Statistical Knowledge Integration into Neural Networks: Novel Neuron Units for Bearing Prognostics

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Abstract

Prognostics and Health Management (PHM) is a framework that assesses the health condition of complex engineering assets to ensure proper reliability, availability, and maintenance. PHM can be used to determine how long a machine can function before failure by predicting the Remaining Useful Life (RUL). Neural networks have been used for RUL prediction, but these data-driven models rely solely on data to explicitly integrate knowledge. Recently, authors have proposed physics-informed neural networks (PINNs) to address this limitation. PINNs are neural networks that incorporate expert knowledge and physics in different ways (observational, inductive, and learning bias). Despite their significance, these models tend to be case-dependent and challenging to configure. In this work, we propose statistical neuron units that can be integrated into any neural network. The proposed neuron units extract features from raw data using various statistical functions. Importantly, these modules can be located in different parts of the neural network, and they can be optimized automatically by backpropagating the modules' weights during training. In a study involving bearing degradation behavior, we compare a classical neural network with our modular version. Our proposed RUL estimation model outperformed the baseline, with a reduction of 13% in the root mean square error and a reduction of 7% in the mean absolute error. We also observe an increase of 40% and 21% for the $\alpha - \lambda$ accuracy metric for an α equal to 0.1 and 0.2 respectively. Our code is available publicly on **Github**.

Keywords: Feature extraction, knowledge integration, optimization of parameters, interpretability, accuracy, modularity, neural network

1. Introduction

Prognostics and Health Management (PHM) is a critical aspect of modern industrial systems, enabling the early detection of faults and the implementation of timely maintenance and repair strategies. One of the key components of PHM is the prediction of the Remaining Useful Life (RUL), which estimates the time until a system or component fails. Accurate RUL prediction is essential for optimizing maintenance schedules, reducing downtime and costs (Ramezani et al., 2019). To predict the RUL, multiple approaches have been developed, which can be classified as physical models, data-driven methods, and hybrid methods (Hasib et al., 2021; Ferreira & Gonçalves, 2022).

Recently, models infused with domain expertise have received much attention, such as physics-informed neural networks (PINNs), a subfield of neural learning that incorporates explicit prior knowledge (Nguyen et al., 2019). This knowledge can come from two sources: scientific knowledge and expert knowledge (Willard et al., 2022; Kang et al., 2021). Scientific knowledge spans a broad spectrum of domains and engineering disciplines, such as empirical equations (J. Wang et al., 2020) or high-resolution bearing dynamic simulations serving as a method for training the model (Sobie et al., 2018). Expert knowledge refers to knowledge obtained through experience that can be used for various purposes during the process of selecting and developing features.

Despite some successful cases of knowledge integration in data-driven models, some limitations persist (Dourado & Viana, 2020; Nascimento & Viana, 2019). Typically, knowledge inclusion is predetermined and fixed, so it cannot be optimized during training. Another challenge is the interpretability of the model, which remains an issue. The lack of explainability power of neural networks makes it difficult to understand how certain models use knowledge in their predictions (Faroughi et al., 2022).

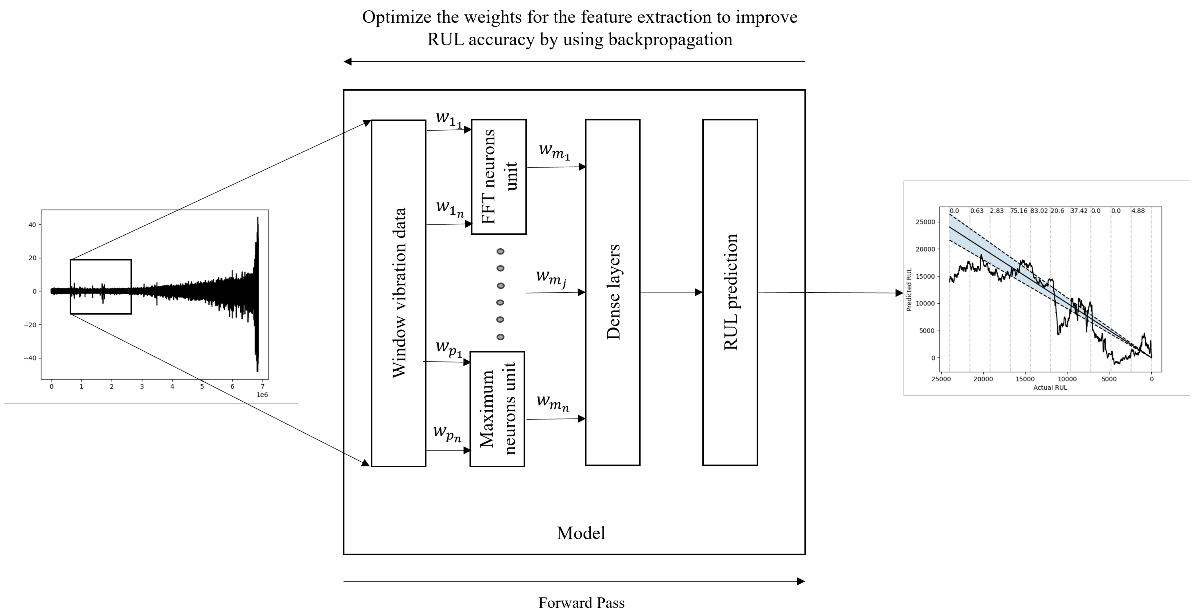


Figure 1. A generic diagram of how one neural network model incorporating the neuron units works. At first, a portion of the vibration signal is fed to the neural network model. This vibration signal is then passed to the different neuron units, which first weight the data received by their own weight and then extract the features needed. The different features extracted are then fed to the dense layers, which are then used to predict the RUL. During training, the neural network model optimizes the weights through backpropagation.

This paper proposes the concept of "knowledge-infused statistics" neuron units for neural networks. These modular units aim to make the structure of neural networks more accurate. Our proposed approach allows the model to train and optimize statistical knowledge during the training stage. Importantly, our proposed neuron units incorporate knowledge that can be fine-tuned and optimized. Since they are modular, these neuron units can be located/ positioned at various locations within the neural network, providing flexibility and adaptability. This novel approach improves neural network performance by optimizing knowledge-infused statistics neuron units.

We investigate the impact of 21 novel neuron units in a bearing case study. Bearings play a crucial role in machinery and mechanical systems, enabling smooth rotation, friction reduction, and support for heavy loads, ensuring operational efficiency and reliability. Our proposed neuron units aim to optimize (improve/enhance) feature extraction during training. The bearing case study is sourced from FEMTO[1] University (Nectoux et al., 2012).

In the implementation of 21 neuron units, we explore the impact of three **novel** neuron configurations: Single Feature Extraction (SFE), Multiple Feature Extraction (MFE), and Weighted Multiple Feature Extraction (WMFE). The SFE type extracts only one feature, while the MFE type extracts multiple features simultaneously. The WMFE layer extracts multiple features and computes/weights the importance of the extracted output features.

The contribution of this paper can be summarized as follows:

- **Modular knowledge-infused statistics Integration:** Introduction of 21 modular and statistical neuron units within a neural network for predicting bearing residual life.
- **Accuracy:** By incorporating these neuron units, we improve the network's ability to extract the features in an optimized way, which, in this case study, led to an improvement in RUL predictions.

In Fig.1, we present a diagram of how our proposed approach works. First, a window of vibration values is given as input to the neural network model. These data are used by the different neuron units to extract features. Each neuron unit has input and output weights (as well as bias) that are used to capture and measure the importance of the features (Fast Fourier transform, skewness factor, maximum amplitude, etc.). The neuron output is given to the dense layers, which then proceed to predict the RUL. The model updates all the weights automatically (by backpropagation) to obtain a better RUL prediction.

The remainder of this paper is organized as follows: Section 2 provides a review of the literature in PHM and the different modeling approaches. Section 3 describes the methodology

[1]FEMTO = Franche-Comté Électronique Mécanique Thermique et Optique

employed in this study and the evaluation metrics. Section 4 presents the case study used in this paper in more detail. Section 5 presents the results obtained and their interpretation. Finally, Section 6 concludes the paper and outlines directions for future research.

2. Related Work

Prognostics and Health Management (PHM) is a significant area of research that has gained attention in recent years. One of the primary goals of PHM is to predict the Remaining Useful Life (RUL) of engineering systems and components. This is important because it helps to ensure the safety and reliability of these systems, reduce maintenance costs, and optimize maintenance schedules (Guo et al., 2019). To predict the RUL, multiple approaches have been proposed: physics of failure (PoF), data-driven (DD) and hybrid approaches (L. Liao & Köttig, 2014).

The PoF approach in PHM employs mathematical representations that describe the underlying physics of the system under study (Cubillo et al., 2016). To improve the precision of the remaining useful life (RUL) estimate, Q. Wang et al. (2021) proposed a linear mapping technique that directly relates the degradation characteristics of the bearing with its remaining useful life. However, when a linear algorithm is not feasible due to nonlinearities, an alternative approach is needed.

For example, the Extended Kalman Filter (EKF) can be employed to transform the nonlinear problem into a linear one. Singleton et al. (2014) applied an EKF to predict the RUL. However, linearization can lead to unstable filters if the assumption of local linearity is violated, affecting the accuracy and reliability of the estimation process. The unscented Kalman filter (UKF) is also used for RUL prediction (Cui et al., 2019). While prognostics methods based on Kalman filtering approaches can provide precise predictions of the RUL, they typically assume perfect knowledge of the failure system, which is not feasible in most cases.

Another type of algorithm used for physics of failure are particle filters (PF). PF are a type of sequential Monte Carlo method that can effectively handle nonlinear and non-Gaussian degradation processes (Y. Wang et al., 2021). They represent the state of a system using a set of weighted particles, which are updated with new measurements (Elfring et al., 2021). Cai et al. (2020) proposes a similarity-based particle filter method for remaining useful life prediction with improved performance by incorporating historical knowledge and providing probabilistic RUL estimates.

The DD approach relies on the historical data of a system to predict its future state. According to Kefalas et al. (2019), data-driven approaches rely mainly on statistics or machine learning. Statistical models rely on statistical parameters to make predictions (Si et al., 2011). Xiao et al. (2018) proposes a modified duration-dependent hidden semi-Markov model for online machine health prognostics. Jia & Zhang (2019) presented a Bayesian model to reduce model uncertainty for the prediction of RUL.

Artificial Neural Networks (ANN) have been used to estimate RUL (See a review in Ge et al., 2021). Kang et al. (2021) used the Principal Component Analysis (PCA) for data preprocessing and a Multi-Layer Perceptron (MLP) for the prediction of RUL in production lines. Zhao et al. (2019) utilized a recurrent neural network (RNN) to capture temporal dependencies in the degradation process. They first evaluated the trend features to feed their model with the best trends. Zhang et al. (2018) introduced a method to predict RUL of lithium ion batteries using an LSTM.

The dependency on historical run-to-failure (RTF) data is a common issue when implementing DD approaches for RUL prediction. The availability of RTF data is limited, especially for critical components (Hakami, 2024). This limitation poses a significant challenge, as the effectiveness of predictive maintenance, condition-based monitoring, and other DD methods is highly dependent on this historical information. Without comprehensive data on past failures, models may struggle to accurately predict and prevent future breakdowns in crucial equipment.

To overcome the limitations of physical and DD approaches, (hybrid) machine learning models integrating knowledge have been developed (Karniadakis et al., 2021; Dash et al., 2022). This knowledge can be incorporated by transforming the input data, the loss function, or the model. We designate this observational bias, learning bias and inductive bias respectively (Karniadakis et al., 2021). Chao et al. (2022) presents a novel hybrid framework that combines information from physics-based performance models with deep learning algorithms for prognostics. Chen et al. (2022) proposes a model that integrates the knowledge of natural degradation of mechanical components, which is monotonic throughout the life of the bearings and is characterized by temperature signals. Y. Yu et al. (2020) introduced a physics-guided Recurrent Neural Network (RNN) for structural dynamics simulation, where they integrate the underlying physics of structural dynamics into data-enabled machine learning models for the training and prediction of ML models. Xiong et al. (2023) proposed a hybrid framework that combined the controlled physics-informed data generation approach with a deep learning-based prediction model for prognostics.

Physics-Informed Neural Network (PINN), have also been proposed as a way to implement knowledge inside a neural network. X. Liao et al. (2023) introduces a self-attention mechanism into the architecture of the neural network, allowing the mapping of raw data to a hidden state space. Dourado & Viana (2020) presented a PINN modeling approach for the estimation of bias in the prognosis of corrosion fatigue.

The physics-informed layers embed well-understood physical phenomena, and the data-driven layers are used to implement the physical processes that are difficult to model.

Despite the introduction of knowledge within the model, limitations persist (Huang & Agarwal, 2023). Although hybrid models offer the advantage of incorporating knowledge into the learning process, the interpretability of the learned representations and the basis for predictions can still be limited. This lack of transparency can cause problems, especially in critical domains. Neural network interpretability is crucial, as it allows one to explain how and why a neural network produces specific outputs, enhancing trust and understanding. Various methods aim to provide interpretability by visualizing activations, weights, or features and generating textual explanations (Linardatos et al., 2020; Fan et al., 2021).

In the context of Artificial Neural Networks (ANNs), a Modular Neural Network (MNN) can be decomposed into subnetworks based on its connectivity pattern, allowing for a more granular understanding of the network's behavior (Kirsch et al., 2018). Amer & Maul (2019) classified modularization techniques into four main classes (domain, topology, learning, and output), where each class represents the attribute of the neural network manipulated by the technique to achieve modularity. Understanding the modular structure of neural networks can provide insight into their inner workings, making them more interpretable.

This study introduces novel (modular) neuron units that integrate statistical knowledge for neural network training. The concept behind these "neuron units" is their ability to extract essential characteristics (features) from the model during training. Importantly, this feature extraction is automatically optimized by the network. Using these modular layers, we can also visualize the significance of different parts of the input signal (in this case a vibration signal) to predict the RUL.

3. METHODOLOGY

The subsection 3.1 presents our hypothesis for our research framework. Subsection 3.2 describes our approach that we used to test our hypothesis. Subsection 3.3 presents the features that we used to train the models and subsection 3.4 presents how we evaluated the different models.

3.1. Research Hypothesis

We investigated the following research question:

How can we develop (modular) knowledge-infused statistics neuron units for the prediction of RUL?

And with this question, we have the following hypothesis:

A neural network incorporating knowledge-infused statistics neuron units will present an improvement in RUL prediction accuracy.

The use of these "knowledge-infused statistics" neuron units is intended to improve the model at the level of accuracy (and interpretability). By incorporating these novel neurons into the neural network architecture, we aim to facilitate the integration of feature extraction within the model, allowing it to optimize feature selection.

In this paper, we infuse statistical knowledge into the neuron units. We develop 21 neuron units, each incorporating a different and specific statistical feature. With these neuron units we can better understand the contributions of each neuron to the overall prediction performance, enabling more informed decision-making and model refinement. In addition, we can reuse these neuron units in different tasks (Castillo-Bolado et al., 2021). The statistical knowledge that is implemented is generic (max, min, Fourier transform, etc.). We can position the neuron units in different locations within the neural network which can result in multiple model configurations.

We evaluate our hypothesis on the PRONOSTIA bearing data provided by FEMTO (Nectoux et al., 2012). This dataset constitutes a prognostics case study for bearings based on laboratory RTF vibration signals. The PRONOSTIA dataset is explained in more detail in Section 4.

3.2. Modular Approach

In this study, we use a Multi-Layer Perceptron (MLP), a type of neural network widely used in artificial intelligence (Park & Lek, 2016). The connections between neurons are defined by weights, and the output signals are determined by the sum of the inputs to the node, adjusted by a nonlinear transfer function known as the activation function.

To train an MLP, features are extracted from the data and then fed to the model. In this paper, we do feature extraction inside the network, by designing modular neurons units. By organizing the feature extraction process into modular units, we aimed to enhance the MLP's capacity to learn and extract relevant features effectively for RUL prediction. Each modular unit acts as a neuron within the MLP, focusing on capturing specific characteristics present in the input data.

For example, we have developed modular neuron units to extract fundamental features such as peak-to-peak amplitudes, frequency domain features, and vibration characteristics. In addition, we incorporated modular neuron units to extract multiple features simultaneously, allowing a more comprehensive representation of the features.

This modular design facilitates the integration of statistical knowledge into the model architecture. The neuron units are called modular because their architecture allows them to be placed in different parts of the model. As these modules are responsible for feature extraction, they are placed after the input layer, and their output is then fed into the hidden layers for further processing. Fig.2 illustrates how these modular neuron units are implemented within the MLP.

Each neuron unit has input- and output trainable weights that are optimized during the training process. The input weights equal the input size. In this case, we fed an input with 500 vibration values. We have chosen 500 for computational effectiveness. The neuron unit have 500 trainable weights. We initialize the weights with ones as values.

The neurons multiply the inputs by the weights and extract the features from these weighted inputs. We have three types of neuron unit: single feature extraction (SFE), multiple feature extraction (MFE) and weighted multiple feature extraction (WMFE).

The SFE neuron unit extracts one feature and performs a single extraction operation. For example, to extract features from the frequency domain, the vibration raw dataset is fed to the Fast Fourier transform neuron units and then given to the other neuron units to extract features. As this type of neuron unit performs a single extraction or operation, we call it Single Feature Extraction (SFE).

The MFE neuron unit integrates multiple features inside of it and extracts an array of features. In this case, there are two variants: one in which the features are then fed to the dense layers and one in which the feature arrays are multiplied by a weighted array. This array modifies the values of the features in a way that allows the model the possibility to choose which one was more impactful for RUL prediction. We designate the first version Multiple Feature Extraction (MFE), and the second one is presented as Weighted Multiple Feature Extraction (WMFE).

The first type of module (SFE) is the most simple, as the weights are updated only to extract one feature or perform one operation. In contrast, in the second one (MFE), the weights are updated to extract multiple features efficiently. The third option (WMFE) is the most complex. We created these three modules to extract multiple features classified into fundamental, frequency, and vibration features.

In this work, we focused on the integration of features inside the model; thus, we did not do feature selection. We used the model to optimize feature extraction by itself, where the implementation of trainable weights could help the model do feature selection. However, as they are modular, adding or removing features in the model can be done in a flexible way. These neuron units were not built with the integration of an activation function, as we did not want to force non-linearity on the features extracted. Instead, the dense neurons use the ReLu activation function.

In this paper, we did not study the impact of modular neuron units as the output layer. However, the output layer can be changed to adapt to any necessary prediction. For example, it is possible to implement a modular neuron unit that extracts the minimum as the last layer if the desired prediction is the minimum RUL remaining. The topic of which activation function to use remains a research question for our group.

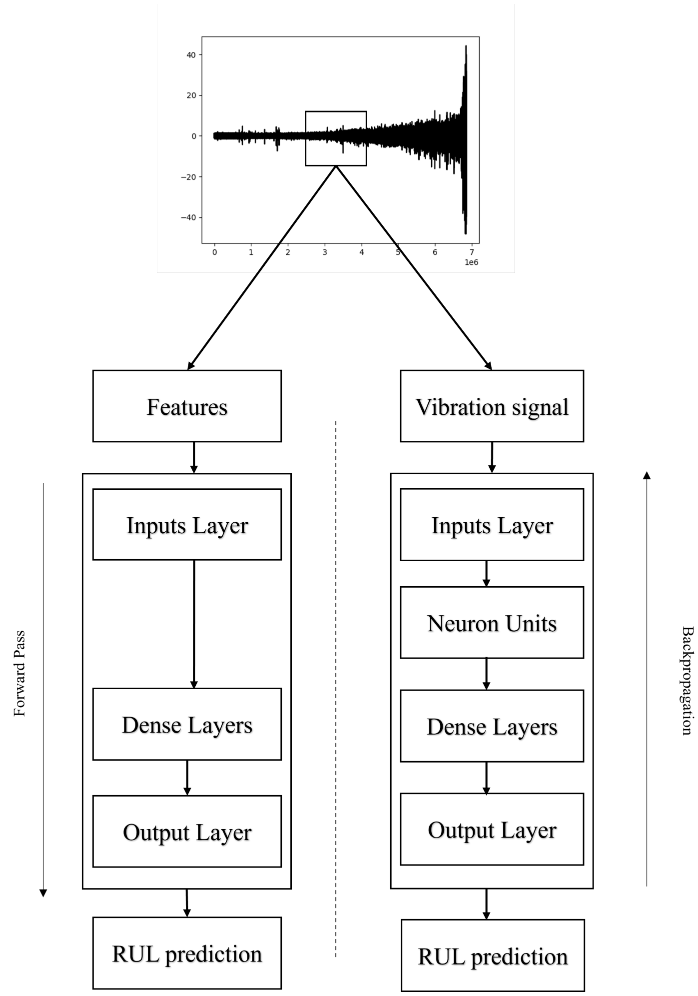
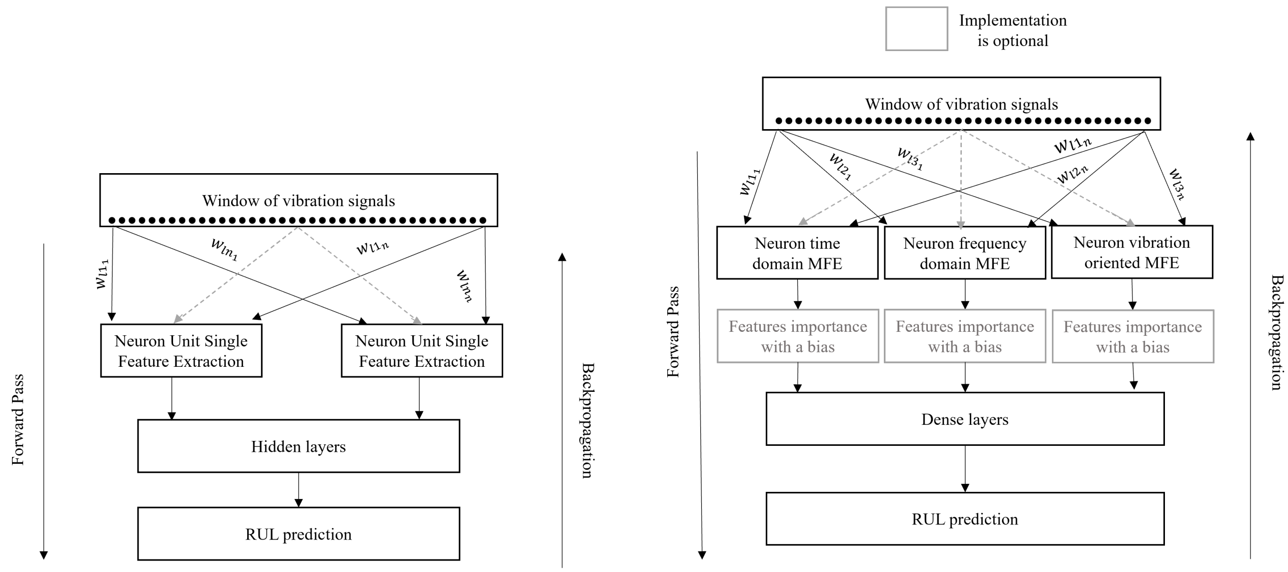


Figure 2. An MLP model without our proposed neuron units on the left and an MLP model with them on the right. The two models have the same number of dense layers with the same number of neurons. The inputs given to the model are different. In the left side model, we feed the model with the features extracted from the vibration signal, while on the right side, we give the model a raw vibration signal.

Table.1 shows the different groups and features used. Fig.3 shows the architecture of the model incorporating SFE, MFE and WMFE neuron units.

3.3. Feature Selection

We utilize multiple features to predict the Remaining Useful Life (RUL). Initially, we implemented classical statistical features, which were extracted from the raw time series data of the vibration signal. These features were termed fundamental because of their general nature. Subsequently, we implemented features in the frequency domain. Initially, we uti-



(a) SFE model

(b) MFE and WMFE model

Figure 3. Figure (a) details how a Single Feature Extraction (SFE) neuron units work inside a MLP. Each SFE has its own weights that they multiply by the inputs received. Figure (b) shows how a Weighted Multiple Feature Extraction (WMFE) and Multiple Feature Extraction (MFE) work. As in the SFE, each neuron unit has its own weights that they multiply on the inputs. However, they extract multiple features in one neuron unit, features that are weighted in a WMFE.

lized the Fast Fourier Transform (FFT) to extract frequency features. Then, we computed the magnitude by taking the absolute value of the FFT. Following the magnitude calculation, we were able to compute the Power Spectral Density (PSD) and the Power ratio of Maximum defective frequency to Mean (PMM) (J. Yu, 2011). From the PSD, we extracted the maximum, sum, mean, and the variance. The final feature type was signal features, encompassing general signal-based statistical metrics applicable to any type of signal, including vibration signals (Khlaief et al., 2019). Table 1 displays all the features used. These features were selected because they are usually used for vibration case studies (Riaz et al., 2017).

3.4. Evaluation Methodology

Since we are dealing with a small dataset, we applied a leave-one-out (LOO) strategy to evaluate the models. In the LOO strategy, we remove one of the bearings from the training set and use it as a test set, leaving us with the remaining bearing vibration signals for the training and validation sets. We employed three widely used metrics in the evaluation: the root mean square error (RMSE), the mean absolute error (MAE) and the $\alpha - \lambda$ metric. These metrics provide valuable insights into the accuracy and precision of the models' predictions. The equations for RMSE and MAE are described in Eqs.1 and 2.

$$\sqrt{\sum_{i=1}^{n}(x_i - y_i)^2} \tag{1}$$

$$\sum_{i=1}^{n}|x_i - y_i| \tag{2}$$

The third assessment method was the α-λ metric, which is a binary measure determining if a prediction at a given time t_λ falls within the α bounds. This metric measures how well predictions remain within an accuracy cone that narrows over time. We split the total time interval into 10 equal time intervals and calculated the percentage of predictions that fell between the $\alpha = 0.1$ and $\alpha = 0.2$ bounds. We have chosen two strict α to evaluate which models predictions were the most accurate, as a higher percentage of predictions inside the cone indicates a more accurate and reliable RUL prediction model.

4. Case Study

To verify the effectiveness of the proposed methodology, we use the PRONOSTIA bearing dataset. PRONOSTIA is an experimentation platform dedicated to testing and validating bearing fault detection. Fig.4 presents an overview of PRONOSTIA.

The PRONOSTIA dataset was part of the IEEE PHM 2012 Prognostic Challenge. PRONOSTIA comprises three main

Table 1. Features used and their formula

Fundamental		Frequency		Vibration	
Name	Formula	Name	Formula	Name	Formula
Maximum	$\max(x)$	Maximum	$\max(x)$	Peak to Peak	$\lvert \max(x) - \min(x) \rvert$
Minimum	$\min(x)$	Sum	$\sum_{i=1}^{n} x_i$	Cress Factor	$\frac{\max(x)}{\sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2}}$
Mean	$\frac{\sum_{i=1}^{n} x_i}{n}$	Mean	$\frac{\sum_{i=1}^{n} x_i}{n}$	Shape Factor	$\frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2}}{\frac{1}{n}\sum_{i=1}^{n} \lvert x_i \rvert}$
Variance	$\frac{\sum_{i=1}^{n}(x_i-\bar{x})^2}{n}$	Variance	$\frac{\sum_{i=1}^{n}(x_i-\bar{x})^2}{n}$	Impulse Factor	$\frac{\max(x)}{\frac{1}{n}\sum_{i=1}^{n} \lvert x_i \rvert}$
Standard deviation	$\sqrt{\frac{1}{n}\sum_{i=1}^{N}(x_i-\overline{x})^2}$	PMM	$\frac{\max(x)}{\frac{\sum_{i=1}^{n} x_i}{n}}$	Clearance Factor	$\frac{\max(x)}{\sqrt{\frac{1}{n}\sum_{i=1}^{n}\sqrt{\lvert x_i \rvert}}^2}$
Root mean square	$\sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2}$			Skewness	$\frac{\sum_{i=1}^{n}(x_i-\bar{x})^3/n}{s^3}$
				Kurtosis	$\frac{\sum_{i=1}^{N}(x_i-\bar{x})^4/n}{s^4}$

parts: a rotating part, a degradation part, and a measurement part:

- The rotating part. The asynchronous motor is the actuator that allows the bearing to rotate through gearing and different couplings. The rotation motion of the motor is transmitted through a gearbox, allowing the motor to reach a speed of 2830 rpm. The human-machine interface of PRONOSTIA allows the operator to change the operating condition.
- The degradation part. A radial force is applied to the test ball bearing, thus reducing the bearing's life duration. This radial load is generated by a force actuator in a pneumatic jack.
- The measurement part. The measurement part acquires the bearing's operation condition and the bearing's degradation. The bearing's degradation is based on two types of sensors: vibration and temperature. The acceleration measures are sampled at 25.6 kHz, and the temperature measures are sampled at 10 Hz.

The dataset consists of three different operating conditions, with a total of seventeen run-to-failure vibration signals given, including six training datasets and eleven testing datasets. The dataset is small, and the life duration of a bearing is relatively large (from 1h to 7h) for the sampling rate. In Fig.5, we present two vibration signals. We did not include all six vibration signals to improve clarity.

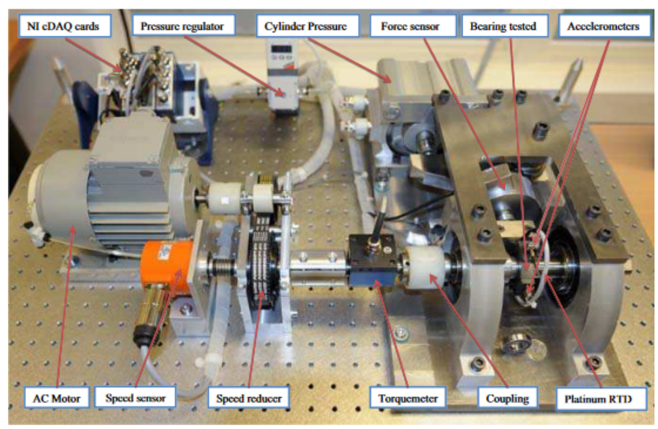


Figure 4. Overview of PRONOSTIA.

5. Results and Discussion

We can confirm our hypothesis: **A neural network incorporating knowledge-infused statistics neuron units will present an improvement in RUL prediction accuracy**. We see in Table.4 and Table.5 on the first bearing that the implementation of MFE neuron units, helped achieve the best $\alpha - \lambda$ score. The MFE model achieved the best RMSE and MAE for the first bearing, according to Table.2. We can see the predictions made by the different models for the first bearing in Fig.6. We can see clearly that the MFE model prediction is the closest one to the true RUL, followed by the baseline model, and then by the SFE and WMFE models.

For the third bearing, despite the baseline model performing better than the other model on the end-of-life, the SFE model

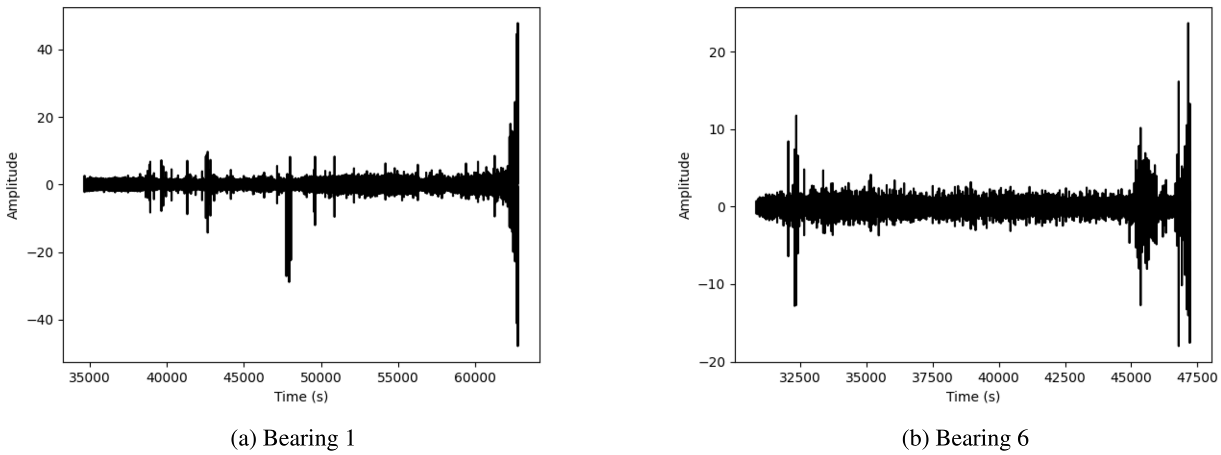


Figure 5. Vibration raw signals of the different bearings.

still performs better on the $\alpha - \lambda$ score. With an $\alpha = 0.2$ the SFE model scores a total $\alpha - \lambda$ score of 29 ± 42 while the baseline model scores a total $\alpha - \lambda$ score of 22 ± 21. However, the baseline, has the lowest RMSE and MAE.

If we compare the mean RMSE and MAE values obtained by the different models, we see that the SFE model obtains the lowest values, as seen in Table.3, whereas the baseline is the second best, the WMFE the third one, and the MFE the last one. For the $\alpha - \lambda$ we achieves the best score with the model incorporating the SFE neuron units, while the MFE model is the second best for a small α while the baseline performs better than the MFE model on a higher α.

The results demonstrate that the implementation of knowledge-informed statistics neuron units present an improvement in RUL prediction accuracy, as we have the MFE outperforming the different models in the first bearings and the SFE performing well on the other bearings. These neuron units leverage statistical properties in the model to enhance the RUL prediction.

By adding these knowledge-infused statistical neuron units, we expect to improve interpretability, as we can study the weight evolution during training. The weight evolution can guide us regarding how the model optimizes the feature extraction to predict the RUL. As we know, the model gives a weight to each vibration value given as input. We could then evaluate which part of the signal is more essential for extracting the features needed for an accurate RUL prediction.

6. Conclusion

The objective of this study was to develop a set of novel neuron units for the classical multi-layer perception (MLP). We have evaluated the importance of having these knowledge-informed neuron units inside a neural network aimed at Remaining Useful Life (RUL) prediction. The neurons were infused with statistical knowledge. Concretely, we have implemented 21 neuron units that capture time domain, frequency domain, and time-frequency domain statistical knowledge. Examples of this type of knowledge are the Fourier transform and kurtosis/skeweness.

By using the proposed neuron units, one can create a neural network that incorporates knowledge in an easy and modular way. To test our methodology, we used our network on a bearing case, PRONOSTIA, to predict the RUL. We have demonstrated that these statistical neuron units improve the model prediction compared to a baseline model with classical feature extraction.

Our results showed that the best overall model was the one that incorporated the single feature extraction (SFE) neuron units. This model was able to outperform the baseline on the overall RMSE, MAE and on $\alpha - \lambda$ accuracy. Regarding the $\alpha - \lambda$ accuracy metrics, the SFE model obtained the best overall accuracy. In contrast, the multiple feature extraction (MFE) obtained the second-best score for a strict α (0.2) and the best $\alpha - \lambda$ accuracy metric for the first bearing.

Despite the good performance of MFE on the first bearing, this approach failed to replicate this performance on the remaining bearings. Importantly, the WMFE obtained the best score at the End-of-Life. However, this model did not achieve good accuracy in the previous time intervals.

One potential reason for the underperformance of the models incorporating MFE and WMFE neuron units could be attributed to their architectural design. As they include more features inside of them, their optimization is more challenging. Another reason is that the selection of the features in-

Table 2. RMSE and MAE results for the predictions made on the different bearings by the different models. WMFE stands for Weighted Multiple Feature Extraction, MFE for Multiple Features Extraction, and SFE for Single Features Extraction.

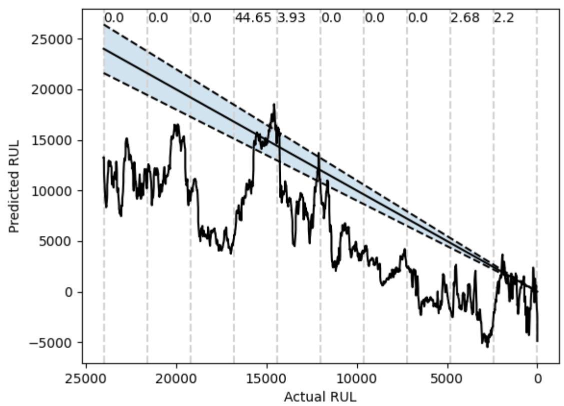
Bearings	**Model with MFE**		**Model with WMFE**		**Baseline**		**Model with SFE**	
	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE
1	**4039**	**3252**	8871	7529	10861	7956	6474	5642
2	11909	9078	5601	4873	**4177**	**3460**	4660	3638
3	7806	6745	8306	7447	3730	2636	**2890**	**2369**
4	11316	9651	7243	5229	**4728**	**3783**	7079	5513
5	16642	15659	9445	9103	6996	5514	**2724**	**2365**
6	14876	13180	9562	8503	**6305**	**5531**	8036	7103

Table 3. Mean and std of the RMSE and MAE for the different models. WMFE stands for Weighted Multiple Feature Extraction, MFE for Multiple Features Extraction, and SFE for Single Features Extraction.

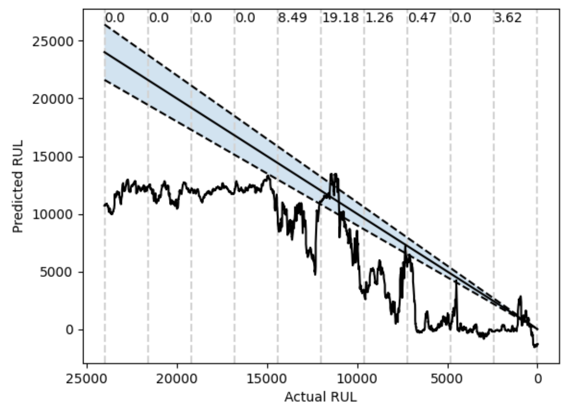
Model with MFE		**Model with WMFE**		**Baseline**		**Model with SFE**	
RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE
11098 ± 4211	9594 ± 4047	8155 ± 1378	7114 ± 1568	6133 ± 2405	4813 ± 1757	$\mathbf{5310 \pm 2036}$	$\mathbf{4438 \pm 1776}$

Table 4. Percentage of predictions within the $\alpha = 0.1$ bound. The interval 10 represents the farthest distance from the bearing failure, whereas the interval 1 represents the last interval before failure. WMFE represents the model with Weighted Multiple Feature Extraction units; SFE represents the model with Single Feature Extraction units; B represents the baseline model; and MFE represents the model with Multiple Feature Extraction units.

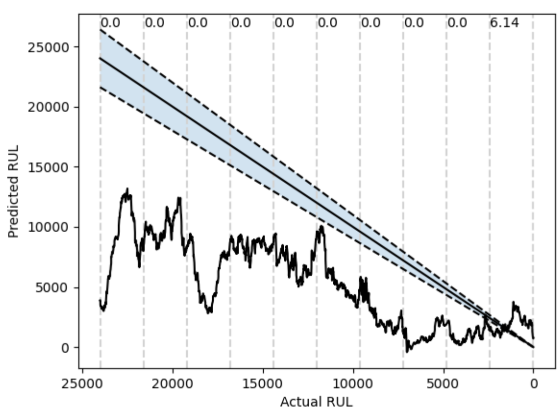
	Bearings							
	1				**3**			
Interval	WMFE	MFE	B	SFE	WMFE	MFE	B	SFE
10	0.00	0.00	0.00	0.00	0.00	0.00	8.70	**13.04**
9	0.00	**0.63**	0.00	0.00	1.09	1.09	5.98	**66.85**
8	0.00	**2.83**	0.00	0.00	0.00	0.00	5.98	**45.11**
7	0.00	**75.16**	44.65	0.00	0.54	0.00	9.78	**49.46**
6	0.00	**83.02**	3.93	8.49	0.00	0.00	**19.13**	0.00
5	0.00	**20.60**	0.00	19.18	0.00	0.00	**31.15**	0.00
4	0.00	**37.42**	0.00	1.26	0.00	0.00	**5.46**	0.00
3	0.00	0.00	0.00	**0.47**	0.00	0.00	**1.09**	0.00
2	0.00	0.00	**2.68**	0.00	0.00	0.00	0.00	0.00
1	**6.14**	2.20	4.88	3.62	0.00	0.00	0.00	0.00



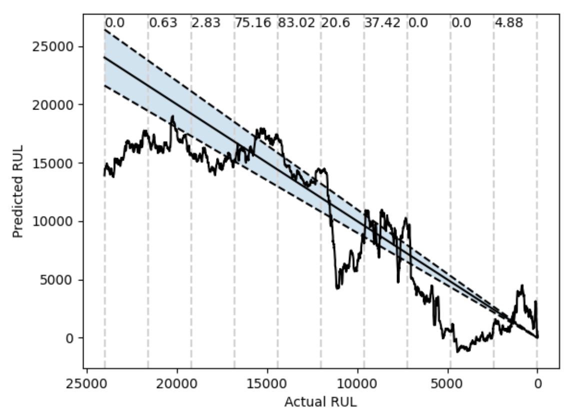
(a) Baseline model



(b) SFE model



(c) WMFE model



(d) MFE model

Figure 6. Prediction of the different models for the first bearing. The interval represented in light gray is the α bond interval, for $\alpha = 0.1$. Predictions inside this interval are considered correct. The numbers on top represent the correct percentage of prediction inside the α bound for each interval. We compare the baseline prediction with the Single Feature Extraction (SFE), the Weighted Multiple Feature Extraction (WMFE), and the Multiple Feature Extraction (MFE). For clarity of the prediction trend, we are showing here their moving average.

Table 5. Percentage of predictions within the $\alpha = 0.2$ bound. The interval 10 represents the farthest distance from the bearing failure, whereas the interval 1 represents the last interval before failure. WMFE represents the model with Weighted Multiple Feature Extraction units; SFE represents the model with Single Feature Extraction units; B represents the baseline model; and MFE represents the model with Multiple Feature Extraction units.

	Bearings							
	1				3			
Interval	WMFE	MFE	B	SFE	WMFE	MFE	B	SFE
10	0.00	0.00	0.00	0.00	2.72	0.00	15.76	**22.28**
9	0.00	**23.90**	0.00	0.00	7.07	4.35	36.41	**97.28**
8	0.00	**34.75**	0.00	0.00	0.00	0.00	20.11	**89.13**
7	0.00	**100.00**	58.18	5.66	1.09	0.00	20.65	**79.89**
6	0.63	**100.00**	9.59	20.13	0.55	0.00	**49.46**	0.00
5	0.00	27.52	1.10	**30.97**	0.00	0.00	**31.15**	0.00
4	0.31	**65.88**	0.00	2.99	0.00	0.00	**16.94**	0.00
3	0.00	0.00	0.00	**0.94**	0.00	0.00	**1.64**	0.00
2	0.16	0.00	**3.46**	0.00	0.00	0.00	0.00	0.00
1	**13.54**	9.61	4.57	6.77	0.00	0.00	**1.09**	0.00

Table 6. Total mean and std of predictions within the α bound for the models.

α	WMFE	MFE	Baseline	SFE
0.1	1.51 ± 2.21	4.50 ± 8.88	3.59 ± 3.00	**5.03**$\pm$ **6.35**
0.2	3.50 ± 5.41	7.76 ± 14.20	7.92 ± 7.13	**9.59** $\pm$ **10.35**

cluded in them was made arbitrarily. A way to improve this type of neuron unit is to have a neuron unit composed of all the features instead of splitting them into three different neuron units. This will be researched in future work. The difference between the performance of the MFE and WMFE can be explained by the weights implemented on the feature output array. As the dense layers already have their own weights that are multiplied by the inputs they receive, in this case the feature array, having a weight that does the same operation in the WMFE can be counterproductive.

The proposed models (SFE, MFE and WMFE) were constructed using a typical neuron unit (dense) from TensorFlow, which limits their ability to retain information from prior raw vibration signals and updates the weights solely for a particular time during the bearing's lifespan. As a result, these neuron units might struggle to capture complex patterns in the vibration data. Another limitation of these neuron units is that they need to adhere to the forward and backward propagation mechanisms, which can restrict the complexity of the extracted features.

Another area of optimization can be the placement of neuron units in different locations of the model. In this study, the neuron units were only added at the beginning of the model, after the input layers but before the hidden layers. We can also study the impact of our neuron units at the output layer. For example, because we are predicting the RUL, the minimum neuron unit can be used as the output layer, as the model is attempting to predict the minimum value of the RUL from the values provided as input.

More research is needed to determine whether the implementation of memory-based modular neuron units can achieve better results. Moreover, given that we are dealing with time series data, changing the model architecture could be beneficial for both the baseline and the proposed models. For instance, incorporating long-short term memory (LSTM) layers could improve the model's ability to capture temporal dependencies and patterns in the data. Additional research may impose constraints on the neuron units trainable parameters, forcing the model to extract features in a manner that differs from the existing neuron units. Given their modular nature, we might consider incorporating them not only after the input layer but also in other parts of the model architecture.

Lately, this model was trained offline, and future research can also focus on how to train these neuron units in an online case study where the data will be fed continuously to the model.

Although the primary focus of this study has been on improving prediction accuracy, we recognize the importance of interpretability and aim to leverage knowledge-infused neuron units as a stepping stone towards more transparent and explainable RUL prediction models. Future research efforts will explore techniques to further enhance the interpretability of these models, for example, by the implementation of different neuron units, tracking the weights value during training, or by creating different neurons units that can replace the usual dense layers.

The contribution of this research is the proposal of knowledge-informed neuron units infused with statistical knowledge. These neuron units implement a novel method of extracting statistical features and feeding them to a model, in which the network optimization by backpropagation has a greater impact on the statistical features extracted than if they were directly fed to the model.

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REFERENCES

Amer, M., & Maul, T. (2019). A review of modularization techniques in artificial neural networks. *Artificial Intelligence Review*, *52*, 527–561.

Cai, H., Feng, J., Li, W., Hsu, Y.-M., & Lee, J. (2020). Similarity-based particle filter for remaining useful life prediction with enhanced performance. *Applied Soft Computing*, *94*, 106474.

Castillo-Bolado, D., Guerra-Artal, C., & Hernández-Tejera, M. (2021). Design and independent training of composable and reusable neural modules. *Neural Networks*, *139*, 294–304.

Chao, M. A., Kulkarni, C., Goebel, K., & Fink, O. (2022). Fusing physics-based and deep learning models for prognostics. *Reliability Engineering & System Safety*, *217*, 107961.

Chen, X., Ma, M., Zhao, Z., Zhai, Z., & Mao, Z. (2022). Physics-informed deep neural network for bearing prognosis with multisensory signals. *Journal of Dynamics, Monitoring and Diagnostics*, 200–207.

Cubillo, A., Perinpanayagam, S., & Esperon-Miguez, M. (2016). A review of physics-based models in prognostics: Application to gears and bearings of rotating machinery. *Advances in Mechanical Engineering*, *8*(8), 1687814016664660.

Cui, L., Wang, X., Xu, Y., Jiang, H., & Zhou, J. (2019). A novel switching unscented kalman filter method for remaining useful life prediction of rolling bearing. *Measurement*, *135*, 678–684.

Dash, T., Chitlangia, S., Ahuja, A., & Srinivasan, A. (2022). A review of some techniques for inclusion of domain-knowledge into deep neural networks. *Scientific Reports*, *12*(1), 1040.

Dourado, A. D., & Viana, F. (2020). Physics-informed neural networks for bias compensation in corrosion-fatigue. In *Aiaa scitech 2020 forum* (p. 1149).

Elfring, J., Torta, E., & Van De Molengraft, R. (2021). Particle filters: A hands-on tutorial. *Sensors*, *21*(2), 438.

Fan, F.-L., Xiong, J., Li, M., & Wang, G. (2021). On interpretability of artificial neural networks: A survey. *IEEE Transactions on Radiation and Plasma Medical Sciences*, *5*(6), 741–760.

Faroughi, S. A., Pawar, N., Fernandes, C., Raissi, M., Das, S., Kalantari, N. K., & Mahjour, S. K. (2022). Physics-guided, physics-informed, and physics-encoded neural networks in scientific computing. *arXiv preprint arXiv:2211.07377*.

Ferreira, C., & Gonçalves, G. (2022). Remaining useful life prediction and challenges: A literature review on the use of machine learning methods. *Journal of Manufacturing Systems*, *63*, 550–562.

Ge, M.-F., Liu, Y., Jiang, X., & Liu, J. (2021). A review on state of health estimations and remaining useful life prognostics of lithium-ion batteries. *Measurement*, *174*, 109057.

Guo, J., Li, Z., & Li, M. (2019). A review on prognostics methods for engineering systems. *IEEE Transactions on Reliability*, *69*(3), 1110–1129.

Hakami, A. (2024). Strategies for overcoming data scarcity, imbalance, and feature selection challenges in machine learning models for predictive maintenance. *Scientific Reports*, *14*(1), 9645.

Hasib, S. A., Islam, S., Chakrabortty, R. K., Ryan, M. J., Saha, D. K., Ahamed, M. H., ... Badal, F. R. (2021). A comprehensive review of available battery datasets, rul prediction approaches, and advanced battery management. *IEEE Access*, *9*, 86166-86193. doi: 10.1109/ACCESS.2021.3089032

Huang, A. J., & Agarwal, S. (2023). On the limitations of physics-informed deep learning: Illustrations using first order hyperbolic conservation law-based traffic flow models. *IEEE Open Journal of Intelligent Transportation Systems*.

Jia, C., & Zhang, H. (2019). Rul prediction: Reducing statistical model uncertainty via bayesian model aggregation. In *2019 caa symposium on fault detection, supervision and safety for technical processes (safeprocess)* (p. 602-607). doi: 10.1109/SAFEPROCESS45799.2019.9213433

Kang, Z., Catal, C., & Tekinerdogan, B. (2021). Remaining useful life (rul) prediction of equipment in production lines using artificial neural networks. *Sensors*, *21*(3), 932.

Karniadakis, G. E., Kevrekidis, I. G., Lu, L., Perdikaris, P., Wang, S., & Yang, L. (2021). Physics-informed machine learning. *Nature Reviews Physics*, *3*(6), 422–440.

Kefalas, M., Yang, K., Apostolidis, A., Olhofer, M., Limmer, S., et al. (2019). A review: Prognostics and health management in automotive and aerospace. *International Journal of Prognostics and Health Management*, *10*(2).

Khlaief, A., Nguyen, K., Medjaher, K., Picot, A., Maussion, P., Tobon, D., … Cheron, R. (2019). Feature engineering for ball bearing combined-fault detection and diagnostic. In *2019 ieee 12th international symposium on diagnostics for electrical machines, power electronics and drives (sdemped)* (pp. 384–390).

Kirsch, L., Kunze, J., & Barber, D. (2018). Modular networks: Learning to decompose neural computation. *Advances in neural information processing systems*, *31*.

Liao, L., & Köttig, F. (2014). Review of hybrid prognostics approaches for remaining useful life prediction of engineered systems, and an application to battery life prediction. *IEEE Transactions on Reliability*, *63*(1), 191-207. doi: 10.1109/TR.2014.2299152

Liao, X., Chen, S., Wen, P., & Zhao, S. (2023). Remaining useful life with self-attention assisted physics-informed neural network. *Advanced Engineering Informatics*, *58*, 102195.

Linardatos, P., Papastefanopoulos, V., & Kotsiantis, S. (2020). Explainable ai: A review of machine learning interpretability methods. *Entropy*, *23*(1), 18.

Nascimento, R. G., & Viana, F. A. (2019). Fleet prognosis with physics-informed recurrent neural networks. *arXiv preprint arXiv:1901.05512*.

Nectoux, P., Gouriveau, R., Medjaher, K., Ramasso, E., Chebel-Morello, B., Zerhouni, N., & Varnier, C. (2012). Pronostia: An experimental platform for bearings accelerated degradation tests. In *Ieee international conference on prognostics and health management, phm'12.* (pp. 1–8).

Nguyen, D., Kefalas, M., Yang, K., Apostolidis, A., Olhofer, M., Limmer, S., & Bäck, T. (2019). A review: Prognostics and health management in automotive and aerospace. *International Journal of Prognostics and Health Management*, *10*(2), 35.

Park, Y.-S., & Lek, S. (2016). Artificial neural networks: Multilayer perceptron for ecological modeling. In *Developments in environmental modelling* (Vol. 28, pp. 123–140). Elsevier.

Ramezani, S., Moini, A., & Riahi, M. (2019). Prognostics and health management in machinery: A review of methodologies for rul prediction and roadmap. *International Journal of Industrial Engineering and Management Science*, *6*(1), 38–61.

Riaz, S., Elahi, H., Javaid, K., & Shahzad, T. (2017). Vibration feature extraction and analysis for fault diagnosis of rotating machinery-a literature survey.. Retrieved from `https://api.semanticscholar.org/CorpusID:40027868`

Si, X.-S., Wang, W., Hu, C.-H., & Zhou, D.-H. (2011). Remaining useful life estimation–a review on the statistical data driven approaches. *European journal of operational research*, *213*(1), 1–14.

Singleton, R. K., Strangas, E. G., & Aviyente, S. (2014). Extended kalman filtering for remaining-useful-life estimation of bearings. *IEEE Transactions on Industrial Electronics*, *62*(3), 1781–1790.

Sobie, C., Freitas, C., & Nicolai, M. (2018). Simulation-driven machine learning: Bearing fault classification. *Mechanical Systems and Signal Processing*, *99*, 403–419.

Wang, J., Li, Y., Zhao, R., & Gao, R. X. (2020). Physics guided neural network for machining tool wear prediction. *Journal of Manufacturing Systems*, *57*, 298–310.

Wang, Q., Xu, K., Kong, X., & Huai, T. (2021). A linear mapping method for predicting accurately the rul of rolling bearing. *Measurement*, *176*, 109127.

Wang, Y., Peng, Y., & Chow, T. W. S. (2021). Adaptive particle filter-based approach for rul prediction under uncertain varying stresses with application to hdd. *IEEE Transactions on Industrial Informatics*, *17*(9), 6272-6281. doi: 10.1109/TII.2021.3051285

Willard, J., Jia, X., Xu, S., Steinbach, M., & Kumar, V. (2022). Integrating scientific knowledge with machine learning for engineering and environmental systems. *ACM Computing Surveys*, *55*(4), 1–37.

Xiao, Q., Fang, Y., Liu, Q., & Zhou, S. (2018). Online machine health prognostics based on modified duration-dependent hidden semi-markov model and high-order particle filtering. *The International Journal of Advanced Manufacturing Technology*, *94*, 1283–1297.

Xiong, J., Fink, O., Zhou, J., & Ma, Y. (2023). Controlled physics-informed data generation for deep learning-based remaining useful life prediction under unseen operation conditions. *Mechanical Systems and Signal Processing*, *197*, 110359.

Yu, J. (2011). Local and nonlocal preserving projection for bearing defect classification and performance assessment. *IEEE Transactions on Industrial Electronics*, *59*(5), 2363–2376.

Yu, Y., Yao, H., & Liu, Y. (2020). Structural dynamics simulation using a novel physics-guided machine learning method. *Engineering Applications of Artificial Intelligence*, *96*, 103947.

Zhang, Y., Xiong, R., He, H., & Pecht, M. G. (2018). Long short-term memory recurrent neural network for remaining useful life prediction of lithium-ion batteries. *IEEE Transactions on Vehicular Technology*, *67*(7), 5695-5705. doi: 10.1109/TVT.2018.2805189

Zhao, S., Zhang, Y., Wang, S., Zhou, B., & Cheng, C. (2019). A recurrent neural network approach for remaining useful life prediction utilizing a novel trend features construction method. *Measurement*, *146*, 279–288.

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