required temperature (Eker et al., 2012).

In this study, the model was constructed using the data from the second run-to-failure test, with a failure time of 9840 minutes. Each sample in this experiment consisted of a vibration signal comprising 20480 samples.

3.2. VHI construction results

Figure 8 illustrates the historical RMS vibration data obtained from the run-to-failure experiments conducted by IMS (2nd run to failure bearing in this case). These data show the fluctuations, noise, and uncertainties resulting from the probabilistic degradation behavior and vibration variations (Ali, Chebel-Morello, Saidi, Malinowski, & Fnaiech, 2015).

From Figure 8, we can see that the behavior of the RMS indicator can be described in three stages. The first one represents normal functioning with a stable RMS. The second stage indicates the initiation of a fault with a linear evolution of the RMS, known as the incipient threshold. Finally, the third stage demonstrates severe degradation with non-linear behavior, referred to as the failure threshold (Ahmad et al., 2017).

To ensure the monotonicity of the Health Indicator (HI) and improve the quality of Remaining Useful Life (RUL) prediction, the RMS curve is fitted using the (WFRF) method. WFRF is chosen due to its ability to reduce fluctuations and noise while maintaining fitting quality and flexibility (Yan et al., 2020). The parameters obtained from previous works (Ali et al., 2015) are used to fit the RMS curve and are provided in Table 2.

Table 2. Fitting parameters

	η	β	Y	K
RMS	281.021	12.092	0.0773	1.38×10^{-5}

The fitting result is presented in Figure 9 (red curve). One can see that employing the WFRF method allows to enhance the accuracy of the RUL estimation by reducing fluctuations and noise of the raw RMS indicator, and thus, better representation of the degradation process is obtained (Thoppil, Vasu, & Rao, 2021).

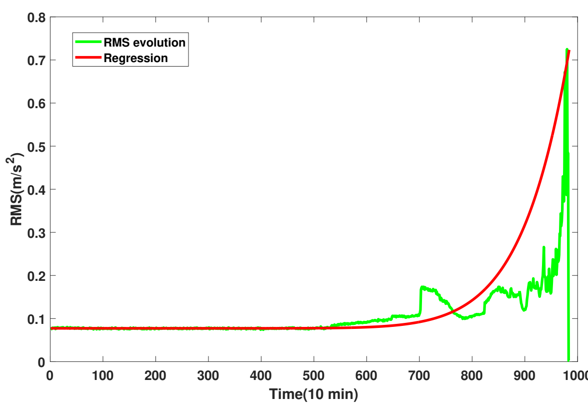

Figure 9. RMS fitting measurement.

3.3. Feature extraction and selection results

The estimation of the RUL is conducted within two thresholds: the incipient threshold (IT) indicating the beginning of degradation and the failure threshold (FT) representing the point at which the machine should be immediately shut down to prevent reaching the end-of-life limit, as shown in Figure 6. In this study, the determination of these thresholds was conducted based on the kurtosis value of the vibration signal, with the criteria obtained from previous works (Kumar, Kumaraswamidhas, & Laha, 2021; Habbouche et al., 2021). Hence, the IT is defined when the kurtosis value of the vibration signal reaches a value of **5**, corresponding to the 702^{nd} sample, signifying abnormal functioning. Normal functioning is observed when kurtosis is between 3 and 4 (Kumar et al., 2021). Whereas the FT is determined when the kurtosis value reaches a value of 16, corresponding to the 977^{th} sample, as illustrated in Figure 10. These results align closely with findings from other frameworks, such as (Y. Wang, Zhao, & Addepalli, 2020).

During the construction of the Health Indicator (HI) and the division of Health States (HS) within the context of monitoring REBs, a concurrent feature extraction procedure is conducted employing the WPD analyzer. The main significant contribution of this framework is the adoption of a single level for degradation assessment, as opposed to utilizing all levels obtained through the feature extraction process. A comprehensive evaluation of performance is presented in Table 3, which clearly demonstrates that the employment of the fourth level of WPD, alongside the utilization of five indicators specifically tailored for this level, yields the most favorable outcomes.

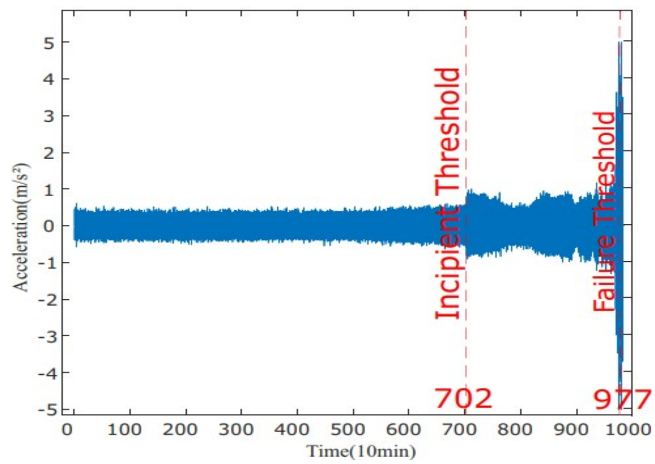

Figure 10. Threshold determination.

Table 3. Different levels of WPD predicted by ANFIS

	MAE	MSE	RMSE
Original signal	2.12e-2	5.17e-3	2.38e-3
2nd level	1.10e-3	3.11e-6	18.00e-4
3rd level	1.76e-4	1.15e-7	3.40e-4
4th level	**1.04e-4**	**2.28e-8**	**1.51e-4**
5th level	7.81e-5	4.68e-8	2.16e-4
6th level	3.11e-4	6.51e-7	8.07e-4
7th level	11.8e-3	5.32e-4	2.30e-2

By focusing on a specific level and then calculating a set of indicators to represent the most significant aspects of that level, the SBS algorithm is employed to determine the most pertinent indicators from the pool of calculated indicators. To ascertain the efficacy of the proposed model, a comparative study is conducted, analyzing the relationship between the number of indicators employed and the performance of the prognostic model. Figure 11 illustrates the performance of the proposed method in relation to the number of indicators employed for prognostic purposes. Notably, the results indicate that optimal performance is achieved when utilizing a set of five indicators for the fourth level.

This streamlined approach offers various advantages, including enhanced efficiency in preprocessing operations, reduced data storage requirements, and the feasibility of real-time implementation of the technique in practical applications. The determination of the optimal decomposition level, which ensures the capture of the most informative data, is achieved through an iterative trial-and-error process. This involves the

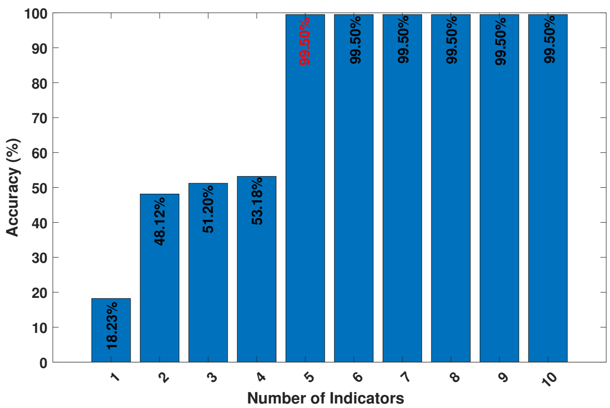

Figure 11. Comparison of Accuracy for Different Indicators.

utilization of the ANFIS training algorithm, along with the application of the Daubechies wavelet family of order 6. Furthermore, the performance evaluation of the proposed methodology is conducted employing two metrics: the maximum error (Max-error) and mean squared error (MSE).

After applying the SBS algorithm among the calculated indicators of Table 1, the following indicators have been selected: **crest**, **energy**, **mean**, **Skewness**, and **the maximum value of the fast Fourier transform**. These selected indicators will serve as the inputs for the ANFIS model in the subsequent steps of the analysis. By carefully choosing these indicators based on their relevance and informativeness, the ANFIS model can effectively capture and analyze the patterns and characteristics of the data, enabling accurate predictions and prognostic assessments.

Table 3 provides an overview of the results obtained when utilizing the raw vibration signal, as well as the different levels obtained through WPD. This comparison allows for a comprehensive assessment of the performance of each level, with particular emphasis on the fourth level, which demonstrates the most favorable outcomes.

3.4. ANFIS model prediction results

In order to select the best membership function for the ANFIS model prediction, a comparative study was conducted between various membership functions, as detailed in Table 4. This table presents the performance of the proposed model when employing different membership functions. This analysis is crucial in order to determine the optimal membership function to utilize throughout the remainder of this work.

To clearly demonstrate the performance of the proposed methodology, Figures 12 and 13 show a representation of the actual and predicted points for the training and test data. In these figures, red points represent the predicted values, while the blue ones stand for the actual HI values. The HI values in this case are rescaled from 0 to 1 and presented in Figures 12 and 13 as survival probabilities, where 0 represents the IT (high probability of survival) and 1 represents the FT (low probability of survival).

Table 4. Performance Metrics for Membership Functions

Membership Function	RMSE	MAE	MSE
Triangular	3.00e-3	1.00e-3	9.27e-6
Gaussian	**1.51e-4**	**1.04e-4**	**2.28e-8**
Trapezoidal	1.2e-1	3.21e-1	3.54e-1
Pi-shaped	6.36e-2	3.07e-2	4.01e-3
Bell membership	2.07e-4	8.88e-5	4.27e-8

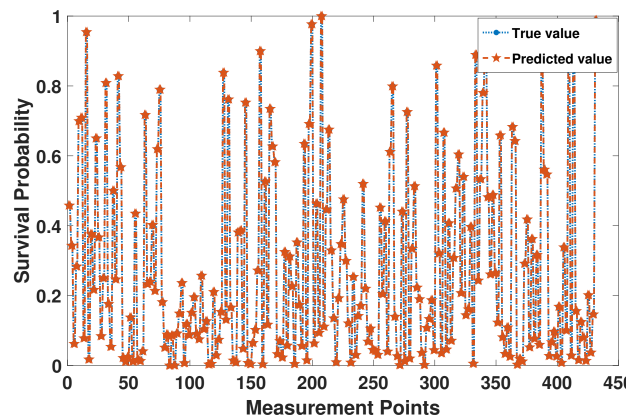

Figure 12. Validation of network with train experimental data.

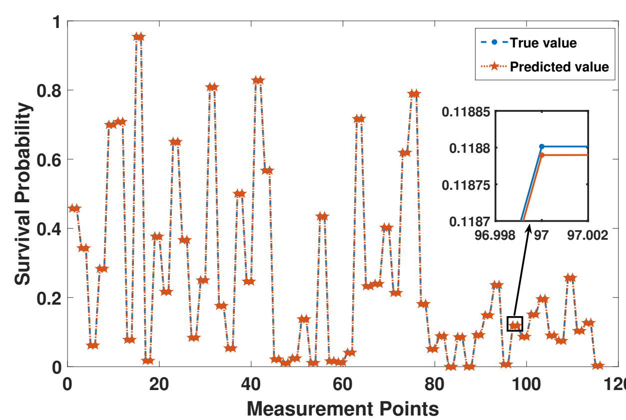

Figure 13. Validation of network with test experimental data.

In Figure 14, the visual representation of the discrepancy between actual and predicted values shows that the maximum observed difference does not exceed 10e-4. The predicted values closely coincide with the actual values in nearly all points, illustrating the model's strong predictive performance and high accuracy in monitoring the degradation process effectively.

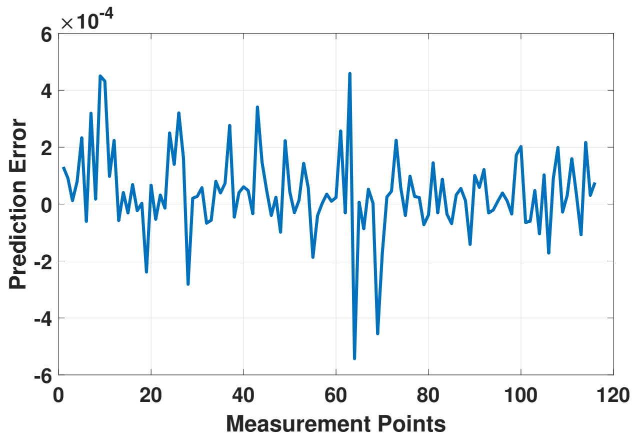

Figure 14. Error Distribution Between Actual and Predicted Values.

In Figures 15 and 16, the evolution of the HI over time is plotted for the training and test datasets. It's important to note that the ANFIS model was learned using the VHI constructed in section 2.2. This methodology serves as a valuable tool for monitoring the progression of bearing degradation using vibration signals, even in cases where the faults in the bearing exhibit low pulse amplitude (Dibaj, Ettefagh, Hassannejad, & Ehghaghi, 2021).

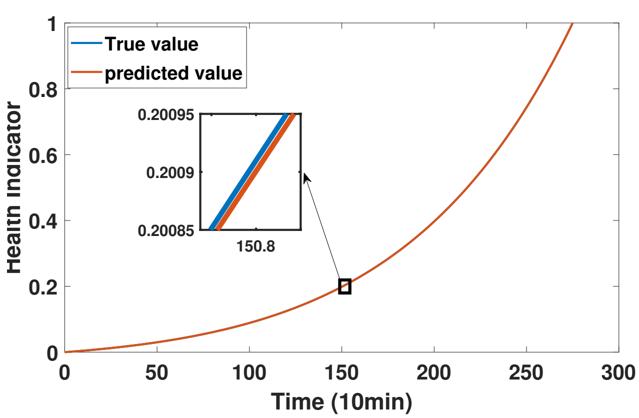

Figure 15. HI with train experimental data.

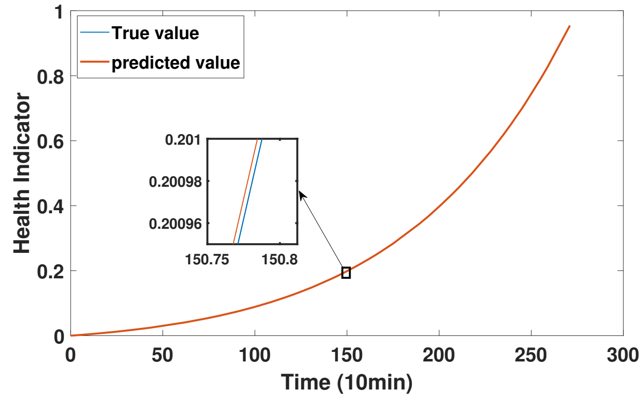

Figure 16. HI with test experimental data.

Based on the health indicator (HI) estimation depicted in previous figures, the prediction of Remaining Useful Life (RUL) can be determined by temporally projecting the reverse operation of Equation 12. The linear RUL prediction is then plotted, as demonstrated in Figure 17, which displays the RUL estimated with the test experimental data. The obtained results show the promising quality of the prediction with the proposed approach.

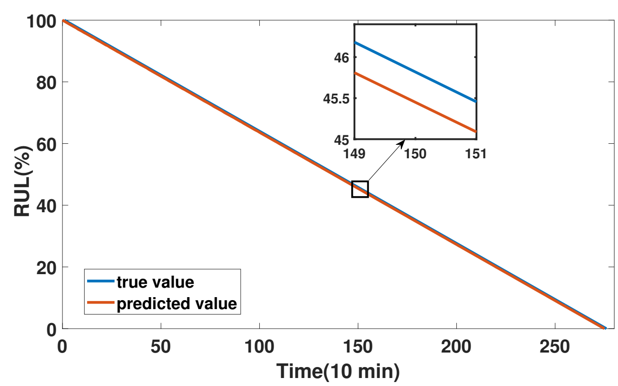

Figure 17. RUL with train experimental data.

To further evaluate the results qualitatively, it is essential to assess the confidence of the obtained outcome, as illustrated in Figure 18. This indicator holds significant importance as it reflects the reliability of the provided monitoring tool, representing the largest percentage error between the true and predicted RUL during the monitoring period. The confidence of the prediction is estimated at 0.5% over the entire bearing health monitoring period, showing encouraging results compared to the 3% confidence found in (Dibaj et al., 2021) and 2.4% confidence in (Habbouche et al., 2021).

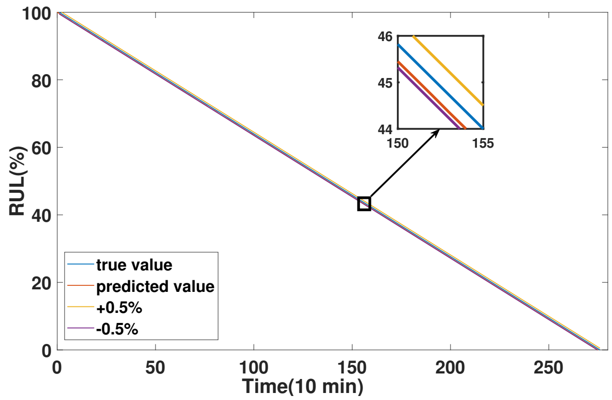

Figure 18. RUL estimation with confidence.

3.5. Performance evaluation

To quantitatively compare the proposed methodology with previous works and evaluate its performance, statistical evaluation metrics are utilized, as mentioned in Section 2. The results are presented in Table 5, showing that the errors achieved in the proposed methodology are the lowest when compared to previous works (Y. Wang et al., 2020; Lan et al., 2022; Tran, Trieu, Tran, Ngo, & Dao, 2021). These findings demonstrate the robustness of the proposed methodology in monitoring the degradation of Rolling Element Bearings (REB).

The paper successfully introduces a monitoring tool for Rolling Element Bearings (REB) utilizing Wavelet Packet Decomposition (WPD) and Adaptive Neuro Fuzzy Inference System (ANFIS). The tool activates at the incipient threshold (IT), initiating Remaining Useful Life (RUL) prediction with acceptable probability to support decision-making processes.

To showcase the methodology's relevance in industrial applications, rigorous testing was performed on an experimental dataset. Various metrics were calculated for comparison with prior works. Results indicate a substantial enhancement in REB health monitoring at the machine level, surpassing previous approaches. This advancement is crucial for proactive addressing of potential REB-related issues, preventing material and human disasters in machinery.

4. CONCLUSION

The study introduces a novel bearing prognostics methodology, integrating Wavelet Packet Decomposition (WPD) for data preprocessing, Sequential Backward Selection (SBS) for feature selection, and Adaptive Neuro Fuzzy Inference System (ANFIS) networks for prognostic modeling. The approach achieves an exceptional 99.5% accuracy in predicting Remaining Useful Life (RUL) of bearings.

WPD enhances data quality and feature extraction, while SBS refines the feature set by selecting significant indicators and eliminating irrelevant ones. The ANFIS network, combining fuzzy logic and neural networks, constructs an accurate prognostic model by learning from the training dataset and leveraging the optimized feature set.

Validation using a real-world dataset (IMS dataset) from a run-to-failure test confirms the methodology's effectiveness in bearing health assessment and proactive maintenance planning. The high accuracy achieved suggests practical applications in rotary machine maintenance, contributing to reduced system failures, minimized unexpected shutdowns, and improved reliability and operational efficiency.

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Table 5. Comparison between current work and previous works

	RMSE-CV	MAE	MSE	Accuracy
Proposed	**1.51e-4**	**1.04e-4**	**2.28e-8**	**99.95%**
(Habbouche et al., 2021)	0.0067	0.0049	4.5e-5	97.24%
(Du & Wang, 2019)	-	0.0403	0.0029	-
(He, Zhou, Li, Wu, & Tang, 2020)	0.0253	0.0052	0.0029	-
(Ali et al., 2015)	-	-	-	96.61%
(Widodo & Yang, 2011)	0.011	-	-	-

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