# RUL Estimation of Rolling Element Bearings Using a Hybrid Wavelet Packet Decomposition–Recursive Feature Elimination–Adaptive Neuro Fuzzy Inference System Framework

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**ABSTRACT**

Rolling element bearings are critical components in rotating machinery, and their unexpected failures can cause severe downtime and economic losses. Therefore, accurate estimation of remaining useful life (RUL) is essential to ensure system reliability and enable predictive maintenance strategies. This paper presents a novel hybrid framework that integrates Wavelet Packet Decomposition (WPD), Recursive Feature Elimination (RFE), and Adaptive Neuro-Fuzzy Inference System (ANFIS) for intelligent RUL estimation of bearings. First, vibration signals from the well-known IMS dataset are acquired and decomposed using WPD to capture multi-resolution information. A comprehensive set of health indicators is then computed from each decomposition level, reflecting the degradation dynamics of bearings. To reduce redundancy and enhance discriminative power, the most relevant features are selected using the RFE algorithm. Finally, the refined features are fed into an ANFIS model to estimate the RUL. Comparative analyses with multiple Artificial Neural Network (ANN)-based models are conducted to assess the effectiveness of the proposed approach. Experimental results demonstrate that the hybrid WPD–RFE–ANFIS framework achieves outstanding predictive performance, reaching an accuracy of 99.98%, thereby outperforming traditional ANN architectures. This study highlights the potential of hybrid intelligent models for advancing prognostics and health management (PHM) in industrial applications.

**keywords:** Wavelet Packet Decomposition (WPD), fault Prognosis, Recursive Feature Elimination (RFE), Adaptive Neuro Fuzzy Inference System (ANFIS), Feature extraction, Feature selection.

## 1. INTRODUCTION

Rolling element bearings are fundamental components in a wide variety of industrial machinery, including motors, turbines, gearboxes, and pumps (Y. Wang, Xu, Zhang, Liu, & Jiang, 2015; Soualhi, Lamraoui, Elyousfi, & Razik, 2022; Heng, Zhang, Tan, & Mathew, 2009; Soualhi, Yousfi, Lamraoui, & Medjaher, 2022; A. w. Lourari, Soualhi, & Benkedjouh, 2024; A. W. Lourari, El Yousfi, Benkedjouh, Bouzar Essaidi, & Soualhi, 2024). Their reliable operation is essential to ensure the safety, efficiency, and productivity of industrial systems (Lei, Lin, Zuo, & He, 2014; Ghods & Lee, 2016; J. Liu, Wang, & Golnaraghi, 2009; Jia, Lei, Lin, Zhou, & Lu, 2016; A. w. Lourari, Soualhi, Medjaher, & Benkedjouh, 2024; A. W. Lourari, Yousfi, & Essaidi, 2025; ?, ?; wahhab LOURARI & BENKEDJOUH, 2026). However, bearings are highly susceptible to fatigue, wear, and lubrication issues, which can lead to progressive degradation and eventual failure(Gohari, Tahmasebi, & Ghorbani, 2023; Lv, Zhao, Zhao, Li, & Ng, 2022; Buchaiah & Shakya, 2022; wahhab Lourari, Benkedjouh, El Yousfi, & Soualhi, 2024; A. W. Lourari, El Yousfi, et al., 2024; Sekini, El Yousfi, Benkedjouh, Medjaher, & Lourari, 2025). Unexpected bearing failures often result in unplanned downtime, reduced productivity, and significant maintenance costs (A. W. Lourari, BENKEDJOUH, & El Yousfi, 2024; wahhab Lourari et al., 2024; El Yousfi, Lourari, Bouzar Essaidi, Soualhi, & Medjaher, 2025; El Yousfi et al., 2025). To address these issues, Prognostics and Health Management (PHM) has emerged as a promising strategy that aims not only to detect and diagnose early faults but also to predict the Remaining Useful Life (RUL) of components before critical failure occurs(Medjaher, Zerhouni, & Gouriveau, 2016; El Yousfi et al., 2025).

Accurate RUL estimation of bearings is particularly challenging due to the nonlinear, non-stationary, and noisy nature of vibration signals. These signals typically exhibit complex patterns of degradation that cannot be effectively captured by simple statistical or physics-based models. This motivates the


https://doi.org/10.36001/IJPHM.2026.v17i1.4634

development of advanced data-driven methods that integrate signal processing, feature engineering, and intelligent learning algorithms to achieve high prognostic accuracy.

Wavelet Packet Decomposition (WPD) is a powerful signal processing tool that allows multiresolution analysis, capturing both time and frequency domain information. Its capability to decompose signals into a full binary tree structure provides a more detailed representation than traditional wavelet transforms, making it especially suitable for analyzing bearing vibration signals(Habbouche, Benkedjouh, & Zerhouni, 2021; wahhab Lourari et al., 2024; Gohari et al., 2023). From these decomposed signals, a wide range of health indicators can be extracted to describe the degradation process. However, the abundance of features often introduces redundancy, noise, and irrelevant information, which may reduce the effectiveness of learning algorithms.

To overcome this issue, feature selection techniques play a critical role. Recursive Feature Elimination (RFE) has gained popularity as a robust method for selecting the most relevant features by recursively ranking and eliminating less informative ones. By doing so, RFE enhances the interpretability, efficiency, and performance of the prognostic model.

On the modeling side, Artificial Intelligence (AI) techniques have been widely applied to RUL estimation. Among them, the Adaptive Neuro-Fuzzy Inference System (ANFIS) stands out due to its hybrid nature, combining the adaptive learning capabilities of neural networks with the reasoning and uncertainty handling of fuzzy logic. This makes ANFIS particularly well-suited for nonlinear and uncertain environments, such as those encountered in bearing prognostics (wahhab Lourari et al., 2024).

In this study, we propose a novel hybrid framework that integrates WPD for signal preprocessing, RFE for feature selection, and ANFIS for intelligent RUL estimation. The effectiveness of the proposed method is validated using the widely adopted IMS bearing dataset, which provides real-world degradation data. Comparative experiments are conducted with various Artificial Neural Network (ANN)-based models to benchmark the performance. The obtained results demonstrate that the proposed WPD–RFE–ANFIS framework achieves outstanding accuracy of 99.98%, outperforming traditional ANN approaches. This work contributes to the advancement of intelligent prognostics by introducing an efficient, interpretable, and high-performing methodology for bearing RUL estimation.

## 2. RELATED WORK

In recent years, significant research efforts have been devoted to developing advanced methods to estimate RUL(Medjaher, Tobon-Mejia, & Zerhouni, 2012; Zhu, Chen, & Peng, 2018; A. Kumar, Parkash, Tang, & Xiang, 2023). Early approaches focused on statistical degradation models, such as Weibull distributions or stochastic processes, which provided mathematical descriptions of failure patterns but often lacked the flexibility to handle non-stationary and nonlinear data(Rathore & Harsha, 2022; Lai, Pan, Ong, & Chen, 2022). Model-based approaches, relying on physical degradation models, were also explored, yet their practical application remains limited due to the complexity of accurately modeling real-world degradation mechanisms(Li & Deng, 2023).

With the rise of data-driven PHM, signal processing techniques and machine learning models have become the dominant paradigm(Q. Liu, Zhang, Si, & Fan, 2023). Wavelet transforms and Empirical Mode Decomposition (EMD) have been widely used for preprocessing vibration signals, enabling the extraction of time–frequency features that capture the evolution of bearing faults(Guo, Wang, Zhang, & Zhang, 2021; Zhan, Sun, Li, & Wang, 2022). More recently, Wavelet Packet Decomposition (WPD) has attracted increasing attention because of its ability to provide richer representations of signals across different frequency bands(Hong, Duan, Peng, Liu, & Zio, 2023). For instance, several studies have shown that WPD-based health indicators can effectively characterize bearing degradation and enhance the prediction accuracy of machine learning models(Lu, Wen, He, Yi, & Yan, 2021).

Feature selection has also been recognized as a crucial step in improving prognostic performance(wahhab Lourari et al., 2024). Methods such as principal component analysis (PCA), sequence feature selection, and relief-F have been adopted to reduce the dimensionality of the features(Y. Wang, Zhao, Yang, Xu, & Ge, 2022; Duan, Shen, Guo, Sheng, & Wang, 2023). However, Recursive Feature Elimination (RFE) has gained particular interest because of its iterative nature, which systematically identifies and retains the most informative features while discarding redundant ones(Alomari, Andó, & Baptista, 2023). Despite its effectiveness, relatively few studies have combined RFE with WPD-based features for RUL estimation.

On the modeling side, Artificial Neural Networks (ANNs)(Kang, Catal, & Tekinerdogan, 2021), Support Vector Machines (SVMs)(Shen & Yan, 2021), and Deep Learning architectures have been applied extensively to bearing prognostics(Bono, Cinquemani, Chatterton, & Pennacchi, 2022; Gupta, Wadhvani, & Rasool, 2023). While these methods achieve good accuracy, they often act as "black-box" models, limiting interpretability. Hybrid approaches that integrate fuzzy logic and neural networks, such as the Adaptive Neuro-Fuzzy Inference System (ANFIS), have shown promising results in handling uncertainty and nonlinearities(Meddour, Messekher, Younes, & Yallese, 2021; wahhab Lourari et al., 2024). Several works have demonstrated that ANFIS can outperform purely neural or statistical models in fault diagnosis and RUL prediction tasks(wahhab Lourari et al., 2024).

Although significant progress has been made, there is still a lack of comprehensive frameworks that seamlessly integrate advanced signal preprocessing, optimal feature selection, and interpretable intelligent models, as illustrated in Figure 1. To bridge this gap, this study introduces a hybrid WPD–RFE–ANFIS framework tailored for accurate remaining useful life (RUL) prediction of rolling element bearings. The proposed methodology combines multiresolution signal decomposition using Wavelet Packet Decomposition (WPD) with systematic dimensionality reduction through Recursive Feature Elimination (RFE), ensuring that only the most discriminative health indicators are preserved. On top of this, the adoption of Adaptive Neuro-Fuzzy Inference Systems (ANFIS) enables adaptive learning while maintaining transparency and interpretability, thereby addressing the limitations of conventional black-box approaches. Validation in the IMS bearing dataset confirms the robustness of the framework, yielding a prediction accuracy of 99.98% and surpassing standard ANN-based methods.

## 3. HYBRID WPD–RFE–ANFIS FRAMEWORK

The proposed methodology represents a crucial element of Prognostics and Health Management (PHM), focusing on the health monitoring of Rolling Element Bearings (REBs), the estimation of their Remaining Useful Life (RUL), and supporting maintenance decision-making. This data-driven approach integrates Wavelet Packet Decomposition (WPD), Recursive Feature Elimination (RFE), and Adaptive Neuro-Fuzzy Inference System (ANFIS), combining expertise from signal processing, feature engineering, and intelligent modeling. All developments and experiments are implemented in the MATLAB environment.

In recent years, maintenance strategies have evolved significantly with the adoption of PHM frameworks based on machine learning and advanced signal analysis. However, several challenges remain unresolved. Chief among them are the reliable detection of early degradation before its propagation, the construction of robust health indicators capable of tracking the evolution of faults over time, and the development of predictive models that effectively exploit historical REB data to estimate defect severity and RUL (Zhang, Zhang, & Li, 2019).

To address these challenges, a hybrid prognostic framework is proposed, as illustrated in Figure 2. The process begins with the acquisition and preprocessing of vibration signals, followed by the decomposition using WPD to capture multiresolution time-frequency information. A set of statistical and frequency-domain features is then computed from the decomposed signals. To reduce redundancy and retain only the most informative health indicators, the RFE algorithm is employed. Finally, the selected features are used to train the ANFIS model, which provides accurate and interpretable RUL estimation. This systematic methodology ensures both robustness and precision, enabling reliable health assessment and prediction of bearing degradation.

### 3.1. Signal Preprocessing with Wavelet Packet Decomposition

Various time–frequency analysis techniques have been developed for machinery signal processing, such as 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, WPD has received considerable attention in prognostics due to its ability to provide high-resolution representations in both the time and frequency domains (Belmiloud, Benkedjouh, Lachi, Laggoun, & Dron, 2018; J. Wang & Liao, 2005). Unlike the traditional Discrete Wavelet Transform (DWT), which decomposes only the approximation coefficients at each stage, WPD applies the decomposition process iteratively to both approximation and detail branches, yielding a complete binary tree structure of sub-bands. This enables a more flexible and detailed characterization of non-stationary signals typically observed in bearing degradation.

Mathematically, the decomposition relies on a pair of quadrature mirror filters: a low-pass filter $h[n]$ and a high-pass filter $g[n]$. Given a discrete signal $x[n]$, the approximation coefficients $a_{j+1}[k]$ and the detail coefficients $d_{j+1}[k]$ at level $j+1$ are obtained as:

$$\begin{aligned} a_{j+1}[k] &= \sum_n h[n-2k]\, a_j[n], \\ d_{j+1}[k] &= \sum_n g[n-2k]\, a_j[n], \end{aligned} \tag{1}$$

with the initialization $a_0[n] = x[n]$. Unlike DWT, WPD applies the same filtering process recursively to both $a_j[n]$ and $d_j[n]$, such that at a given level $L$, the signal is decomposed into $2^L$ sub-bands, each representing a specific frequency range.

The choice of wavelet family and order (e.g., Daubechies db2, db4, Haar, Symlets) is crucial, as it determines the time–frequency localization properties of the decomposition. The decomposition level $L$ is typically selected based on the sampling frequency and the frequency range of interest in bearing vibrations. An illustration of a second-order decomposition is shown in Figure 3 (Gouriveau, Medjaher, & Zerhouni, 2016).

Once the decomposition is performed, statistical features and health indicators (HIs) are extracted from the sub-band signals. The organized dataset can be expressed as:

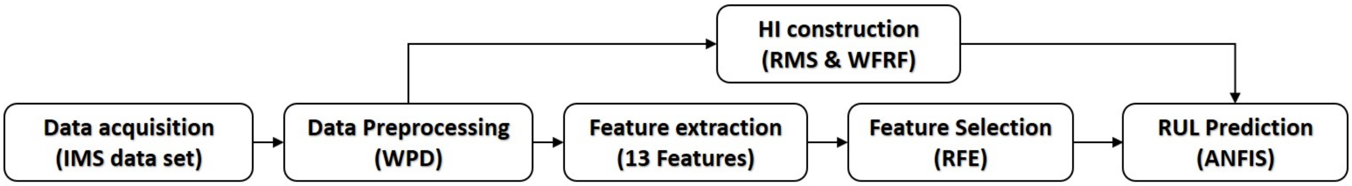


Figure 1. Proposed Approach: An Overview.

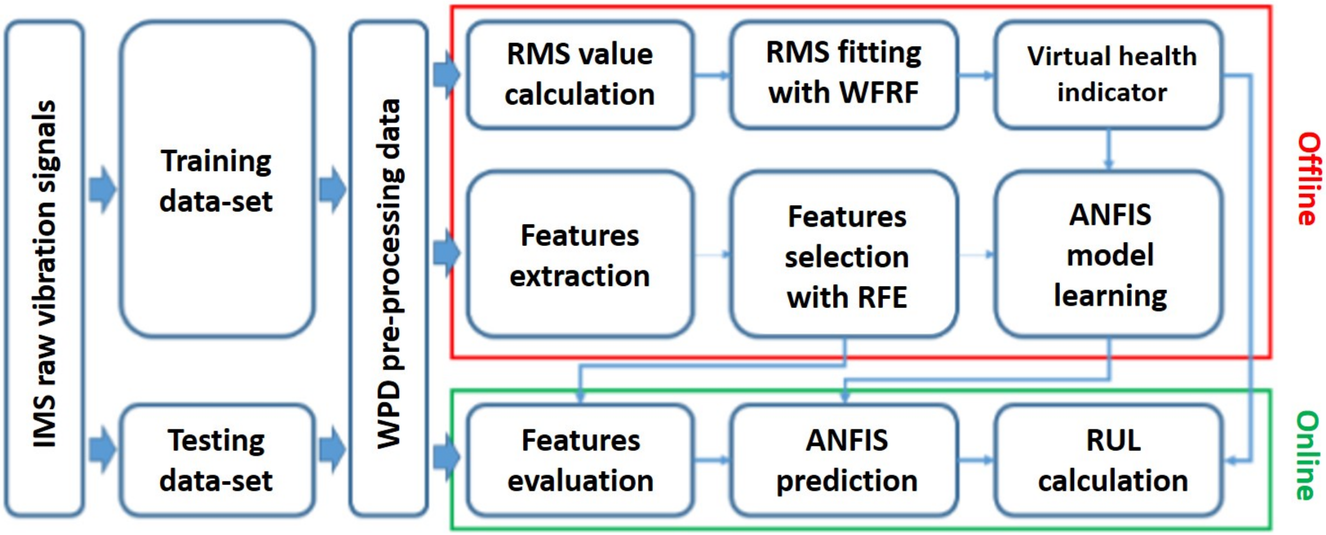


Figure 2. Architecture of the proposed bearing fault prognostic methodology.

$$X = \{x_t, x_{t-1}, x_{t-2}, \ldots, x_{t-n}\}, \tag{2}$$

where $x_t$ represents the WPD-derived coefficients at time $t$. The target output vector corresponds to a health indicator normalized within $[0, 1]$, mapping the complete degradation trajectory of the bearing from a healthy state to failure. This organized feature space serves as the input for the prognostic model developed in the subsequent stages.

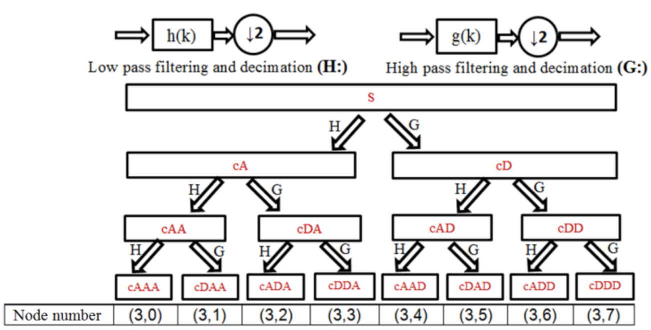


Figure 3. Principle and Functioning of the Wavelet Packet Decomposition Tree

### 3.2. Construction of a Virtual Health Indicator

Monitoring the health status of REBs has traditionally relied on periodic inspections, which are often time-consuming and disruptive to production. Furthermore, the detection of localized faults, such as cracks or spalls, frequently requires sophisticated and costly techniques. In contrast, continuous monitoring using sensors (e.g., accelerometers and microphones) offers an efficient solution, providing real-time insight into bearing health. However, raw sensor signals inherently contain both informative content and noise, necessitating the extraction of a representative Health Indicator (HI) to characterize degradation trends (Lei et al., 2018). An effective HI should capture the actual bearing condition while maintaining a clear and preferably monotonic progression throughout the degradation process (Zhang et al., 2019).

Among various statistical features, the Root Mean Square (RMS) is widely recognized as a robust HI for bearing degradation monitoring (Cheng, Cheng, Lei, & Tsai, 2020). The suitability of RMS in this investigation is justified by its strong correlation with the bearing's operating state (Ahmad, Khan, & Kim, 2017) and its proportional relationship with the energy content of vibration signals (Lei et al., 2018). These properties make RMS particularly effective for tracking progressive fault development.

For accurate representation of degradation, the selected HI must be coupled with a degradation model. Two widely used approaches in the literature are the Weibull Failure Rate Function (WFRF) and the Exponential Degradation Model (EDM) (Yan, Wang, Wang, Chang, & Muhammad, 2020). In this work, a modified WFRF (Wu, Li, Qiu, et al., 2017) is adopted to model the irreversible degradation process based on the RMS indicator. The model formulation requires the estimation of specific parameters $Y$, $K$, $\beta$, and $\eta$ as follows:

$$\vartheta(t) = Y + K\frac{\beta}{\eta^{\beta}}t^{\beta-1} \tag{3}$$

One of the major advantages of using an HI lies in its ability to reduce the need for full-life monitoring of the bearing, which is often unnecessary in practice. Instead, the temporal evolution of the HI allows the operating life to be segmented into multiple Health Stages (HS), thereby providing a structured interpretation of the bearing's condition. This partitioning enables the identification of different degradation levels and facilitates more effective prognostic and maintenance planning. By integrating HI evolution with health-stage division, maintenance strategies can be optimized, fault severity can be mitigated, and overall system reliability can be significantly enhanced.

### 3.3. Health-Oriented Feature Representation

Signal processing is a cornerstone in Prognostics and Health Management (PHM), as it enables the transformation of raw sensor data into informative representations that reflect the evolving condition of mechanical systems. For rolling element bearings (REBs), vibration signals acquired from accelerometers contain valuable information about degradation, but this information is often embedded within noise and requires advanced processing to extract meaningful patterns. Feature extraction, therefore, plays a pivotal role in constructing reliable Health Indicators (HIs) that describe the degradation trajectory and support accurate Remaining Useful Life (RUL) estimation.

In this study, a set of statistical and frequency-domain indicators is derived to quantify different aspects of bearing behavior, such as energy concentration, impulsiveness, distribution asymmetry, and entropy-related measures. These indicators are chosen because of their sensitivity to early fault initiation, their monotonic evolution with progressing damage, and their ability to highlight degradation phenomena that may remain hidden in raw signals. By combining features derived from Wavelet Packet Decomposition (WPD) with classical statistical descriptors, a richer representation of the degradation process is achieved.

Table 1 presents the consolidated list of health indicators employed in this work, along with their mathematical formulations. This unified representation eliminates redundancies and integrates both traditional vibration features and more advanced statistical measures. The selected features span multiple perspectives: amplitude-based descriptors (e.g., RMS, peak-to-peak), distribution-based indicators (e.g., kurtosis, skewness), sparsity and entropy measures (e.g., negentropy, Gini index), and hybrid ratios (e.g., Peak-to-RMS, L2/L1). Together, these indicators provide a robust foundation for characterizing degradation patterns and constructing predictive models.

Here, $u_i$ represents the signal amplitude at time index $i$, $T$ is the total number of samples, $\mu$ denotes the mean of the signal, and $\|U\|_p$ corresponds to the $\ell_p$-norm of the signal vector $U$. The combination of these complementary indicators ensures that both time-domain and frequency-domain characteristics of the vibration signals are adequately captured, supporting the accurate monitoring of degradation trends in REBs.

### 3.4. Selection of Health Indicators

The Recursive Feature Elimination (RFE) algorithm is a widely used and powerful method for feature selection in machine learning and statistical modeling. Unlike exhaustive search strategies, RFE operates through a recursive procedure that iteratively ranks and removes the least relevant features based on their importance to the predictive model. At each iteration, a learning model (e.g., regression, support vector machine, or neural network) is trained, and the contribution of each feature is evaluated. The feature with the lowest importance score is eliminated, and the model is retrained on the reduced feature set. This process continues until the desired number of features is reached or the optimal subset is identified.

The main advantage of RFE lies in its ability to enhance model generalization by discarding features that either introduce redundancy or contribute little to the prediction. In doing so, RFE effectively reduces data dimensionality while retaining the most informative indicators, thereby improving both interpretability and performance.

Mathematically, let $\mathcal{F} = f_1, f_2, \ldots, f_M$ denote the initial feature set of size $M$. At iteration $k$, a predictive model is trained on the current feature subset $\mathcal{F}^{(k)}$, and an importance score $I(f)$ is assigned to each feature $f \in \mathcal{F}^{(k)}$. The feature with the smallest score is removed:

$$\mathcal{F}^{(k+1)} = \mathcal{F}^{(k)} \setminus \arg\min_{f\in\mathcal{F}^{(k)}} I(f). \tag{4}$$

This elimination procedure is repeated until a stopping criterion is met, such as reaching a predefined number of features or achieving optimal model performance.

By following this systematic ranking and elimination process, RFE identifies the most discriminative subset of health indicators, ensuring robust and reliable decision-making. Fig-

Table 1. Consolidated health indicators and their mathematical descriptions.

| Indicator | Mathematical Formula | Reference |
|---|---|---|
| Root Mean Square (RMS) | $\sqrt{\frac{1}{T}\sum_{i=1}^{T} u_i^2}$ | - |
| Peak-to-RMS | $\frac{\max\{\lvert u_i\rvert\}}{\sqrt{\frac{1}{T}\sum_{i=1}^{T} u_i^2}}$ | - |
| Peak-to-Peak Value | $\max(u_i) - \min(u_i)$ | - |
| Crest Factor | $\frac{\max(\lvert u_i\rvert)}{\mathrm{RMS}(u_i)}$ | - |
| Skewness | $\frac{E[u^3]}{(\mathrm{RMS}(u))^3}$ | - |
| Kurtosis | $\frac{1}{T}\sum_{i=1}^{T} u_i^4 \Big/ \left(\frac{1}{T}\sum_{i=1}^{T} u_i^2\right)^2$ | (Dwyer, 1983) |
| Variance | $E[(u-\mu)^2]$ | - |
| Energy | $\sum_{i=1}^{T} u_i^2$ | - |
| Negentropy | $\frac{1}{T}\sum_{i=1}^{T} \frac{u_i^2}{\frac{1}{T}\sum_{i=1}^{T} u_i^2} \ln\left(\frac{u_i^2}{\frac{1}{T}\sum_{i=1}^{T} u_i^2}\right)$ | (Antoni, 2016) |
| Ratio L2/L1 | $\sqrt{T}\frac{\lVert U\rVert_2}{\lVert U\rVert_1}$ | (Peter & Wang, 2013) |
| Hoyer Index (HI) | $\frac{\sqrt{T}-\frac{\lVert U\rVert_1}{\lVert U\rVert_2}}{\sqrt{T-1}}$ | (Hoyer, 2004) |
| Gini Index (GI) | $1-\sum_{i=1}^{T} \frac{U_{(i)}}{\lVert U\rVert_1}\left(\frac{2(T-i)+1}{T}\right)$ | (Gini, 1921) |
| Improved Gini Index (IGI) | $1-\sqrt[p]{\sum_{i=1}^{T} \frac{U_{(i)}^p}{\lVert U\rVert_p}\left(\frac{2(T-i)+1}{M}\right)}$ | (Chen et al., 2022) |

ure 4 illustrates the selection procedure and highlights its effectiveness in optimizing both accuracy and interpretability.

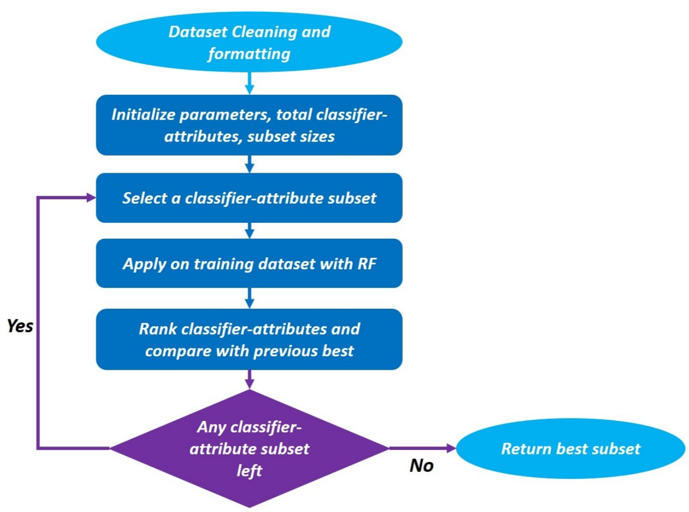


Figure 4. Recursive Feature Elimination (RFE) process for selecting the most relevant health indicators.

### 3.5. Adaptive Neuro Fuzzy Inference System

Adaptive Neuro-Fuzzy Inference Systems (ANFIS) combine the learning capability of neural networks with the uncertainty-handling strength of fuzzy logic. Unlike classical binary logic, fuzzy logic enables the modeling of uncertainty by assigning membership degrees to variables through appropriate membership functions. This characteristic makes ANFIS particularly suitable for estimating the severity of bearing degradation across different operating stages. The general architecture of an ANFIS model, composed of five functional layers, is depicted in Figure 5. Each layer performs a distinct role in the inference process.

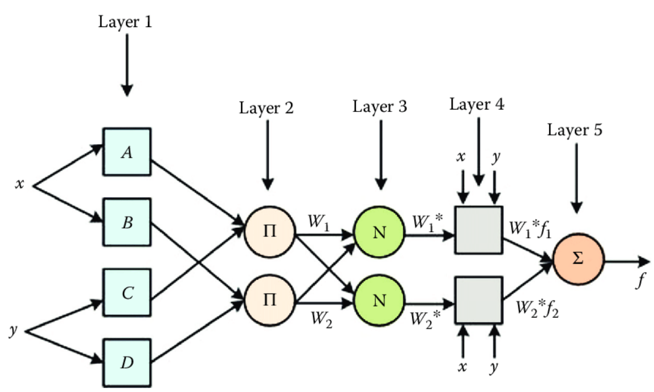


Figure 5. ANFIS architecture composed of five layers.

For a basic ANFIS network, the operation of each layer can be summarized as follows:

1. **Fuzzification layer:** The membership degree of each input is determined using a predefined membership function, typically Gaussian:

$$A(X) = \exp\left(-\left(\frac{X-\mu_i}{\sigma_i}\right)^2\right), \tag{5}$$

where $\mu_i$ and $\sigma_i$ ($i = 1, \ldots, 4$) are premise parameters controlling the center and width of the membership function.

2. **Rule (Inference) layer:** This layer evaluates the firing strength of fuzzy rules by combining the input membership degrees:
$$W_1 = A(X) \cdot C(Y), \quad W_2 = B(X) \cdot D(Y). \tag{6}$$
3. **Normalization layer:** The firing strengths are normalized to ensure proportional contributions:
$$W_1^* = \frac{W_1}{W_1 + W_2}, \quad W_2^* = \frac{W_2}{W_1 + W_2}. \tag{7}$$
4. **Consequent (Aggregation) layer:** Linear functions of the inputs are weighted by the normalized firing strengths:
$$f_1 = p_1 X + q_1 Y + r_1, \quad f_2 = p_2 X + q_2 Y + r_2, \tag{8}$$
where $p_i$, $q_i$, and $r_i$ are consequent parameters.
5. **Defuzzification layer:** The final output is obtained by aggregating all rules:
$$f = W_1^* \cdot f_1 + W_2^* \cdot f_2. \tag{9}$$

In the context of Prognostics and Health Management (PHM), ANFIS can be exploited for Remaining Useful Life (RUL) prediction. RUL is defined as the time interval between the current operating point and the failure threshold (FT). This can be expressed as the difference between the estimated End-of-Life ($t_{EOL}$) and the time corresponding to the current health indicator (HI) level:
$$RUL(t) = t_{EOL} - HI^{-1}(t). \tag{10}$$

Two modeling paradigms are generally applied in PHM:

*classification-based approaches*, which segment the bearing lifetime into discrete health stages, and *regression-based approaches*, which provide a continuous degradation trajectory. As illustrated in Figure 6, regression-based models can capture gradual degradation trends, but they are sensitive to local fluctuations. To address this limitation, smoothing techniques such as moving average filters are often employed to denoise the HI evolution before mapping it to RUL.

**Performance Evaluation Metrics:** To ensure a rigorous assessment of RUL prediction performance, several statistical metrics are employed:

- The *Root Mean Squared Error (RMSE)* emphasizes large deviations by penalizing squared residuals, making it highly sensitive to rare but critical mispredictions:
$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (\hat{y}_i - y_i)^2}. \tag{11}$$

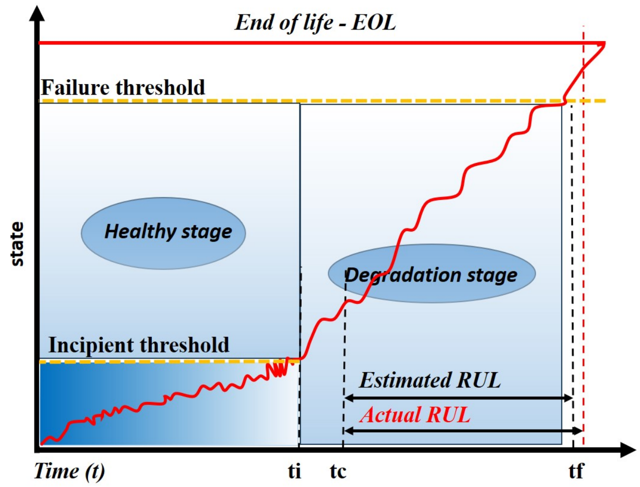


Figure 6. Illustration of the prognostic process for RUL estimation (wahhab Lourari et al., 2024).

- The *Mean Absolute Error (MAE)* quantifies the average magnitude of prediction errors without overemphasizing outliers, thus providing a robust measure of overall accuracy:
$$MAE = \frac{1}{n}\sum_{i=1}^{n} |\hat{y}_i - y_i| \,. \tag{12}$$

- The *Mean Squared Error (MSE)* offers a compromise between RMSE and MAE, reflecting both the variance and the bias of the estimator:
$$MSE = \frac{1}{n}\sum_{i=1}^{n} (\hat{y}_i - y_i)^2 \,. \tag{13}$$

These metrics are estimated using random sub-sampling cross-validation to ensure robust comparisons and to minimize bias due to dataset partitioning. Moreover, accuracy is expressed in relation to the Mean Absolute Percentage Error (MAPE), with:
$$Accuracy = 100\% - MAPE. \tag{14}$$

Such a multi-metric evaluation provides complementary insights: RMSE captures worst-case deviations, MAE reflects average error magnitude, and MSE balances bias-variance trade-offs. Together, they offer a comprehensive assessment of ANFIS-based RUL prediction performance.

## 4. EXPERIMENTAL VALIDATION AND DISCUSSION

### 4.1. Experimental setup

The effectiveness of the proposed approach was assessed using the well-known IMS vibration dataset (Eker, Camci, & Jennions, 2012), which includes three run-to-failure experiments. In each experiment, one or more bearings were operated until failure occurred. The measurements were acquired at a rate of one record per second, with a sampling frequency of 20 kHz, and stored every 10 minutes using a NI DAQ 6062E system. The test rig employed a Rexnord ZA-2115 double-row bearing (Figure 7) subjected to a radial load of 6000 lbs. The shaft rotated at a constant speed of 2000 RPM, and an external lubrication system was applied to regulate the temperature (Eker et al., 2012).

For the present study, the model was developed using data from the second run-to-failure experiment, in which bearing degradation progressed until failure at 9840 minutes. Each record in this dataset corresponds to a vibration signal containing 20,480 points.

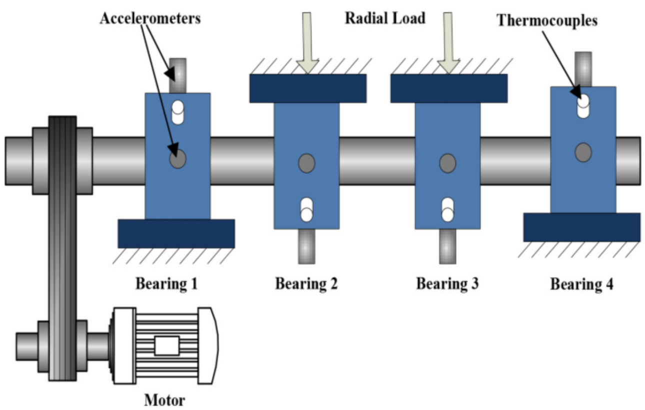


Figure 7. bearing prognosis bench.

### 4.2. Results of Health Indicator Construction

Figure 8 presents the temporal evolution of the RMS vibration signal obtained from the IMS run-to-failure dataset (specifically the second bearing test). The trend highlights the inherent fluctuations, noise, and variability that arise from the stochastic nature of bearing degradation and the dynamic characteristics of vibration measurements (Ali, Chebel-Morello, Saidi, Malinowski, & Fnaiech, 2015).

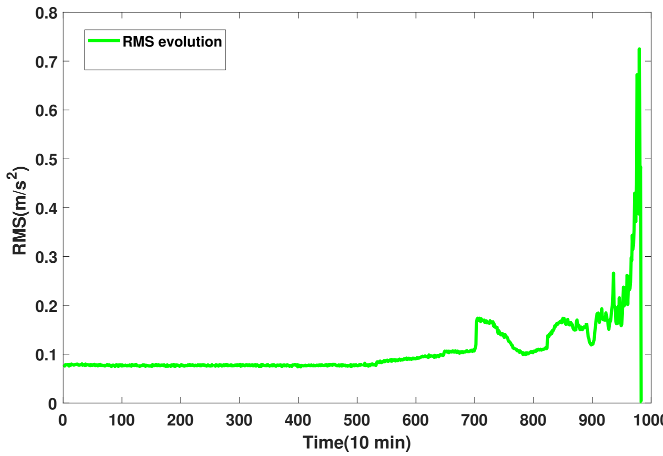


Figure 8. RMS temporal evolution.

From Figure 8, the progression of the RMS indicator can be distinguished into three characteristic stages. The first stage corresponds to normal operation, where the RMS remains stable. The second stage reflects the initiation of a fault, marked by a linear increase in RMS, commonly referred to as the incipient threshold. The final stage represents severe degradation, characterized by nonlinear behavior and identified as the failure threshold (Ahmad et al., 2017).

To enhance the monotonicity of the Health Indicator (HI) and improve the reliability of Remaining Useful Life (RUL) prediction, the RMS trajectory is approximated using the Weighted Fuzzy Regression Function (WFRF) method. This approach is selected for its ability to attenuate fluctuations and suppress noise while preserving both fitting accuracy and adaptability (Yan et al., 2020). The parameters adopted from prior studies (Ali et al., 2015), which are employed for RMS fitting, are summarized in Table 2.

Table 2. Fitting parameters

| | $\eta$ | $\beta$ | $Y$ | $K$ |
|---|---|---|---|---|
| RMS | 281.021 | 12.092 | 0.0773 | $1.38 \times 10^{-5}$ |

The fitting outcome is depicted in Figure 9 (red curve). It can be observed that the application of the WFRF method significantly improves the accuracy of RUL estimation by suppressing the fluctuations and noise present in the raw RMS indicator. As a result, a smoother and more reliable representation of the underlying degradation process is achieved (Thoppil, Vasu, & Rao, 2021).

### 4.3. Evaluation of Extracted and Selected Features

In this part, the evaluation of the extracted and selected features is addressed with a particular focus on threshold determination and feature relevance analysis. The degradation

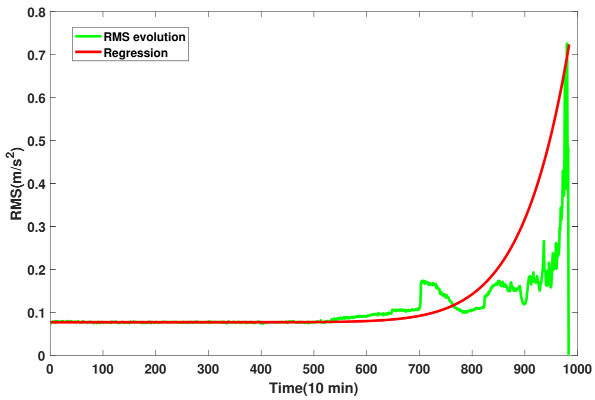


Figure 9. RMS fitting measurement.

thresholds, namely the incipient and failure limits, are established to provide reference points for the RUL estimation process. Furthermore, a comparative study is carried out to determine the optimal number of health indicators required for reliable prognosis. For this purpose, the Recursive Feature Elimination (RFE) algorithm is employed, enabling systematic reduction of redundant or less informative features while preserving those with the highest diagnostic significance.

#### 4.3.1. Threshold Definition for RUL Estimation

The estimation of the Remaining Useful Life (RUL) is performed using two reference thresholds: the incipient threshold (IT), which marks the onset of degradation, and the failure threshold (FT), which indicates the point where machine shutdown is necessary to avoid complete functional breakdown, as illustrated in Figure 6. In this study, both thresholds are established based on the kurtosis of the vibration signal, following criteria reported in previous works (P. S. Kumar, Kumaraswamidhas, & Laha, 2021; Habbouche et al., 2021).

In line with standard practice in the literature, RUL estimation is performed within the *degradation window*, defined between the *incipient threshold* (IT) and the *failure threshold* (FT) of the monitored component. These thresholds are typically determined based on the *kurtosis* of the signal, with IT corresponding to a kurtosis of 5 and FT to a kurtosis of 16. In the present study, the RUL prediction was carried out from the 702$^{\text{nd}}$ sample to the 977$^{\text{th}}$ sample, which represents the portion of the signal where degradation is observable (see Figure 10). The IT marks the beginning of the prediction, while the FT corresponds to the end, ensuring that the RUL is estimated exclusively during the progressive deterioration of the bearing.

Normal operating states are generally characterized by kurtosis values between 3 and 4 (P. S. Kumar et al., 2021).

These findings are consistent with previous studies, such as (Y. Wang, Zhao, & Addepalli, 2020), confirming the suitability of kurtosis as a robust statistical criterion for degradation threshold determination.

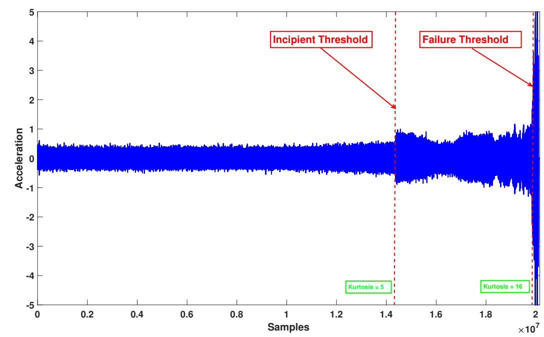


Figure 10. Threshold determination.

#### 4.3.2. Comparative Study Using RFE-Based Feature Selection

While numerous health indicators (HIs) can be extracted from vibration signals, not all contribute equally to accurate prognosis. To identify the most relevant subset of indicators, a comparative study is conducted using the Recursive Feature Elimination (RFE) algorithm. RFE systematically removes less informative features and evaluates model performance at each iteration, ultimately determining the optimal number of indicators to be retained.

Figure 11 illustrates the performance of the proposed methodology when varying the number of selected indicators. As observed, the use of **five indicators** yields the highest prediction accuracy, outperforming configurations that employ either fewer or all available features. This result highlights the effectiveness of RFE in eliminating redundancy while preserving discriminative power. Consequently, only the five most relevant indicators are retained for the subsequent RUL estimation process, which ensures both higher accuracy and reduced computational complexity.

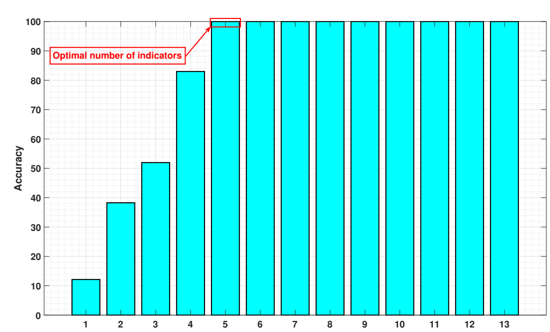


Figure 11. Performance comparison with different numbers of indicators using RFE.

### 4.4. Preprocessing Performance Using Wavelet Packet Decomposition

The preprocessing step is performed through Wavelet Packet Decomposition (WPD) in order to enhance the quality of the vibration signals before feature extraction. Different decomposition levels were analyzed to evaluate their impact on the prediction accuracy when integrated with the ANFIS model. Performance metrics, including Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE), were calculated for each decomposition level.

Table 3 summarizes the obtained results. As observed, the 4th-level decomposition achieved the most consistent and lowest error values, thereby demonstrating its superiority compared to other levels. This finding indicates that the 4th-level WPD provides the optimal signal representation for the subsequent feature extraction and prognostic modeling process.

Table 3. Different levels of WPD predicted by ANFIS

| | MAE | MSE | RMSE |
|---|---|---|---|
| Original signal | 1.19e-2 | 3.38e-3 | 2.38e-3 |
| 2nd level | 1.12e-3 | 3.26e-6 | 18.06e-4 |
| 3rd level | 1.62e-4 | 1.09e-7 | 3.58e-4 |
| **4th level** | **7.55e-5** | **2.17e-8** | **1.47e-4** |
| 5th level | 7.92e-5 | 4.72e-8 | 2.18e-4 |
| 6th level | 3.18e-4 | 6.74e-7 | 8.17e-4 |
| 7th level | 11.92e-3 | 5.54e-4 | 2.48e-2 |

This optimized preprocessing strategy brings several advantages, notably improving computational efficiency, minimizing storage demands, and supporting real-time applicability in industrial contexts. The determination of the most informative decomposition level is carried out through an iterative process, in which the vibration signal is decomposed using the Daubechies wavelet of order 8 and then evaluated through ANFIS-based learning. This process ensures that the selected level retains the most discriminative information while avoiding redundancy or noise amplification. To guarantee reliable selection, performance was systematically assessed using multiple error metrics, including the mean absolute error (MAE), mean squared error (MSE), and root mean squared error (RMSE).

In parallel, the Recursive Feature Elimination (RFE) algorithm was applied to refine the set of calculated health indicators presented in Table 1. The outcome of this feature selection process highlighted the following indicators as the most relevant: **Crest Factor**, **Energy**, **L2/L1**, **Hoyer Index**, and **GMIGI**, These features outperform the combination used in our previous (wahhab Lourari et al., 2024) (Energy, Mean, Skewness, Crest, and FFT maximum), providing a more informative representation of the degradation process across the monitored signals.. These selected indicators will serve as the inputs for the ANFIS model in the subsequent stages of the analysis. By carefully selecting indicators with strong relevance and discriminative power, the ANFIS model can more effectively capture degradation patterns, thereby enhancing the accuracy of predictions and prognostic assessments.

Table 3 summarizes the results obtained when using the raw vibration signal in comparison with different decomposition levels generated through WPD. Among these, the fourth level exhibits the most favorable outcomes, confirming its suitability as the optimal level for subsequent prognostic modeling.

### 4.5. Validation Protocol and Overfitting Prevention

To ensure reliable performance evaluation and to prevent temporal leakage, a random subsampling cross-validation strategy was adopted. In each validation iteration, the dataset was partitioned into training and testing subsets composed of *non-overlapping signal segments*, guaranteeing that no identical samples appeared simultaneously in both subsets. Feature extraction using Wavelet Packet Decomposition (WPD), feature selection via Recursive Feature Elimination (RFE), and model training were performed exclusively on the training subset in each cross-validation run. The selected feature subset and the learned ANFIS parameters were then applied unchanged to the corresponding test subset, without any re-optimization or parameter tuning. Furthermore, the ANFIS architecture was deliberately designed to remain compact by limiting the number of fuzzy rules and membership functions, thereby controlling model complexity and reducing the risk of overfitting. The consistent prediction accuracy observed across multiple random validation runs demonstrates that the reported performance reflects genuine generalization capability rather than model overfitting.

### 4.6. ANFIS-Based Prognostic Performance

In order to identify the most suitable membership function for the ANFIS prediction model, a comparative evaluation was carried out using different types of membership functions, as summarized in Table 4. The results illustrate how the choice of membership function influences the performance of the proposed framework.

Furthermore, a sensitivity analysis was performed to determine the appropriate number of membership functions to be assigned to each input. As shown in Figure 12, the accuracy of the methodology significantly improves when four membership functions are employed, leading to the best trade-off between complexity and prediction performance. Therefore, in the remainder of this study, four membership functions are adopted to ensure reliable and accurate prognostic results.

### 4.7. Performance Evaluation of the Proposed Methodology

The performance of the proposed ANFIS-based framework was assessed using the optimal configuration of five selected

Table 4. Performance Metrics for Membership Functions

| Membership Function | RMSE | MAE | MSE |
|---|---|---|---|
| Bell membership | 3.52e-3 | 1.18e-3 | 9.63e-6 |
| Triangular | 1.72e-4 | 1.25e-4 | 2.38e-8 |
| Trapezoidal | 1.34e-1 | 3.62e-1 | 3.68e-1 |
| Pi-shaped | 6.82e-2 | 3.85e-2 | 4.15e-3 |
| **Gaussian** | **1.47e-4** | **7.54e-5** | **2.16e-8** |

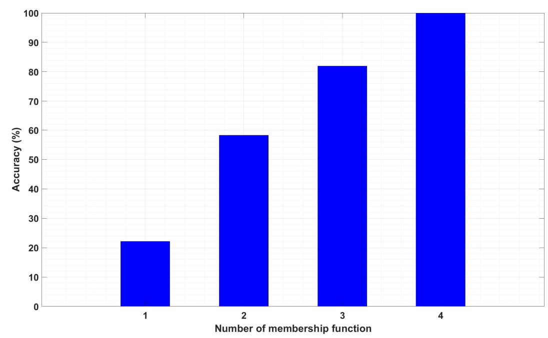


Figure 12. Effect of the number of membership functions on the prediction accuracy of the ANFIS model.

indicators and four Gaussian membership functions. The results demonstrate that the predicted outputs follow the target values with high fidelity, highlighting the ability of the model to capture the degradation trend effectively.

As shown in Figure 13, the training phase results confirm the consistency of the predictions with the actual data, while Figure 14 illustrates the robustness of the model when applied to the testing dataset. To further evaluate the accuracy, Figures 15 and 16 display the residual errors for both training and testing phases, respectively. In both cases, the error values remain on the order of $10^{-3}$, confirming the reliability and precision of the proposed methodology in predicting the remaining useful life of rolling element bearings.

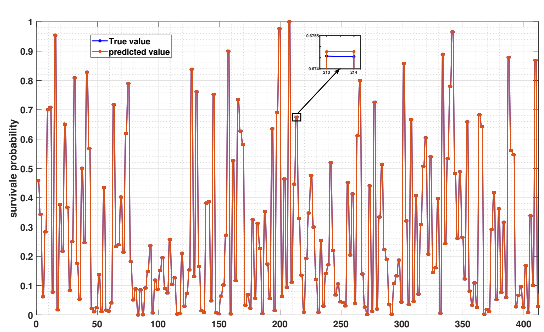


Figure 13. Performance evaluation of the proposed methodology on the training dataset.

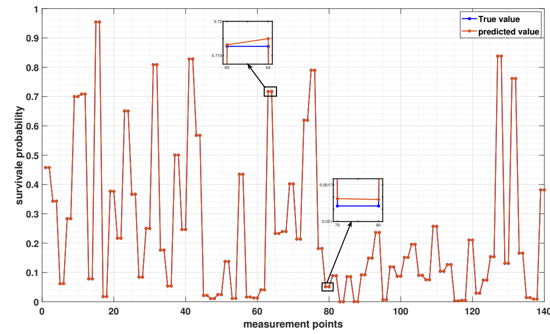


Figure 14. Performance evaluation of the proposed methodology on the test dataset.

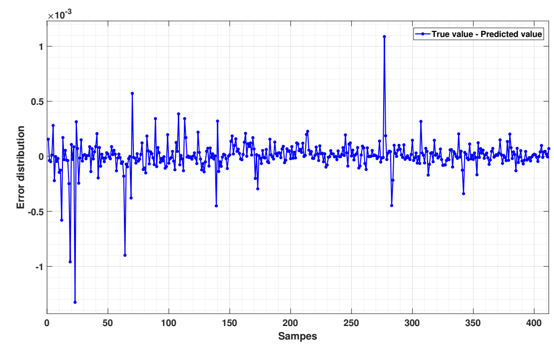


Figure 15. Prediction error between actual and estimated values for the training dataset.

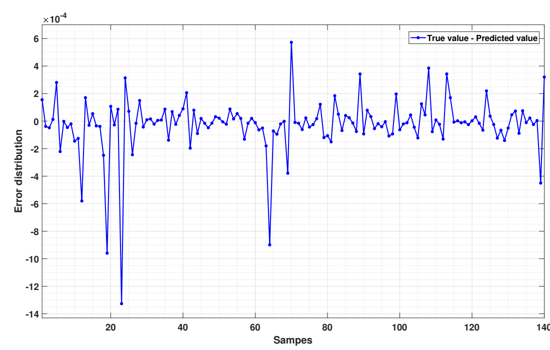


Figure 16. Prediction error between actual and estimated values for the test dataset.

### 4.8. Comparative Analysis with Previous Works

In order to validate the performance of the proposed methodology and enable a quantitative comparison with previous contributions, the statistical evaluation metrics described in Section 2 are employed. The corresponding results are reported in Table 5. From this comparison, it is evident that the proposed approach achieves the lowest error values when contrasted with earlier studies (Y. Wang et al., 2020; Lan et al., 2022; Tran, Trieu, Tran, Ngo, & Dao, 2021; wahhab

Lourari et al., 2024). These results confirm the robustness of the developed methodology in tracking the degradation process of rolling element bearings. By following the proposed steps, this study introduces an effective framework for monitoring Rolling Element Bearings (REB) based on Wavelet Packet Decomposition (WPD) and Adaptive Neuro-Fuzzy Inference System (ANFIS). The developed tool is capable of detecting the incipient threshold (IT) and subsequently initiating Remaining Useful Life (RUL) prediction with a reliable probability, thereby assisting in informed decision-making processes.

To validate the industrial relevance of the proposed methodology, extensive experiments were carried out on an experimental dataset. Statistical metrics were computed to enable a fair comparison with existing approaches. The obtained results highlight a clear improvement in REB health monitoring at the machine level, outperforming previous methods. Such progress is of considerable importance, as it contributes to preventing both material losses and potential human hazards by enabling proactive maintenance strategies for rotating machinery. It should be noted that not all literature results reported in Table 5 are directly comparable to the present study. Specifically, the works in (wahhab Lourari et al., 2024) and (Habbouche et al., 2021) address bearing Remaining Useful Life (RUL) estimation using degradation data and intelligent modeling, under experimental conditions comparable to those considered in this paper. These studies therefore provide a direct benchmark for evaluating the proposed WPD–RFE–ANFIS framework. In contrast, the approaches presented in (Du & Wang, 2019), (He et al., 2020), (Ali et al., 2015), and (Widodo & Yang, 2011) are highly relevant to the broader field of predictive maintenance and machinery health management, but they focus on different problem formulations, degradation indicators, or learning paradigms. As such, these works are qualitatively comparable in terms of maintenance objectives, yet not strictly equivalent to bearing RUL estimation under the same experimental and validation settings.

## 5. CONCLUSION

In this work, a novel hybrid framework for the prognostics of rolling element bearings was developed by integrating Wavelet Packet Decomposition (WPD), Recursive Feature Elimination (RFE), and Adaptive Neuro-Fuzzy Inference System (ANFIS). The main motivation was to overcome the limitations of conventional prognostic approaches, which often rely either on raw signal processing, heuristic feature selection, or black-box learning models with limited interpretability.

The use of WPD enabled a multiresolution analysis of vibration signals, allowing the extraction of rich time–frequency features that effectively capture the degradation dynamics of bearings. To reduce redundancy and avoid the curse of dimensionality, RFE was employed as a systematic feature selection strategy to retain only the most informative health indicators. This step not only improved computational efficiency but also enhanced the robustness of the final model. Finally, ANFIS was adopted to combine the adaptive learning capabilities of neural networks with the interpretability of fuzzy inference systems, thereby providing a balance between accuracy and transparency in RUL estimation.

The proposed methodology was validated using the IMS bearing dataset, where experimental results confirmed its superiority over conventional ANN-based approaches. The framework achieved a prediction accuracy of 99.98%, demonstrating its ability to capture the underlying degradation patterns and provide highly reliable RUL estimations. In addition to its accuracy, the framework benefits from interpretability, which is essential for industrial applications where decision-making must be supported by transparent and explainable models.

Overall, the results underline the significance of integrating advanced signal preprocessing, optimal feature selection, and interpretable learning models for accurate and reliable prognostics. Beyond rolling element bearings, the proposed framework can be generalized to other rotating machinery and critical industrial components, thus offering a versatile tool for predictive maintenance and condition-based monitoring. Future research will focus on extending the approach to non-stationary operating conditions, multi-sensor data fusion, and real-time implementation to further enhance its applicability in practical industrial environments. Future work will focus on extending the WPD–RFE–ANFIS framework to multiple bearing runs. Our investigation showed that the Fitted RMS (WFRF-based) health indicator effectively tracks degradation only for the selected run, while failing to capture consistent trends in other IMS runs. This highlights the need for more robust, degradation-sensitive indicators. Developing adaptive or fused health indicators will therefore be a priority to enhance generalization. Once suitable indicators are identified, the full validation of the proposed methodology across several runs will be conducted.

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Table 5. Comparison between current work and previous works

| | RMSE-CV | MAE | MSE | Accuracy |
|---|---|---|---|---|
| **Proposed** | **1.47e-4** | **7.54e-5** | **2.16e-8** | **99.98%** |
| (wahhab Lourari et al., 2024) | 1.51e-4 | 1.04e-4 | 2.18e-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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