Xu, Z, Bashir, M, Liu, Q, Miao, Z, Wang, X, Wang, J and Ekere, NN

A Novel Health Indicator for Intelligent Prediction of Rolling Bearing Remaining Useful Life based on Unsupervised Learning Model

Article

Abstract: Construction of an intelligent Health Indicator (HI) that can accurately describe the degradation process is a prerequisite to accelerating the development of an automatic remaining useful life (RUL) prediction model for rotating machinery such as bearings. This research aims to develop an intelligent model that can predict the remaining useful life of bearings without physical human intervention. The intelligent HI model, named Multi-Scale-Multi-Head Attention with Automatic Encoder-Decoder (MSMHA-AED), is constructed based on an unsupervised neural network model and can extract multi-scale coded features of bearings from raw vibration signals. The model is fitted with an ensemble health indicator designed to fuse the metrics of healthy and damaged coded features of bearings to create a more reliable health indicator for RUL prediction. The intelligent HI model is subsequently used to develop three neural network-based prognostic models to examine the reliability of the proposed health indicator in RUL predictions. Using the prognostic model, the magnitude of degradation in the bearings is estimated by measuring the similarity between the coded features of healthy and unknown damaged bearings using three measurement methods. It was found that the similarity measured by the Wasserstein distance method offers more suitable results for damage quantification due to its unique capability of measuring health indicators in more monotonic condition. It is also found that the proposed model is less prone to giving false alarms even when used to detect degradation for the first time. All performance indicators of the proposed approach show better and more robust metrics than the state-of-art methods.

Keyword: Health Indicator; Prognosis; Remaining useful life prediction; Automatic Encoder-Decoder

Nomenclature

HI	Health indicator
RUL	Remaining useful lifetime

AED	Auto encoder-decoder
DCN	Deep convolutional neural network
MSMHA	Multi-scale convolutional revolution neural network with multi-head attention
MSCNN	Multi-scale convolutional neural network
CNN	Convolutional neural network
BILSTM	Bidirectional long short-term memory
CNN-BILSTM	Convolutional neural network-bidirectional long short-term memory
GAN	Generative Adversarial Network
DLN	Deep Learning Network
D_{health}	Dataset, consisting of vibration signals X_{health}
X_{health}	The health signal in a health condition within a domain $\mathcal{X}_{health}$
$\mathcal{X}_{health}$	Healthy domain
Z_{health}	Coded features generated by the encoder
f_{enc}, θ_{enc}	Encoder and the parameters of the encoder
$\hat{X}_{health}$	The generated signal
f_{dec}, θ_{dec}	Decoder and the parameters of the decoder
X_{damage}	The damage signal in damage condition within a unknown domain $\mathcal{X}_{damage}$
$\mathcal{X}_{damage}$	Unknown domain
$Multihead(\mathrm{Q}, \mathrm{K}, \mathrm{V})$	Multi-head attention module, K for Key, Q for Query, V for Value
Q, K, V	The inputs of the multi-head attention
$\mathrm{softmax}(\cdot)$	A activation function
RMSE	Root mean squared errors
MSE	Mean squared errors
ADAM	An optimizer of parameters derived from adaptive moment estimation
ReLU	A kind of activation function
DAQ	Data Acquisition system

1. Introduction

Rotating machinery has been widely used in aerospace, energy, and manufacturing industries as power drive components for process and system. Understanding the evolution of damages in rotatory machinery is crucial in ensuring that equipment or system's operation and maintenance (O&M) are proactively managed to reduce downtime. This is an essential requirement to ensuring that equipment or system continuously remains in good working condition and it is able to remove any potential occurrence of damages to property and personnel caused by unexpected failures (Rinaldi et al., 2021) (Shields et al., 2021). These damages generally arise from progressive components degradation or failure that occurs during the operating lifecycle of the machinery. Although degradation in any machinery components is considered as unacceptable, they still exist because most of the components experience fatigue due the cyclic nature of their operations. Fatigue is a fundamental driver of failure that ultimately impairs the operational efficiency of a machinery production and output (Farhan et al., 2022). The resulting impact of failures from these impairments is an expensive maintenance and operational cost of the equipment, especially the bearings (Wanget al 2022).

Structural Health Monitoring (SHM) and condition-based maintenance offer a path that ensures the rotating machinery does not experience major failure as a result of a gradual or rapid damage accumulation, thereby preventing accidents and improving reliability (Zhao et al. 2021)(Malekimoghadamet al. 2021). Consequently, developing automatic and robust monitoring and prognostic techniques is significant to delivering a reliable and effective maintenance approach for the bearings. This is because of the impact that such techniques could have on cost reduction for maintenance and in accelerating the uptake of rotating machinery technologies (Wang et al. 2020)(Nejad et al., 2014).

As important mechanical components that transmit rotation, bearings are vital in mechanical equipment and systems. Development of maintenance strategies based on prognostic health management method could richly enhance the lifecycle cost savings of the machinery. Generally, in condition-based maintenance the prognostic approach in bearings maintenance management relies on effective damage diagnosis and accurate remaining useful lifetime (RUL) prediction. This is because RUL is the core of the decision-making process in bearing maintenance (Zhai & Ye, 2017). Hence, accurate RUL prediction of components arising from defects can help maintenance engineers plan suitable maintenance strategies in advance and reduce maintenance costs that guarantee the machine 's reliability and safety (Nuñez and Borsato 2018, Wei et al. 2019).

There are two broad classification of RUL prediction models that are widely in use, namely the physic-based model and data-driven model (Liet al. 2018; Wang et al. 2020). The physic-based model needs significant prior knowledge and experiences due to certain limitations which have already been identified. For this reason, the focus of modern RUL studies has been gradually moving from physics-based towards a data-driven model (Singletonet al. 2015). Application of a data-driven model to conduct health prognosis of engineering system has been gaining considerable popularity due to its importance in facilitating the development of an intelligent prognostic management system. Several data-driven prognosis methods have been used in studies on RUL prediction of bearings (Fan et al., 2019). Outcomes of these studies, if combined with rational decision-making systems, can be used to develop an intelligent system for RUL prediction (Shafiee & Animah, 2022). Therefore, one of the motivations of this study is to develop intelligent and automatic decision-making models for real-time and virtual management of the rotating machinery (Zhao et al. 2019).

In the studies on data-driven RUL prediction models for the bearings, traditional processes of RUL prediction are followed (Lei et al., 2018). The health and degradation indicators in these processes are manually constructed using complex signal processing techniques (Zhouet al. 2016). The procedure for constructing the RUL prediction model consists of data acquisition and pre-processing, extraction and construction of health or degradation indicators, and RUL estimation and health prognosis. For example, Yang et al. (2022) calculated the degradation indicator of a rolling bearing based on an improved independent component analysis and Mahalanobis distance to predict its RUL, which is examined by experiments to prove its accuracy and reliability. Li et al., (2017) used a general mathematical morphology particle theory to construct a degradation indicator that can represent the degradation process of bearings. Panet al.,(2010) estimated the degradation process of bearings by combining the lifting wavelet packet decomposition and fuzzy c-mean to construct the health indicator for bearings' RUL prediction. Rai and Upadhyay (2017) applied empirical mode decomposition (EMD) and k-medoids clustering to assess the degradation performance of the bearings and obtained a degradation indicator for RUL prediction. Wang and Shen (2016) introduced an equivalent cyclic energy indicator as the degradation indicator for the bearing's RUL estimation. All the aforementioned studies share a common feature of being limited by the system's experiences when setting suitable parameters for extracting optimal features. These parameters are required in constructing the health and degradation indicators. While the health indicator is the core of the data-driven based RUL prediction model, the quality of a manually constructed health and degradation indicator is easily affected by both environment and users' experiences. This could be problematic to its reliability and with huge consequence on accuracies of the eventual RUL prediction (Wang et al. 2021; Chen et al. 2020). Thus, it is necessary to develop an accurate, effective, and reliable method for obtaining the health and degradation indicator to reduce the O&M cost of a machinery.

Neural Network (NN) based models such as Deep Learning Networks (DLN) and Convolutional Neural Networks (CNN), have emerged as credible alternatives to traditional methods and they are widely used in the areas of image processing, pattern recognition and data prediction. Techniques developed based on these models have been applied to fault diagnosis and prognosis due to their strong capability in automatically extracting damage or fault features (Zhiyi et al. 2020; Zhao et al. 2021; Li et al. 2019; Ismail et al. 2020; Xu et al. 2021). However, the DLN technique still faces some challenges and limitations in prognostic applications, especially in producing a robust health and degradation indicator, including the following:

(1) The construction of a health indicator (HI) for the bearings still relies on prior knowledge by using either a linear or nonlinear label in which the total degradation data is used to label the RUL to obtain the HI. However, in the real industrial application, there is near absence of or just limited fatigue dataset available for training a DLN model. Also, there is insufficient life-cycle dataset of the bearings available in the public domain.

(2) The possibility to successfully collect training and test data from the same sensors is remote. This is because it is very difficult for the data obtained from numerical simulations of the operating conditions to be the same as the data distribution from real equipment operations. For example, a simple unsupervised learning-based prognostic approach, which lacks the capability to capture multi-

scale information, does not work in a typical known operating environment. Thus, designing and building a robust and reliable HI model is a prerequisite to developing an automated intelligent RUL prediction for the bearing maintenance.

Therefore, in dealing with the above challenges, this study is inspired by the possibility to achieve a remarkable prognosis using deep neural networks with a rational decision-making model that reduces human interface in RUL prediction. Consequently, this study has developed a high-performance encoder-decoder, named "Multi-Scale Revolution Convolutional Neural Network with Multi-Head Attention Automatic Encoder-Decoder (MSMHA-AED)", to reconstruct a HI for intelligent bearings RUL prediction. This robust auto-encoder-decoder offers an unsupervised learning framework where the training data relies only on the healthy condition data. In contrast to existing supervised learning approaches, no labelling of degraded data is required. In this study, health indicators are constructed by measuring the similarity between coded features of healthy and unknown damaged condition of bearings. The main motivation for adopting this approach is to achieve rapid improvement in the quality of the coded features and guarantees the reliability of health indicators. Consequently, a feature fusion method is proposed to fuse the multiple health indicators produced by MSMHA-AED with the aim of improving its ability to predict monotonicity in the health indicators. The MSMHA-AED model is trained by only using the normal (healthy) data, an important capability that minimizes prognostic latency and false positive results. Following optimization of the MSMHA-AED model parameter, Wasserstein distance is added to the proposed model to improve its stability and reliability in determining the first prediction point (FPT). The health indicator of the bearing works by invoking the MSMHA-AED model-based approach to use the Wasserstein distance to measure the similarity between the test coded features and the baseline coded features. In the RUL prediction, the reliability of the RUL prognosticator developed by three models including CNN, BILSTM and CNN-BILSTM are examined. The health indicator constructed by the proposed approach are used as the input features to train the predictor. Consequently, the main contributions of this research are summarized below.

1) After considering the multiscale information present in typical multi-scale resolution features, this research developed an unsupervised approach based on DLN/CNN, named MSMHA-AED to intelligently extract features for the purpose of recording the health state of a bearing in the coded features. In the model, self-attention mechanism is added to enhance the quality of the coded features, the aim of which is to improve the reliability and accuracy of the constructed health indicators.

2) The research investigated the influence of three similarity functions on the reliability of health indicator construction for intelligent RUL prediction of a rotating engineering system. It is found that using Wasserstein distance to measure the similarity offers more reliable results than other measurements techniques. Hence, a novel construction approach for an automatic health indicator has been proposed by combining the excellent capability of MSMHA-AED with the similarity indicating capability of Wasserstein distance.

3) This study uses an accelerated bearing failure experimental data to examine the performance of the proposed health indicator construction method. The superiority of the health indicator is compared with state-of-art methods. The reliability of the application of this health indicator in predicting the RUL of bearings is examined by three neural network models. The whole prognostic processes, which consist of the HI construction and RUL prediction, are fully integrated into the intelligent system framework without any need for human experience or interference as opposed to the

current practice that relies on various degree of human interface. In addition, A novel prognosticator developed based on Bayesian Neural Network is used to predict the RUL with uncertainty. This can provide more information and establish confidence level for reliable maintenance decision-making.

Following an introduction in Section 1, the rest of the paper is organized as follows. Section 2 reviews the related works while Section 3 presents details of the proposed method. Section 4 presents and discusses both quantitative and qualitative experimental results as part of the validation process. Section 5 concludes the outcome of the research.

2. Related Works

Several researchers have used DLN-based methods to construct health and degradation indicator. Cheng et al., (2021) used a CNN to extract degradation indicator from raw signals with a complete ensemble empirical mode-based label. Guo et al., (2018) adopted a CNN with linear labels to supervise the network and construct the health indicator. As a similarity work, Guo et al., (2017) used a Recurrent Neural Network (RNN) with kurtosis-based nonlinear labels to construct the degradation indicator for bearing RUL prediction. Zhao et al., (2021) used Guo's study as a basis for utilizing the advantages of CNN capabilities for feature extraction to construct health indicator for a bearing RUL estimation. Chen et al., (2020) studied different types of RNNs to extract degradation features only using a prior experience to construct the HI. However, in all the above studies the HI was constructed by implementing supervised NN learning models in which the processes of feature extraction incorporate prior knowledge. Outcomes of these studies do not qualify them to be called a fully automated and intelligent HI because the prior knowledge is manually obtained from a labelled dataset.

Some researchers have attempted to expand the knowledge frontiers of this subject by investigating the construction of HI based on unsupervised learning. Peng et al., (2019) combined particle filter and Deep Belief Network (DBN) to establish the HI of bearings and predicted their RUL. Dai et al., (2020) used Generative Adversarial Network (GAN) to achieve a bearing monitoring without any manual supervision. Dai et al., (2020) used a multi-scale network with an attention mechanism to extract features and predicted RUL. Suhet et al. (2022) designed a novel GAN with a U-net architecture to deal with the prediction of bearing RUL. In order to enhance the performance of convolutional networks and make them more powerful in performing system prognosis, Guo et al. (2022) introduced a multi-scale feature extraction process in an auto encoder-decoder to achieve the development of an unsupervised HI. This study pointed that the feature fusion of the decoder had a significant effect on the performance of the prognostic model.

Although a supervised DLN model can be quickly adapted to fit degradation indicators, the labeling process is time-consuming and labor-intensive. This approach is almost unsuitable for industrial-scale application because it is difficult to supervise and label all data in a practical engineering application. Notwithstanding, the unsupervised DLN models are dedicated to learning and establishing the response patterns of the bearing in the healthy state. Consequently, it is still possible to construct a HI by comparing the similarity between the baseline and test coded features data in which the challenges of these methods are the robustness of an unsupervised DLN model and the performance of the chosen similarity function.

3. Baseline Method

The assumption of this method is that the similarity between the healthy and damaged data raises with increase in damage magnitude. The similarity between the raw healthy and damaged vibration signals can quantify the HI. However, some unclear factors, such as unstable rotational speed and noise in the signals, often lead to less robustness of the constructed HI. Thus, in this study, a Neural Network (NN) based Auto Encoder-Decoder (AED) is designed as a communication tool for the HI construction of the rolling bearing. The framework of this baseline model (D. Chen et al., 2021), shown in Figure 1, is intended to describe the task of this study.

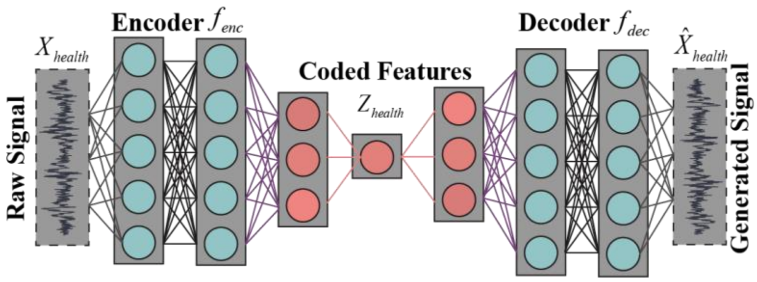


Figure 1 The DCN-AED architecture

As shown in Figure 1, The dataset D_{health} consists of vibration signals X_{health}, which denotes a health condition within the domain $\mathcal{X}_{health}$. The training data ($X_{health} = \{x_{health}^i\}_{i=1}^N$) sampled from $\mathcal{X}$ are sent into the encoder f_{enc} to obtain the coded features $Z_{health} = f_{enc}(X_{health} \mid \theta_{enc})$, where $Z_{health} = \{z_{health}^i\}_{i=1}^N$, and $z_i = f_{enc}(x_{health}^i \mid \theta_{enc})$. The coded features are fed into the decoder, f_{dec} , to reconstruct the $\hat{X}_{health} = \{\hat{x}_{health}^i\}_{i=1}^N = f_{dec}(Z_{health} \mid \theta_{dec}) = f_{dec}(z_{health}^i \mid \theta_{dec})$. The mean Squared error (MSE) is used as a loss function to minimize the distance between the X and $\hat{X}$ for parameters optimization. In the model training process, the coded features Z_{health} are extracted by the encoder f_{enc} , which consists of a series of convolutional kernels, batch normalization and ReLU activation from the input X_{health}. The coded features Z_{health} are resized by the decoder f_{dec} that consists of sets of deconvolutions, batch normalization and leaky ReLU activation to rebuild the $\hat{X}_{health}$. The parameters of the DCN-AED model are optimized by gradient descent optimizer based on the Mean Squared Error (MSE) function as $L(X_{health}, \hat{X}_{health}) = \frac{1}{N}\sum_{i=1}^{N}(X_{health} - \hat{X}_{health})^2$. In view of an optimized DCN-AED model, the parameters of encoder are θ_{enc} and the parameters of decoder are θ_{dec}. The HI is the similarity between the coded features Z_{health} and the damage coded features $Z_{damage} = \{z^i_{damage}\}_{i=1}^{N}$, where $z_{i\ damage}^{N} = f_{enc}(x_{i\ damage}^{N} \mid \theta_{enc})$, $X_{damage} = \{x^i_{damage}\}_{i=1}^{N}$ is obtained from the unknown vibration signals in the domain $\mathcal{X}_{damage}$. The similarity is calculated by the distance function, $Similarity = \mathrm{Distance}(Z_{health}, Z_{damage})$. Where $\mathrm{Distance}(\cdot)$ is a function used to calculate the difference between the two inputs, which can be a function for any distance.

4. Proposed Method for HI

4.1 Convolutional Encoder

Convolutional encoder is used to encode the spatial patterns of raw signals. More specifically, the vibration features are directly collected from the sensor placed on a bearing, as 1D tensor $X^{t,0} \in \Re^{n\times1\times1}$, which is fed into convolutional layers. $X^{t,l-1} \in \Re^{n_{l-1}\times1\times d_{l-1}}$is the advanced feature in the $(l-1)^{th}$ layer, which is an output of $(l)^{th}$ and it is given by Equation 1:

$$X^{t,l} = f(W^l \times X^{t,l-1} + b_l) \tag{1}$$

where $\times$ is the convolutional operation, $f(\cdot)$ is the activation function, $W^l \in \Re^{k_l\times d_{l-1}\times d_l}$ which includes d_l convolutional kernels with size $k_l \times d_{l-1}$. $b_l \in \Re^{d_l}$ is the bias of the output $X^{t,l} \in \Re^{n_l\times1\times d_l}$, The activation function is denoted by ReLU.

4.2 Self-attention mechanism for multi-scale revolution features

Motivated by the work of Zhang et al. (2019), this study adopted the multi-scale revolution features to improve the performance of the reconstruction model. Thus, the process requires the application of self-attention modules to generate weighted coded features based on the deep features respectively from the encoder and decoder. The process for coded features relies on the given advanced features $X^{t,l}$ from the l^{th} encoder f_{enc}^{i} and the last advanced features $\hat{X}^{t,l}$ from $l-1^{th}$ decoder f_{dec}^{i-1} to update the weighted features $Multihead(Q,K,V)$, where Q is the features in the decoder f_{dec}^{i-1}, K and V are the features in encoder f_{enc}^{i}. Figure 2 illustrates the deep multi-scale revolution features modeling procedure. The weighted coded features in each self-attention module are used for the construction of health indicator.

4.3 The MSMHA-AED model

An ‘end to end’ multi-scale CNN network embedded in the Multi-Head Attention Mechanism is described in this section. The development of the MSMHA-AED algorithm consists of four steps. The *first step* is the development of the multi-scale resolution extractors, which are constructed using different depths of convolutional layers. The *second step* deals with the development of the spatial information collection modules in which advanced features are encoded using the designed module and based on self-attention mechanism. A key function of this step is to enable it to consider the correlation between the encoded and decoded features using the multi-head attention mechanism. The *third step* is the application of advanced features processor of the health data after encoding. In this step, the Multi-Head Attention-based modules are called to invoke the baseline coded features, which are transmitted to the convolutional decoder for processing. The residual between the reconstructed and real signals is used to construct the loss function. The *last step* is to measure the similarity between the healthy and damaged attention of weighted coded features.

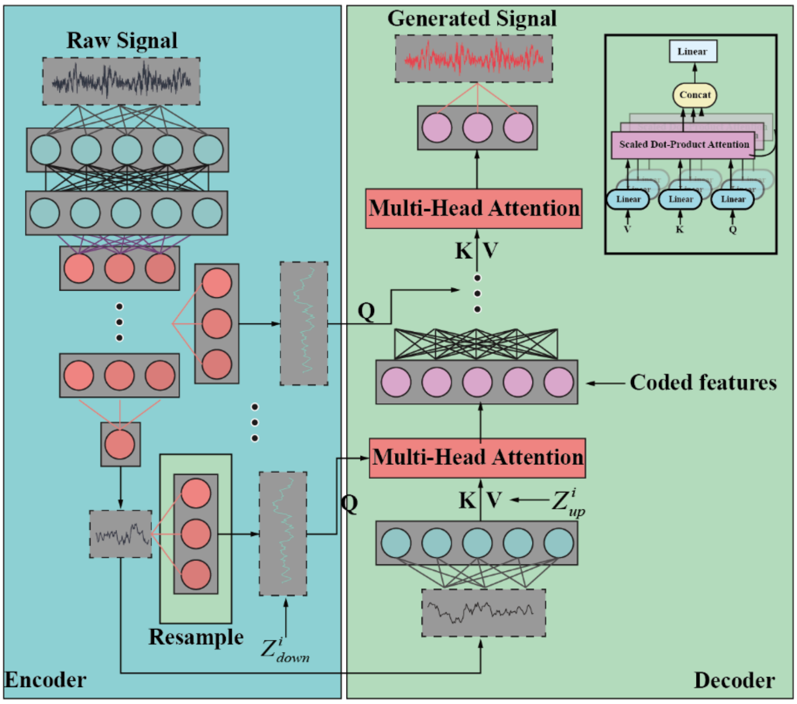


Figure 2: The framework of MSMHA-AED for HI construction

Figure 2 presents the framework of MSMHA-AED. In order to enhance the performance of the HI, the number of convolution filters in the down sampling process is increased from 16 to 512. while each down sampling process is used to reduce the length of the advanced sequence by half. As shown in Figure 2, The process assumes that the feature corresponding to each round of the up-sampling is Z^i_{up}, and the resampling feature connected to the down-sampling is Z^i_{down}. By considering Z^i_{up} as the Key K, Value V, and resampling Z^i_{down} as the Query Q, the attention features can be obtained through the Multi-Head Attention mechanism, and the attention features of each layer will be regarded as the coded features of different scales. The head attention is computed as $\mathrm{Attention(Q,K,V)} = \mathrm{softmax}(\frac{QK^T}{\sqrt{d}})V$,where d is the dimension of the Q, K and V. The training loss function adopts the mean Squared errors (MSE), and the optimizer adopts the ADAM gradient search method, while a maximum of 500 epochs are used in the training phase.

4.4 Ensemble Healthy Indicator

The main function of the HI is to evaluate the degradation of the bearings. The degradation of the bearing may lead to a higher vibration induced by fatigue or manual creaks of a bearing, which means that the current state will have distinct dynamic response in the normal state. In this study, a robust encoder-decoder is proposed as a component of MSMHA-AED to characterize the metric of bearing degradation by using the similarity between the encoded information of the existing state (possibly a damaged condition) and the healthy state. In Figure 2, using self-attention mechanism is proposed to obtain the weighted coded features. The procedure assumes that there are k times down-samplings in the encoder and k-1 coded features within the attention. These coded features with attention weights are used to construct the health indicators, giving the total MSMHA-AED the ability to the construct k-1 health indicators. The constructed k-1 health indicators are developed to have different characteristic scales. Therefore, a fusion method is proposed to fuse the k-1 health indicators to achieve the desired robustness.

The pseudo-code of the construction method for the proposed health indicator is given as follows: The code consists of three parts: modelling, similarity measurement and multi-scale indicators fusion.

Algorithm 1: Multi-Scale revolution Convolutional Neural Network with Multi-Head

Attention Automatic Encoder-Decoder for HI construction

1. Obtain parameters $\boldsymbol{\theta}$ including weights and bias of the MSMHA-AED **model $\boldsymbol{G}$**

Input: $X^{t,0} \in \Re^{n\times1\times1}$ and initial parameters θ

Output: $\hat{\theta}$ **-** the estimation of the MSMHA-AED model

While $i \le Epochs$ (*i.e. number of epochs*) **do**

Repeat

$\theta \leftarrow$ Update parameter in model G via Adam Descent

Until *convergence of* θ

End

End

2. Estimate the Similarity function between coded-features of baseline $\hat{\boldsymbol{X}}_{base}$ and current $\hat{\boldsymbol{Y}}_{current}$

Input: $\{X_{base}, X_{current}\} \in \Re^{n\times1\times1}, G$, Similarity defined by distance funcion.

Output: D_l^k

Estimation the coded features: $\hat{X}_{base}^{d,l} = G(\hat{\theta} \mid X_{base})$ and $\hat{Y}_{current}^{d,l} = G(\hat{\theta} \mid X_{current})$

Estimate the Similarity between coded features with different multi-scale features $D_l^k = \frac{1}{l}\sum_{i=1}^{l} \text{Similarity}(\hat{X}_{base}^{d,i}, \hat{Y}_{current}^{d,i})$ as *HI* under each scale *k*

End

3. Multiple health indicators fusion

Input: $D_i^k, i \in [1,n]$, i represents the i^{th} sample, total times of sample is *n*.

Output: $\mathbf{HI}_i$

For $i = 1 : n-1$

$\mathbf{HI}_i = \min(D_i^1, \dots D_i^k)$ **where** $D_i^k > D_i^{k-1}$

$\mathbf{HI}_i = \max(D_i^1, \dots D_i^k) + [\max(D_i^1, \dots D_i^k) - \min(D_i^1, \dots D_i^k)] / k - 1$ **where** $D_i^k <= D_i^{k-1}$

End

End

4.5 Prognosticator Training

The combination of the Convolutional Neural Network and Bi-directional LSTM network (CNN-BILSTM) model, as the predictor for instance (The predictor could be any neural model to map the relationship between the health indicator and RUL labels), is used to estimate the RUL of the bearings, which takes the RUL estimation as a regression problem. The complexity of the CNN-BILSTM network for RUL estimation is lower than existing methods because the network only maps the features between the constructed health indicators that have been constructed by MSMHA-AED and RUL labels rather than by directly mapping the actual signals and the RUL labels. The HI constructed via the proposed MSMHA-AED method is the input features of the CNN-BILSTM, and their corresponding RUL is labeled to supervise the network in the training process. The procedure for training the CNN-BILSTM model for regression in the RUL prediction with MSMHA-AED-based health indicator is summarized in Algorithm 2. Furthermore, a novel prognosticator is developed based on a fusion of CNN-BILSTM with Bayesian Neural Network. The prognosticator is fitted with uncertainty quantification capability. The parameters of the novel prognosticator are optimized via gradient descend in which the variational inference is used to approximate the prior and posterior distribution of the model parameters. Kullback–Leibler (KL) divergence is adopted in the construction of the loss function.

Algorithm 2: RUL prediction of the bearings based on CNN-BILSTM model with MSMHA-AED -based health indicators

1. The CNN-BILSTM Network Training for Prognosis H as the RUL Predictor

Input: $\{XTrain, YTrain\}^N$, Initial parameters η, $XTrain$ is the HI constructed by MSMHA-AED

Output: $\hat{\eta}$ **-**CNN-BILSTM Network parameters

While $i \le Epochs$ (*i.e. number of epochs*) **do**

Repeat

$\eta \leftarrow$ Update parameter in model H via Adam

Descent

Until *convergence of* η

End

End

2. RUL estimation based on CNN-BILSTM Predictor

Input: $\{X\}^N$, G and H

Output: $\hat{y}$

for n = 1:N do

Estimation the coded features: $\hat{X}_{current} = G(\hat{\theta} \mid X_{current})$,

Estimate the Similarity between coded features to get the multiple indicators D_l^k and the ensemble health indicator *HI to be the* $XTest_n, n \in N$

Estimate RUL: $y_n = H(\hat{\mu} \mid XTest_n)$

End

End

The whole process of simulating the RUL including HI construction and RUL estimation for the bearing prognosis is shown in Figure 3.

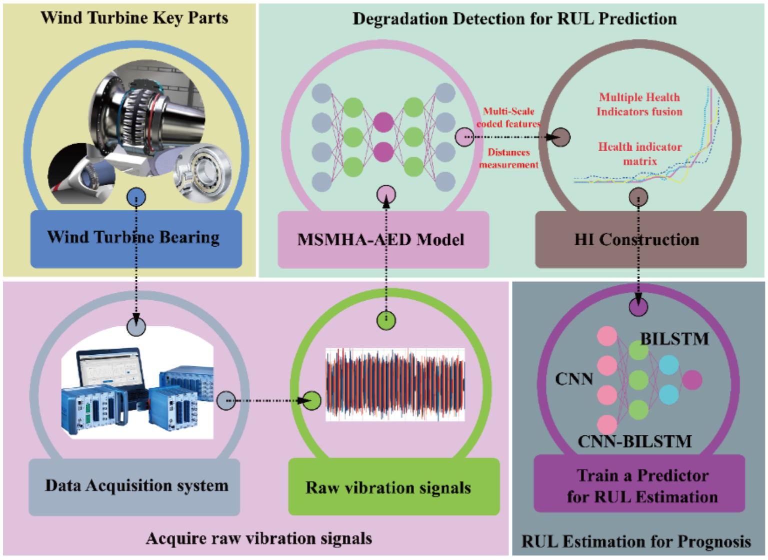


Figure 3: The framework of the proposed bearing prognostic approach using the MSMHA-AED model

As shown in Figure 3, the proposed approach uses a data acquisition system to obtain the raw vibration signals from the bearing key components, such as bearings, for structural health monitoring. The proposed MSMHA-AED model is used to record the coded features of the bearing in different health states. The similarity is calculated by the distance function, which measures and compares the distance between the coded healthy features and the current state coded features. This is used to construct the health indicator for monitoring the bearing degradation process. Multiple HIs are constructed using a high-dimension features matrixes to feed into a neural network to train the predictor for RUL prediction. The proposed approach, from the beginning of health indicator construction to the RUL estimation, is conducted without any manual interface involved.

5. Experimental verification and discussion

5.1 Experimental Details

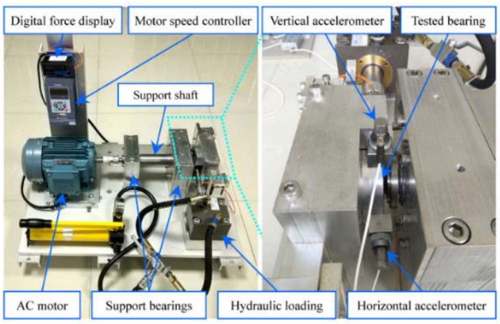
The accelerated degradation bearing vibration rig from Xi'an Jiaotong University (XJTU) (P.

Wang, et al., 2020), is used to examine the performance of the proposed approach. In the XJTU bearing dataset, 15 rolling element bearings were acquired by conducting several accelerated degradation experiments in three working conditions. Details of XJTU dataset are shown in Table 1 and Figure 3.

Table: 1 Details of the XJTU scenario 2 for examining the performance of HI construction methods

Operating condition	dataset (Bearing lifetime)				
C1: 35Hz/12kN	Bearing1_1 (2h 3min)	Bearing1_2 (2h 41min)	Bearing1_3 (2h 38min)	Bearing1_4 (2h 2min)	Bearing1_5 (52 min)
C2: 37.5Hz/11kN	Bearing2_1 (8h 11min)	Bearing2_2 (2h 41min)	Bearing2_3 (8h 83min)	Bearing2_4 (42min)	Bearing2_5 (5h 59 min)
C3: 40Hz/10kN	Bearing3_1 (42h 18min)	Bearing3_2 (41h 36min)	Bearing3_3 (6h 11min)	Bearing3_4 (25h 15min)	Bearing3_5 (1h 52 min)

The reliability of the designed MSMHA-AED model with three different similarity functions to construct HI is examined based on the datasets. The datasets for these bearings, which have the same fatigue characteristics but obtained under different operation conditions, are used to examine the reliability and effectiveness of the proposed RUL prediction method.



(a) Normal (b) Inner race (c) Cage (d) Ball (e) Outer race

Figure 3: The experiment platform

5.2 Evaluation metrics for estimation of HI and RUL

In this research, monotonicity function (including Signum Formula and Spearman's rank correlation coefficient) is used to evaluate the quality of the constructed HI. The higher the monotonicity score, the better the quality of the HI for RUL prediction. The RMSE function is used to evaluate the quality of the RUL prediction. The Signum Formula for monotonicity is calculated using Equation (2).

$$Monotonicity(x_i) = \frac{1}{m}\sum_{j=1}^{m}\frac{\left|\text{No. of positive diff}(x_i^j) - \text{No. of negative diff}(x_i^j)\right|}{n-1} \tag{2}$$

Where n is the number of measurement points, in this case n equals to the length of sampling times for each bearing. m is the number of machines monitored, in this case $m=1$. x_i^j is the i^{th} feature measured on j^{th} machine $\text{diff}(x_i^j) = x_i^j(t) - x_i^j(t-1)$, which means the difference between the feature x_i^j.

The Equation of the Spearman's rank correlation coefficient monotonicity is:

$$Monotonicity(x_i) = \frac{1}{m}\sum_{j=1}^{m}\left|corr(rank(x_j), rank(t_j))\right| \tag{3}$$

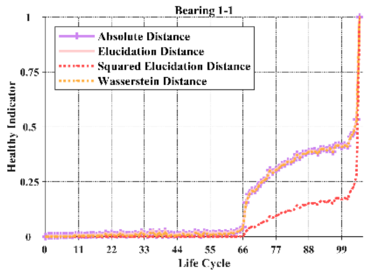
Where M is the number of the monitored systems, in this case equals to 1, the t_j is the time vector corresponding to the x_j, $rank(\cdot)$ is the rank function, $corr(\cdot)$ is the Spearman's rank correlation coefficient function. To define the hybrid monotonicity as $Mon = (Signum + Spearman)/2$.

RMSE: RMSE is an evaluation metric in the field of prognostics and health management. The RMSE value is calculated by:

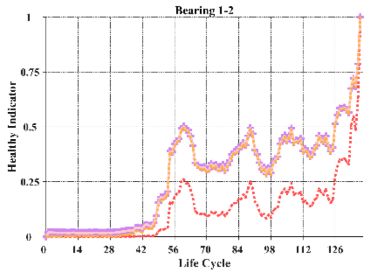
$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N} error_i^{\,2}} \tag{4}$$

5.3 The HI construction procedure

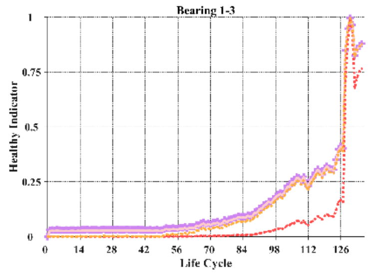
The baseline model, which comprises of the auto encoder-decoder and DCN, is used to examine the reliability of HI constructed based on different similarities.



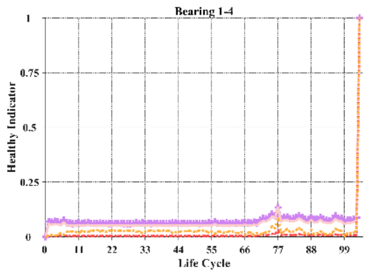
(a) Bearing 1-1



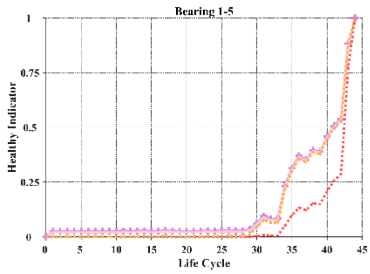
(b) Bearing 1-2



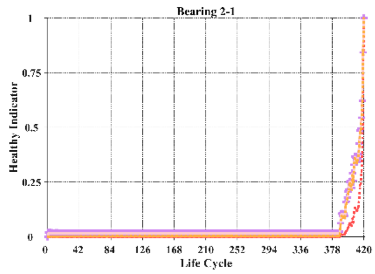
(c) Bearing 1-3



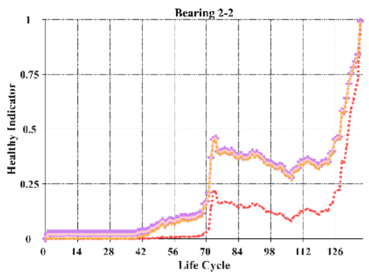
(d) Bearing 1-4



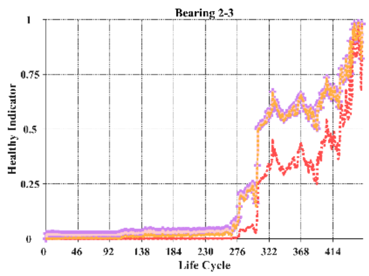
(e) Bearing 1-5



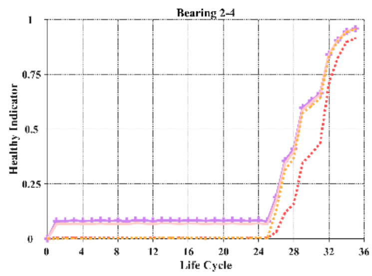
(f) Bearing 2-1



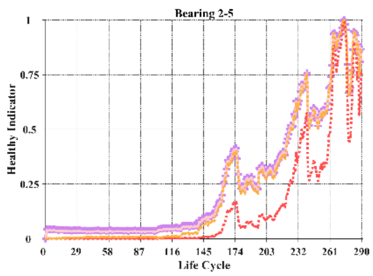
(g) Bearing 2-2

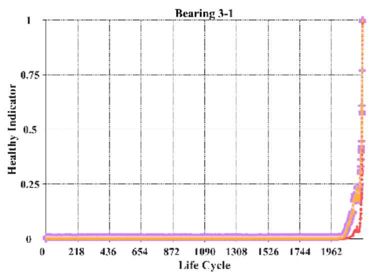


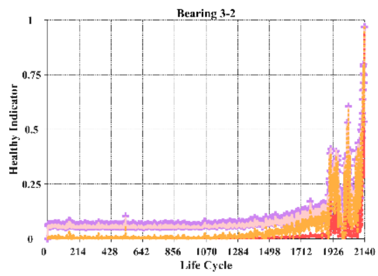
(h) Bearing 2-3



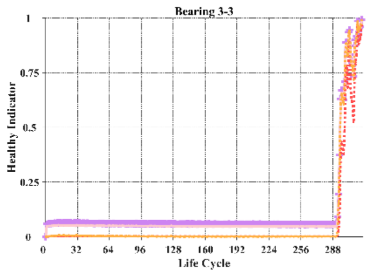
(i) Bearing 2-4



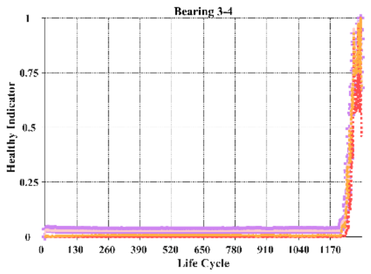




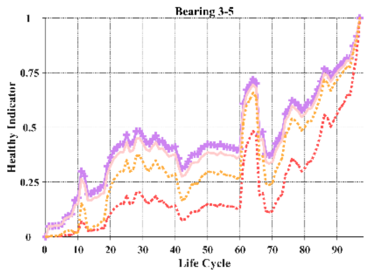
(j) Bearing 2-5 (k) Bearing 3-1 (l) Bearing 3-2



(m) Bearing 3-3



(n) Bearing 3-4



(o) Bearing 3-5

Figure 4: Examination of the distance function in the construction of the health indicator

In Figure 4, four types of distance calculation functions are used to measure the similarity between the healthy and defective bearings. The quantified HI of bearing1_1 for instance, in relation to the Squared Elucidation Distance to the constructed HI, shows different curve from other three functions. This indicates that using distance functions to measure the similarity between the healthy and damaged bearing is the most effective method to construct the HI. It is interesting to note that (as shown in sub-Figure Bearing 1-5) before the first prediction time (FPT) was recorded, the health indicators constructed based on Squared Elucidation Distance and Wasserstein Distance are nearly closed to zero but the other two are slightly higher than zero. A bearing begins to transition into degradation state when its health indicator is consistently greater than zero, thus the health indicator constructed using the Squared Elucidation Distance and Wasserstein Distance is more suitable in determining the FPT. More evidence to prove the performance of the similarity measurement is presented in Table 2.

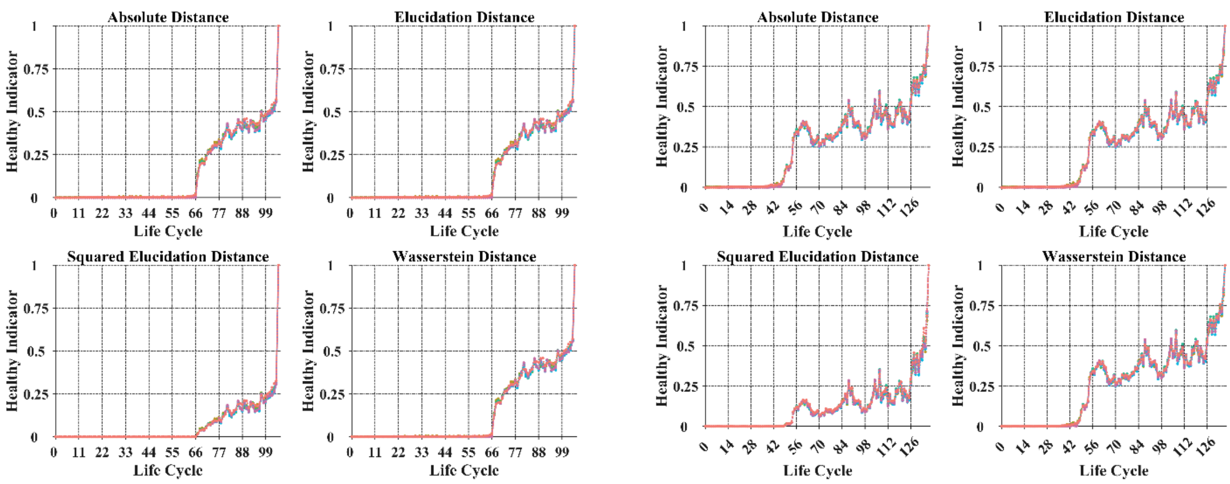
Table 2 The FPT of the bearings

Method / Bearing	Absolute Distance (mins)	Elucidation Distance(mins)	Squared Elucidation Distance(mins)	Wasserstein Distance(mins)
Bearing 1-1	65	33	69	66
Bearing 1-2	34	36	54	41

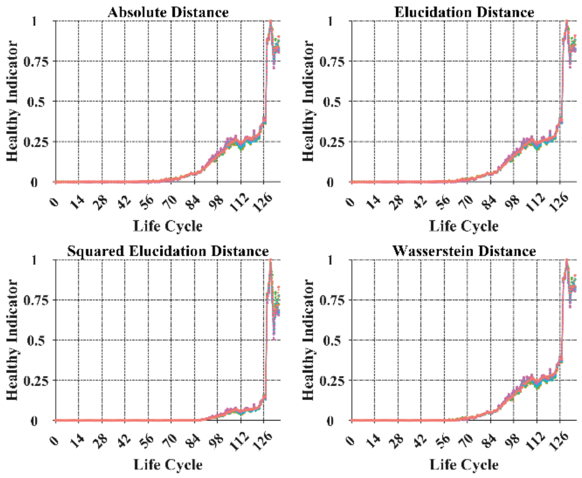
Bearing 1-3	2	2	96	65
Bearing 1-4	2	2	78	10
Bearing 1-5	2	30	35	31
Bearing 2-1	390	390	398	390
Bearing 2-2	2	41	70	47
Bearing 2-3	110	114	281	260
Bearing 2-4	2	2	27	27
Bearing 2-5	2	2	160	130
Bearing 3-1	2056	2056	2113	2059
Bearing 3-2	2	2	1774	147
Bearing 3-3	2	2	295	294
Bearing 3-4	2	2	1238	1217
Bearing 3-5	2	2	12	8

Bearings 1-3 to 1-5, 2-2 to 2-5 and 3-2 to 3-5, whose health indicators were constructed based on Squared Elucidation Distance and Wasserstein Distance are more stable than others in terms of attaining the FPT without false alarm. The FPT determined by the health indicators that were constructed based on the Squared Elucidation Distance is regarded as the effective tool for identifying the initial degradation point of bearing.

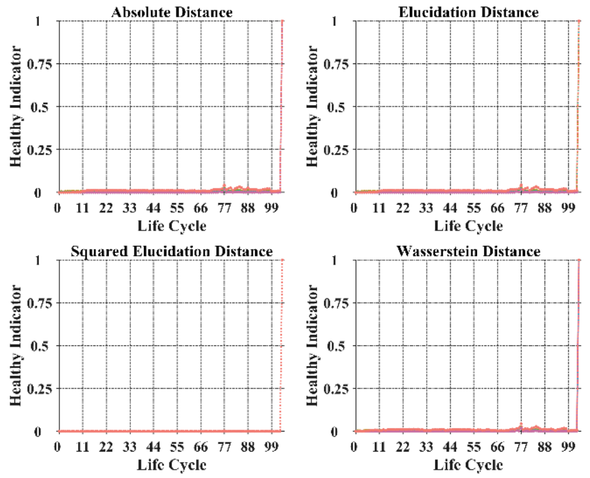
The HI construction method proposed in this study consists of the MSMHA-AED and the multi-scale HI fusion algorithms. The reliability of the proposed HI construction method is examined, and the results are presented in Figure 5.



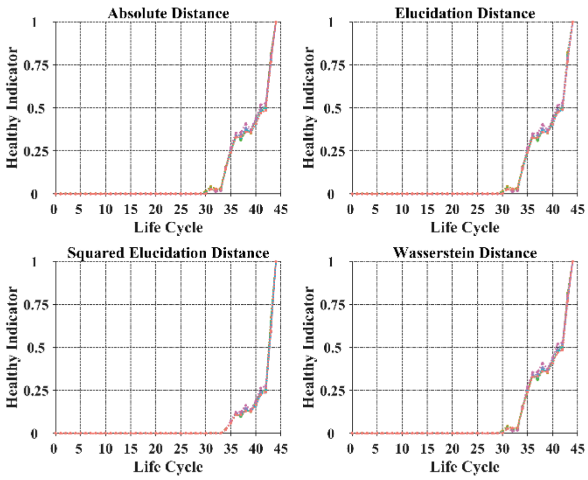
(a) Bearing 1-1



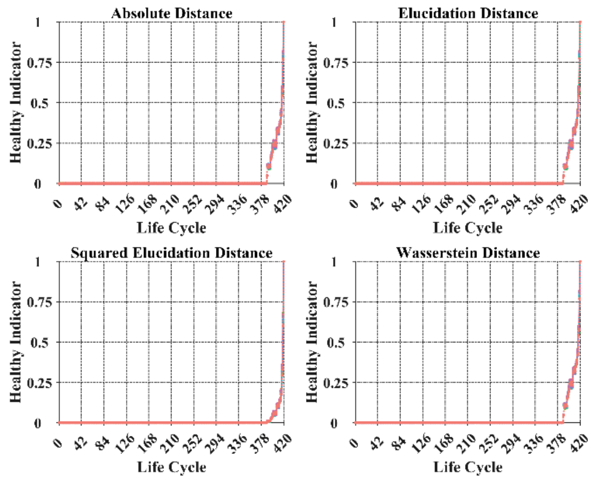
(b) Bearing 1-2

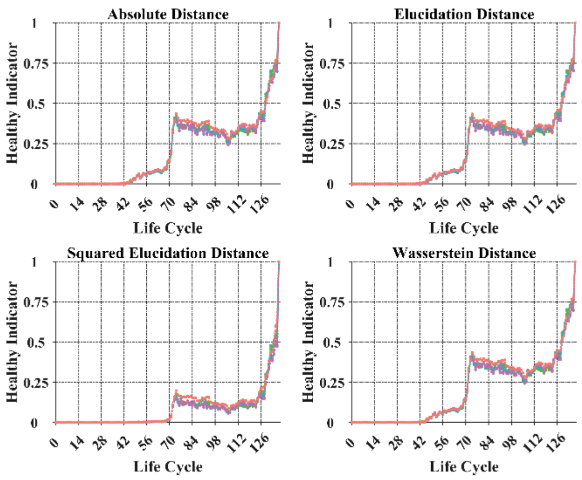


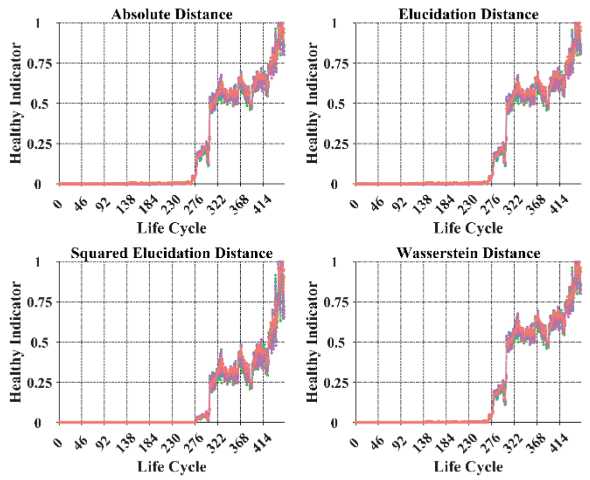
(c) Bearing 1-3

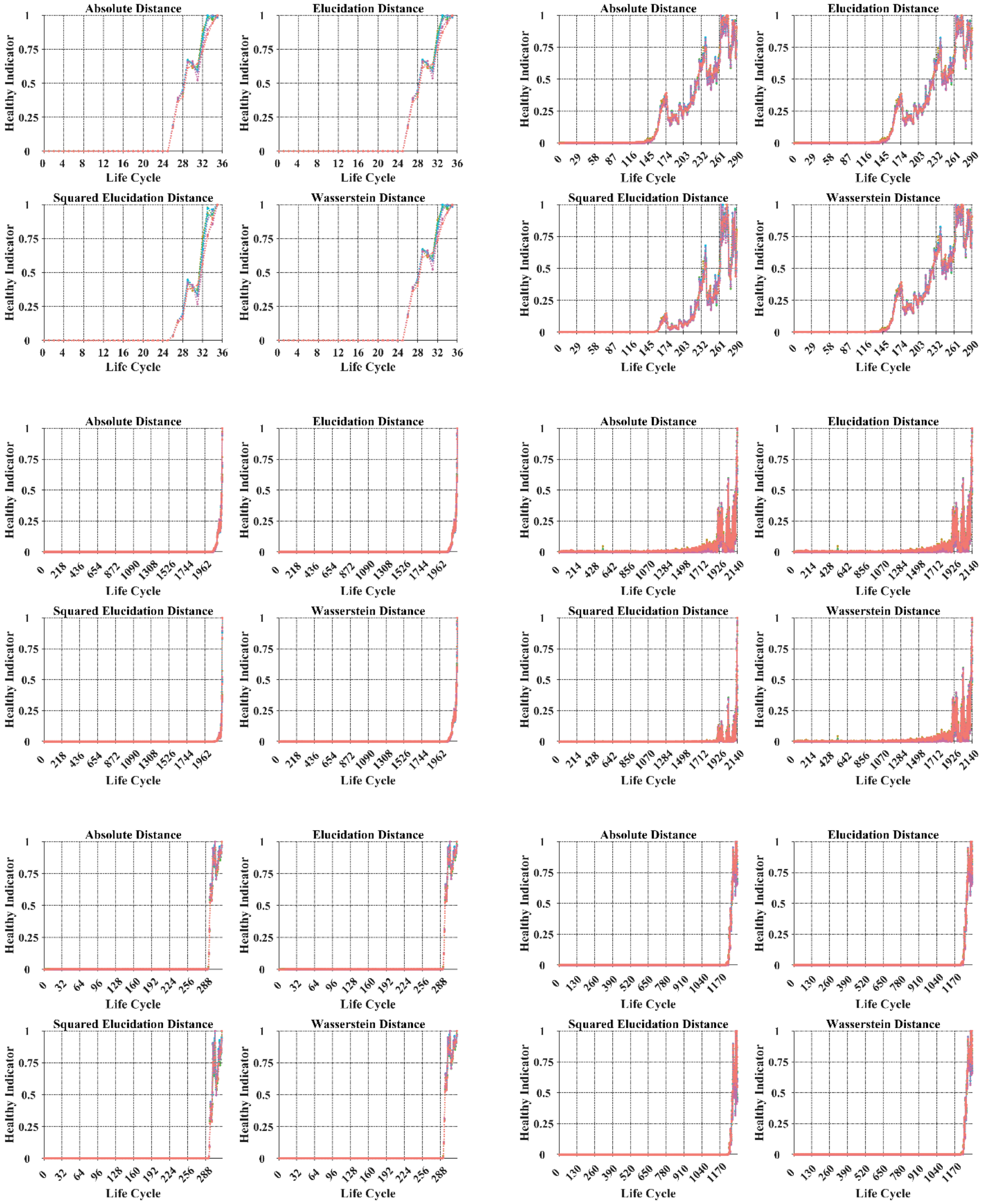


(d) Bearing 1-4








Absolute Distance
Elucidation Distance
Squared Elucidation Distance
Wasserstein Distance
Healthy Indicator
Life Cycle

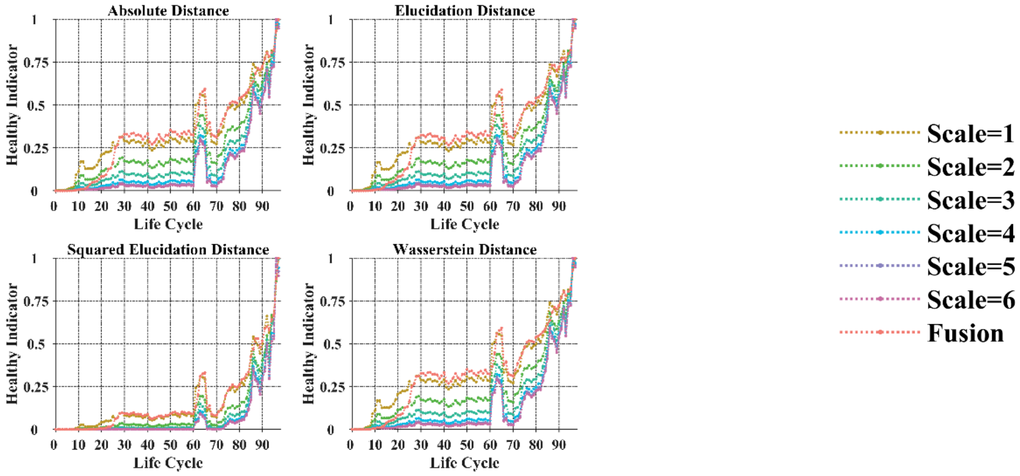


Figure 5: Comparison of the MSMHA-AED based on HI constructed with different similarity functions.

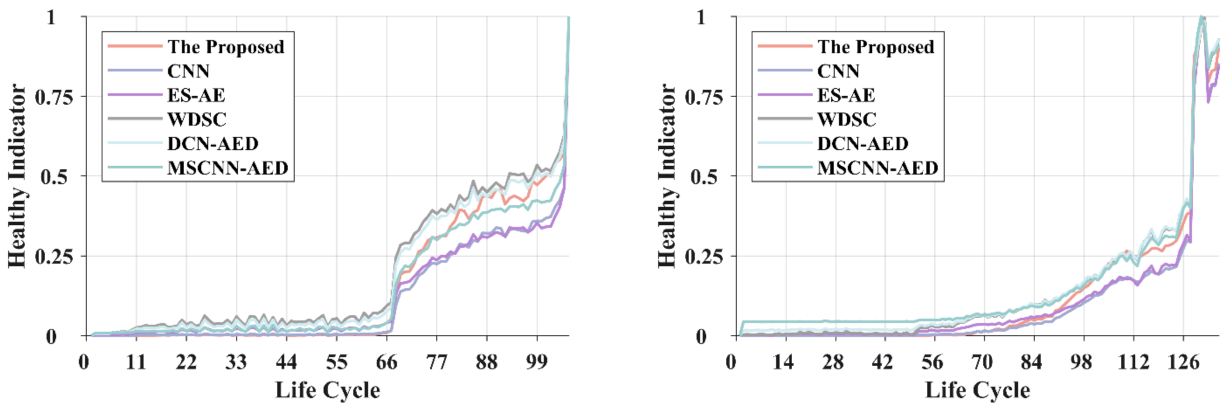
In Figure 5, 'Scale=k' represents the health indicator measured based on the similarity of coded features extracted from the k^{th} multi-head attention mechanism module. The 'Fusion' in the procedure represents the proposed ensemble health indicator. Using the health indicator of bearing 3-5 for instance, it is found that the magnitude of the degradation is overestimated by the superficial coded features. This is because deeper coded features are much clearer than which are obtained from shallow layers. It should be noted that bearings 3-5 have already entered the degradation phase within a short period after its operation and the bearing life cycle from 0 to 30 is highlighted for further discussion. The similarity measured by the squared Elucidation distance is least sensitive when quantifying the performance degradation of the bearing. The similarities measured based on other three distance metrics show similar trends when estimating the fatigue. The quantified value of structural damage of the bearing decreases with increase in the k but reflected the same trend. It is worth noting that the degradation magnitude estimated by the proposed ensemble health indicator becomes larger over time. This is important for RUL prediction because it is more difficult to predict the RUL of the bearing if its health indicator fluctuates irregularly. Thus, e monotonicity of a health indicator is important in predicting the RUL. The monotonicity of three bearings' health indicators is examined to show the reliability and effectiveness of the proposed ensemble health indicator.

Table 3 The monotonicity of different health indicators examined over bearings

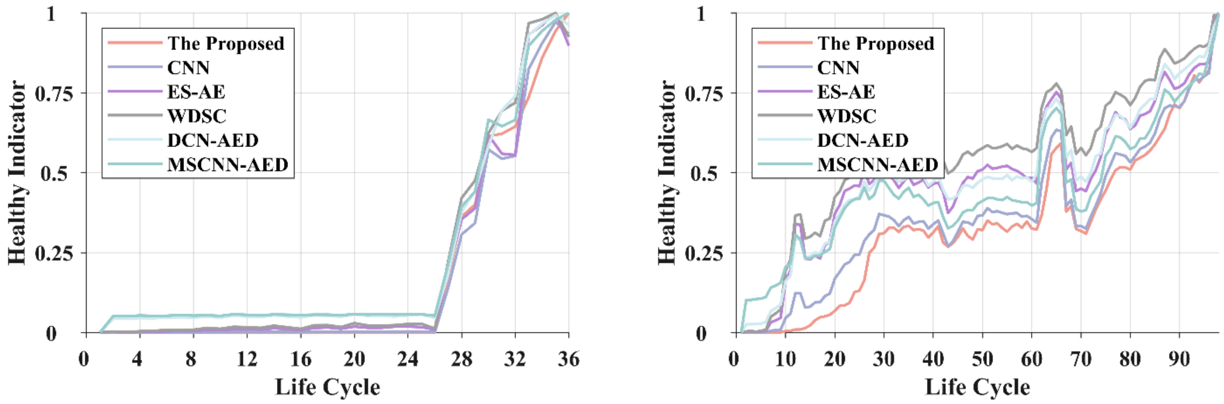
Scale or Fusion \ Method		Absolute (1_3/2_4/3_1)	Elucidation (1_3/2_4/3_1)	Squared Elucidation (1_3/2_4/3_1)	Wasserstein (1_3/2_4/3_1)
Scale = 1	Signum:	0.50/0.78/0.62	0.55/0.78/0.62	0.55/0.78/0.52	0.50/0.78/0.65
	Spearman:	0.98/0.99/0.95	0.97/0.99/0.95	0.97/0.99/0.95	0.97/0.99/0.95
Scale = 2	Signum:	0.55/0.78/0.59	0.55/0.78/0.62	0.55/0.78/0.40	0.55/0.78/0.59
	Spearman	0.98/0.99/0.95	0.97/0.99/0.95	0.97/0.99/0.94	0.97/0.99/0.95
Scale = 3	Signum:	0.50/0.78/0.59	0.50/0.56/0.62	**0.65**/0.78/0.33	0.50/0.78/0.59
	Spearman	0.96/0.99/0.95	0.97/0.98/0.95	0.96/0.99/0.94	0.97/0.95/0.95
Scale = 4	Signum:	0.50/0.56/0.52	0.50/0.56/0.52	0.45/0.78/0.40	0.50/0.56/0.52
	Spearman	0.96/0.95/0.95	0.96/0.95/0.95	0.96/0.99/0.93	0.96/0.99/0.95
Scale = 5	Signum:	0.45/0.56/0.56	0.50/0.56/0.56	0.50/1.00/0.30	0.45/0.56/0.56
	Spearman	0.96/0.98/0.95	0.96/0.98/0.94	0.96/1.00/0.94	0.96/0.98/0.95
Scale = 6	Signum:	0.50/0.78/0.52	0.50/0.78/0.52	0.50/0.78/0.33	0.50/0.78/0.52
	Spearman	0.96/0.96/0.95	0.96/0.96/0.95	0.96/0.99/0.93	0.96/0.96/0.94
Fusion	Signum:	**0.70/1.00/0.71**	**0.60/1.00/0.71**	0.55/**1.00/0.56**	**0.70/1.00/0.72**
	Spearman	**0.99/1.00/0.96**	**0.98/1.00/0.96**	**0.98/1.00/0.96**	**0.99/1.00/0.96**

The effectiveness of the four distance functions in measuring the similarity of the coded features used to construct the health indicators is presented in Table 3. The ensemble health indicator obtained using the proposed multiple indicators fusion algorithm are significantly better in terms of monotonicity. Although the degradation measured by Wasserstein distance is similar to that of the absolute distance-based measurement in terms of monotonicity, however, as can be seen from the analysis in Table 2, the use of health indicators constructed based on absolute value distances is susceptible to noise leading to false positives in the detection of FPT. In summary, the analysis shows that the degradation indicator constructed based on the Wasserstein distance has advantages in terms of both monotonicity and determination of FPT.

Thus, the Wasserstein distance is used to measure the similarity for health indicator construction in this study. To highlight the efficiency and effectiveness of the proposed method (MSMHA-AED model with Wasserstein distance) in establishing health indicator, a comparison of the proposed method with state-of art HI construction methods is conducted. Noise in the signals can have a detrimental effect on the estimation of health indicator and a causal moving mean filter with a lag window of 3 steps is applied to each health indicator to alleviate the effects. Five data-driven based state-of-art methods for HI construction are chosen for comparison to determine the performance of the proposed method. The comparison focused on monotonicity, trendability and prognosability of the hybrid model quantified HIs metrics. The examined construction methods of the six health indicators are presented in Figure 6 and the corresponding magnitudes of the predicted metrics are presented in Table 4. Results show the similarity between the proposed approach and the state-of-the-art methods, demonstrating consistency and reliability. This comparison further reaffirms that the proposed approach can deliver a high-quality health Indicator needed for constructing a better RUL model.



(a) Bearing1-1 (b) Bearing 1-3



(c) Bearing 2-4 (d) Bearing 3-5

Figure 6：Comparison of the health indicators

The HI constructed based on traditional statistics has fluctuated with temporal variation. These fluctuations will cause interference in the selection of the starting point of the prediction and have effects on whether the equipment reaches the degraded state or not.

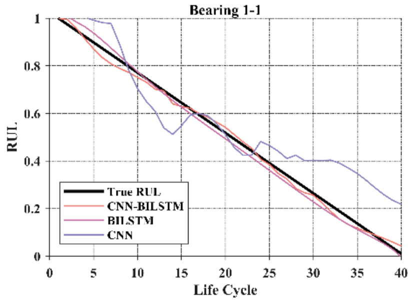
Table 4: The Comparison of different HI construction methods

Methods	Description	Monotonicity	Trendability	Prognosability
1	CNN (Guo, Lei, et al., 2017)	0.6273	0.7649	0.9290
2	ES-AE (Lin & Tao, 2019)	0.6635	0.7400	0.9335
3	MSCNN-AED (Guo et al., 2022)	0.7442	0.7417	0.9446
4	DCN-AED (F. Xu et al., 2020)	0.7327	0.7532	0.9479
5	WDSC (Ni et al., 2022)	0.7604	0.7616	0.9501
6	Proposed Method	**0.9049**	**0.8287**	**0.9515**

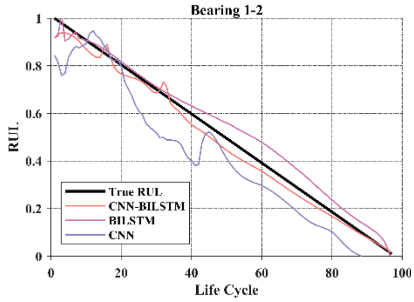
The hybrid model monotonicity, prognosability and trendability are used to examine the quality of the constructed health indicator. As presented in the Table 4, the proposed method has the highest monotonicity metric. This is because the coded features produced using the module are cleaner than those in raw vibration signals since the convolutional filters in the encoder will filter the noise in raw signals. The proposed method also offers other significant advantages (improved reliability, low false alarms etc.) compared to the state-of- HI construction methods.

5.4 Remaining Useful Life Estimation

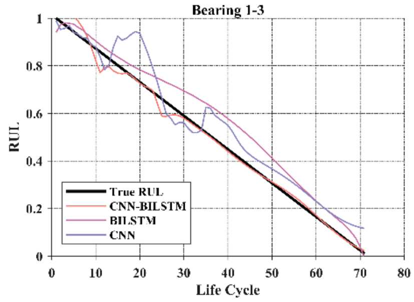
To demonstrate the reliability and effectiveness of the proposed prediction method, 15 bearings are used to examine the reliability of the proposed health indicator construction method in RUL prediction. The training and testing datasets are independent of each other.



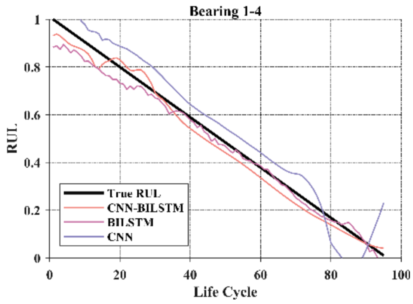
(a) Bearing 1-1



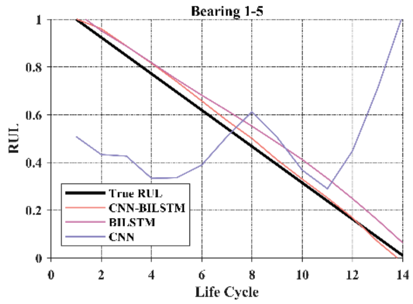
(b) Bearing 1-2



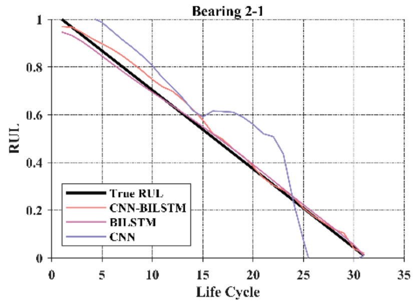
(c) Bearing 1-3



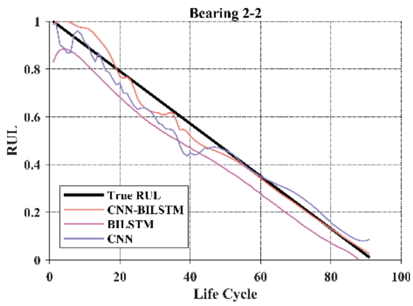
(d) Bearing 1-4



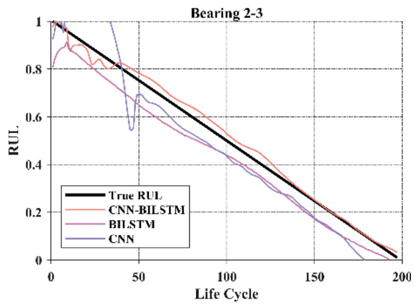
(e) Bearing 1-5



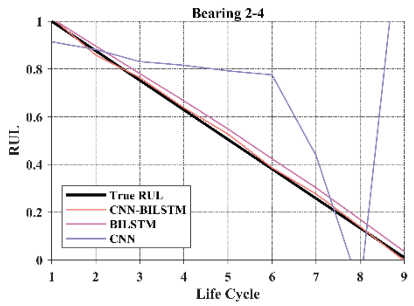
(f) Bearing 2-1



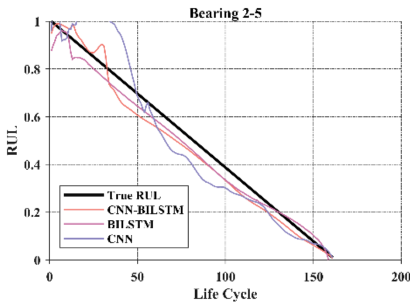
(g) Bearing 2-2



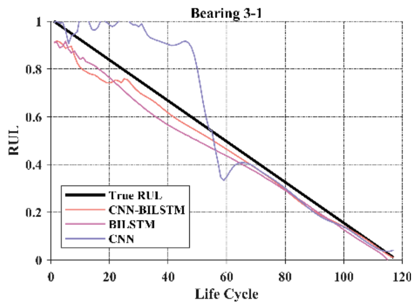
(h) Bearing 2-3



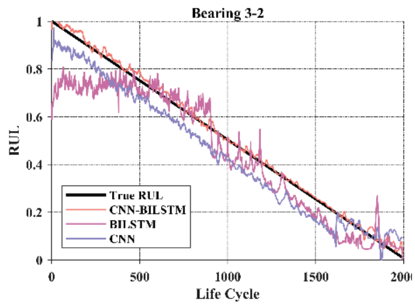
(i) Bearing 2-4



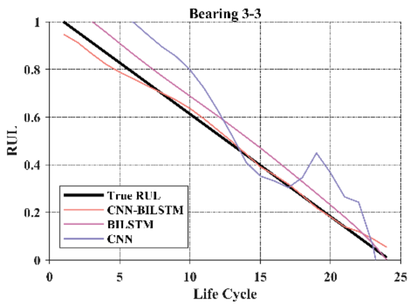
(j) Bearing 2-5

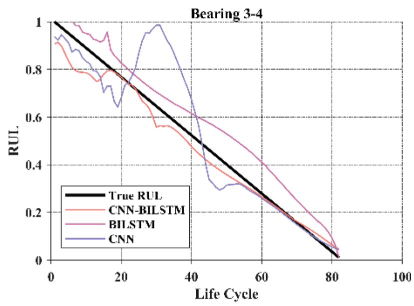


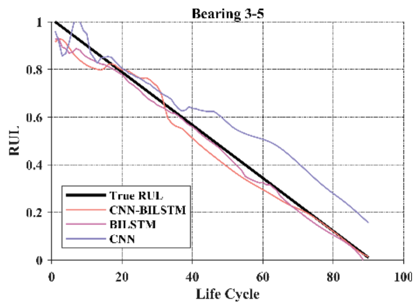
(k) Bearing 3-1



(l) Bearing 3-2





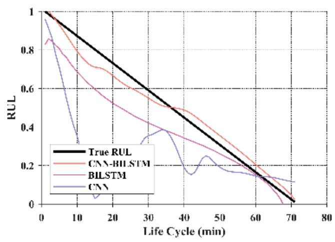


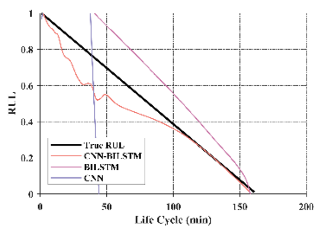
(m) Bearing 3-3 (n) Bearing 3-4 (o) Bearing 3-5

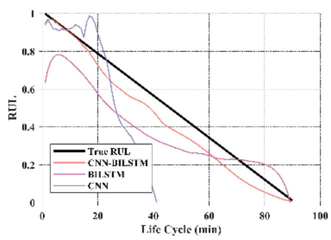
Figure 7：The RUL estimation of ten bearings based on 3 types of recurrent neural networks

As shown in Figure 7, taking bearing 1-1 as an example, this study compares the performance of three DLN based predictors in estimating the RUL. It is shown that the prediction of RUL using only CNN has the largest error while the BILSTM network has the smallest error. By observing the features in Figure 6 (i), the CNN-BILSTM model performs better than the BILSTM in mapping the relationship between the health indicators and the remaining useful lifetime. The prediction error is smaller than errors from other models. This examination demonstrates the advantage of CNN-LSTM-based predictor in RUL estimation applications.

Bearings 1-3, 2-5 and 3-5 are respectively examined to further prove the effectiveness of the proposed health indicator construction methodology in RUL prediction. In this examination, the predictor used to estimate the RUL of bearing 1-3 is trained with bearings 1-1, 1-2 and 1-5. The predictor used for bearings 2-5 is trained with bearings 2-1 to 2-4 data; the predictor for bearings 3-5 is trained with bearings 3-1 to 3-4 datasets.







(a) Bearing1-3 (b) Bearing2-5 (c) Bearing 3-5

Figure 8 The RUL predicition of three bearings

From observation of the plots in Figure 8 (a) to (c), it is clearly very difficult to accurately predict the RUL of bearings using only CNN predictor. This is because CNN has a weak capability to effectively process the time series. However, the weakness in using CNN can be overcome by using BILSTM model which predicts the remaining lifetime in a more accurate manner.. Although the accuracy of the estimated RUL values is debatable, it is still possible to capture trends in performance degradation using the CNN model. Consequently, using a combination of CNN-BILSTM model presents the best performance among the three prognosticators. The model combines the feature extraction capability of CNN with the time series processing ability of BILSTM. Thus, the CNN-BILSTM can estimate the degradation trend and also predict the exact remaining lifetime.

The prognostic performance of the proposed RUL prediction is examined forbearing 3-2. The results of three RUL prediction methods are compared to demonstrate the superiority of the proposed method. The RUL results used in the comparison are obtained from health indicators constructed using the other three state-of-art methods, which are neural network-based models. The values of the final estimation by four methods are presented in Table 5.

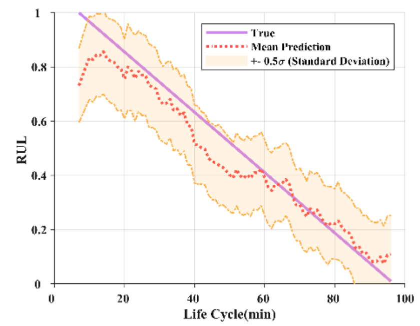
Table 5: The prognostic performance

Predictor	CNN-BILSTM				BILSTM				CNN			
Health indicator	The Proposed	DCN-AED	MSCNN-AED	WDSC	The Proposed	DCN-AED	MSCNN-AED	WDSC	The Proposed	DCN-AED	MSCNN-AED	WDSC
RMSE	**0.0301**	0.0596	0.0650	0.1121	**0.0847**	0.1713	0.1842	0.1971	**0.3578**	0.3696	0.3764	0.3616

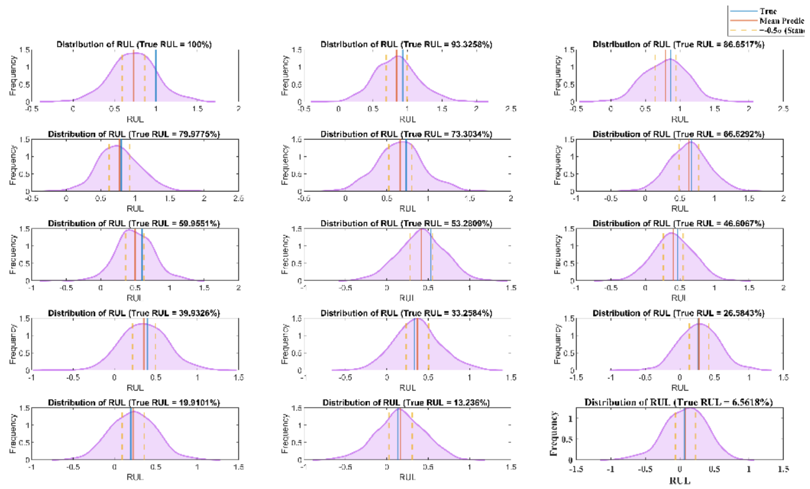
The superiority of the proposed health indicator is presented in Table 5. When CNN-BILSTM is used as the prognosticator, the RMSE of the deviation of the predicted RUL from true RUL is only 0.0301. The prediction results based on the proposed health indicator have the relatively lowest RMSEs. This is because the proposed health indicator provides a more accurate picture of trends in the bearing degradation process. As for the selection of the prognosticator for real industrial world application, a simple BILSTM model is still unable to meet the accuracy requirements for predicting the remaining life of an unknown bearing from the known data of multiple bearings. This confirms that the model requires the addition of a convolution module for feature extraction.

5.5 Remaining Useful Life Estimation with Uncertainty Quantification

A novel RUL prognosticator is developed by combining CNN-BILSTM with Bayesian Neural Network to consider uncertainty in the RUL prediction. Figure 9 presents the results of the predicted RUL with uncertainty (Figure 9a) and the uncertainty analysis (Figure 9b).



(a) RUL prediction



(b) Uncertainty analysis

Figure 9 RUL prediction with uncertainty analysis

As shown in Figure 9, the mean values of predicted RUL using the proposed CNN-BILSTM with Bayesian Neural Network are close to the true value of the examined bearing. The prediction was carried out by analyzing every estimated RUL point with uncertainty as a means of assessing the overall uncertainty quantification capability of the prognosticator. Similarly, this approach is critical in establishing the reliability of the RUL prediction. From these results, it is noted that RUL estimation with lowest uncertainty will be used in the next decision-making process for bearing maintenance. In Figure 9(b), the real RUL = 100% implies the result is out of the fiducial interval of the RUL prediction by the prognosticator. This means that the RUL prediction result at this point is outside of the confidence interval, suggesting that a maintenance expert would have to require more information from the developed prognosticator. In contrast, as shown in Figure (b) for RUL = 6.5618%, the true RUL result is in the middle of the fiducial interval of the RUL prediction by the prognosticator. This confirms the reliability of the RUL prediction result and the confidence level of its application for maintenance decision-making.

6. Conclusions

In this study, a novel prognostic framework for prediction of RUL of a bearing is proposed. The study developed a multi-scale auto encoder-decoder consisting of convolutional neural network and multi-head attention mechanism, which is used to filter the less useful information from the raw vibration signals. Based on the coded features of the proposed auto-encoder-decoder, the health indicator is constructed by measuring the similarity between the healthy and damaged conditions. The multi-scale health indicators are fused to with the ensemble health indicator using a fusion algorithm developed in the study proposed. The convolutional network with bidirectional long short-term memory (BiLSTM) is used to map the relationship between the health indicators and the remaining use lifetime. The reliability and superiority of the proposed method is examined using an accelerated bearing degradation dataset. The effectiveness of four distance measurements in constructing the health indicators is examined. It is found that the health indicators constructed based on Wasserstein distance is able to avoid false alarm when condition detection for the first prediction time and has a stronger monotonicity. The proposed method demonstrated higher monotonicity scores compared with other health indicators developed based on state-of-art construction methods. The reliability of the proposed health indicators for remaining life prediction was also examined. The health indicators constructed based on the proposed method produced results that are closer to the true values during prediction of the remaining life of bearings, with a root mean square error of only 0.03. A novel CNN-BiLSTM with Bayesian Neural Network model is developed to consider the uncertainty in RUL prediction. The reliability of the RUL prediction can be quantified through the uncertainty analysis, which is helpful in providing more reliable information and establishing confidence in maintenance decision-making.

7. Acknowledgments

The authors would like to acknowledge the financial support from Royal Society (grant number: IEC\NSFC\170054). European Regional Development Fund (ERDF), Interreg Atlantic Area (grant number: EAPA_344/2016)

References

Chen, D., Qin, Y., Wang, Y., & Zhou, J. (2021). Health indicator construction by quadratic function-based deep convolutional auto-encoder and its application into bearing RUL prediction. *ISA Transactions*, *114*, 44–56. https://doi.org/10.1016/j.isatra.2020.12.052

Chen, L., Xu, G., Zhang, S., Yan, W., & Wu, Q. (2020). Health indicator construction of machinery based on end-to-end trainable convolution recurrent neural networks. *Journal of Manufacturing Systems*, *54*(June 2019), 1–11. https://doi.org/10.1016/j.jmsy.2019.11.008

Chen, Y., Peng, G., Zhu, Z., & Li, S. (2020). A novel deep learning method based on attention mechanism for bearing remaining useful life prediction. *Applied Soft Computing Journal*, *86*, 105919. https://doi.org/10.1016/j.asoc.2019.105919

Cheng, Y., Hu, K., Wu, J., Zhu, H., & Shao, X. (2021). A convolutional neural network based degradation indicator construction and health prognosis using bidirectional long short-term memory network for rolling bearings. *Advanced Engineering Informatics*, *48*(June 2020), 101247. https://doi.org/10.1016/j.aei.2021.101247

Dai, J., Wang, J., Huang, W., Shi, J., & Zhu, Z. (2020). Machinery Health Monitoring Based on Unsupervised Feature Learning via Generative Adversarial Networks. *IEEE/ASME Transactions on Mechatronics*, *25*(5), 2252–2263. https://doi.org/10.1109/TMECH.2020.3012179

Fan, J., Yu, S., Chu, J., Chen, D., Yu, M., Wu, T., Chen, J., Cheng, F., & Zhao, C. (2019). Research on multi-objective decision-making under cloud platform based on quality function deployment and uncertain linguistic variables. *Advanced Engineering Informatics*, *42*(April), 100932. https://doi.org/10.1016/j.aei.2019.100932

Farhan, M., Schneider, R., & Thöns, S. (2022). Predictive information and maintenance optimization based on decision theory: a case study considering a welded joint in an offshore wind turbine support structure. *Structural Health Monitoring*, *21*(1), 185–207. https://doi.org/10.1177/1475921720981833

Guo, L., Lei, Y., Li, N., & Xing, S. (2017). Deep convolution feature learning for health indicator construction of bearings. *2017 Prognostics and System Health Management Conference, PHM-Harbin 2017 - Proceedings*. https://doi.org/10.1109/PHM.2017.8079167

Guo, L., Lei, Y., Li, N., Yan, T., & Li, N. (2018). Machinery health indicator construction based on convolutional neural networks considering trend burr. *Neurocomputing*, *292*, 142–150. https://doi.org/10.1016/j.neucom.2018.02.083

Guo, L., Li, N., Jia, F., Lei, Y., & Lin, J. (2017). A recurrent neural network based health indicator for remaining useful life prediction of bearings. *Neurocomputing*, *240*, 98–109. https://doi.org/10.1016/j.neucom.2017.02.045

Guo, L., Yu, Y., Duan, A., Gao, H., & Zhang, J. (2022). An unsupervised feature learning based health indicator construction method for performance assessment of machines. *Mechanical Systems and Signal Processing*, *167*(PB), 108573. https://doi.org/10.1016/j.ymssp.2021.108573

Ismail, W. N., Hassan, M. M., Alsalamah, H. A., & Fortino, G. (2020). CNN-based health model for regular health factors analysis in internet-of-medical things environment. *IEEE Access*, *8*, 52541–52549. https://doi.org/10.1109/ACCESS.2020.2980938

Lei, Y., Li, N., Guo, L., Li, N., Yan, T., & Lin, J. (2018). Machinery health prognostics: A systematic review from data acquisition to RUL prediction. *Mechanical Systems and Signal Processing*, *104*, 799–834. https://doi.org/10.1016/j.ymssp.2017.11.016

Li, H., Wang, Y., Wang, B., Sun, J., & Li, Y. (2017). The application of a general mathematical morphological particle as a novel indicator for the performance degradation assessment of a bearing. *Mechanical Systems and Signal Processing*, *82*(97), 490–502. https://doi.org/10.1016/j.ymssp.2016.05.038

Li, J., Li, X., & He, D. (2019). A Directed Acyclic Graph Network Combined With CNN and LSTM for Remaining Useful Life Prediction. *IEEE Access*, *7*, 75464–75475. https://doi.org/10.1109/ACCESS.2019.2919566

Li, X., Ding, Q., & Sun, J. Q. (2018). Remaining useful life estimation in prognostics using deep convolution neural networks. *Reliability Engineering and System Safety*, *172*(November 2017), 1–11. https://doi.org/10.1016/j.ress.2017.11.021

Lin, P., & Tao, J. (2019). A novel bearing health indicator construction method based on ensemble stacked autoencoder. *2019 IEEE International Conference on Prognostics and Health Management, ICPHM 2019*. https://doi.org/10.1109/ICPHM.2019.8819405

Malekimoghadam, R., Krause, S., & Czichon, S. (2021). A Critical Review on the Structural Health Monitoring Methods of the Composite Wind Turbine Blades. In M. Abdel Wahab (Ed.), *Proceedings of 1st International Conference on Structural Damage Modelling and Assessment* (pp. 409–438). Springer Singapore.

Nejad, A. R., Odgaard, P. F., Gao, Z., & Moan, T. (2014). A prognostic method for fault detection in wind turbine drivetrains. *Engineering Failure Analysis*, *42*, 324–336. https://doi.org/10.1016/j.engfailanal.2014.04.031

Ni, Q., Ji, J., & Feng, K. (2022). Data-driven prognostic scheme for bearings based on a novel health indicator and gated recurrent unit network. *IEEE Transactions on Industrial Informatics*, *3203*(c). https://doi.org/10.1109/TII.2022.3169465

Nuñez, D. L., & Borsato, M. (2018). OntoProg: An ontology-based model for implementing Prognostics Health Management in mechanical machines. *Advanced Engineering Informatics*, *38*(December 2017), 746–759. https://doi.org/10.1016/j.aei.2018.10.006

Pan, Y., Chen, J., & Li, X. (2010). Bearing performance degradation assessment based on lifting wavelet packet decomposition and fuzzy c-means. *Mechanical Systems and Signal Processing*, *24*(2), 559–566. https://doi.org/10.1016/j.ymssp.2009.07.012

Peng, K., Jiao, R., Dong, J., & Pi, Y. (2019). A deep belief network based health indicator construction and remaining useful life prediction using improved particle filter. *Neurocomputing*, *361*, 19–28. https://doi.org/10.1016/j.neucom.2019.07.075

Rai, A., & Upadhyay, S. H. (2017). Bearing performance degradation assessment based on a combination of empirical mode decomposition and k-medoids clustering. *Mechanical Systems and Signal Processing*, *93*, 16–29. https://doi.org/10.1016/j.ymssp.2017.02.003

Rinaldi, G., Garcia-Teruel, A., Jeffrey, H., Thies, P. R., & Johanning, L. (2021). Incorporating stochastic operation and maintenance models into the techno-economic analysis of floating offshore wind farms. *Applied Energy*, *301*(July), 117420. https://doi.org/10.1016/j.apenergy.2021.117420

Shafiee, M., & Animah, I. (2022). An integrated FMEA and MCDA based risk management approach to support life extension of subsea facilities in high-pressure–high-temperature (HPHT) conditions. *Journal of Marine Engineering \& Technology*, *21*(4), 189–204. https://doi.org/10.1080/20464177.2020.1827486

Shields, M., Beiter, P., Nunemaker, J., Cooperman, A., & Duffy, P. (2021). Impacts of turbine and plant upsizing on the levelized cost of energy for offshore wind. *Applied Energy*, *298*, 117189. https://doi.org/10.1016/j.apenergy.2021.117189

Singleton, R. K., Strangas, E. G., & Aviyente, S. (2015). Extended kalman filtering for remaining-useful-life estimation of bearings. *IEEE Transactions on Industrial Electronics*, *62*(3), 1781–1790. https://doi.org/10.1109/TIE.2014.2336616

Suh, S., Lukowicz, P., & Lee, Y. O. (2022). Generalized multiscale feature extraction for remaining useful life prediction of bearings with generative adversarial networks. *Knowledge-Based Systems*, *237*, 107866. https://doi.org/10.1016/j.knosys.2021.107866

Wang, C., Jiang, W., Yang, X., & Zhang, S. (2021). Rul prediction of rolling bearings based on a dcae and cnn. *Applied Sciences (Switzerland)*, *11*(23). https://doi.org/10.3390/app112311516

Wang, D., & Shen, C. (2016). An equivalent cyclic energy indicator for bearing performance degradation assessment. *JVC/Journal of Vibration and Control*, *22*(10), 2380–2388. https://doi.org/10.1177/1077546314547224

Wang, J., Liang, Y., Zheng, Y., Gao, R. X., & Zhang, F. (2020). An integrated fault diagnosis and prognosis approach for predictive maintenance of wind turbine bearing with limited samples. *Renewable Energy*, *145*, 642–650. https://doi.org/10.1016/j.renene.2019.06.103

Wang, P., Long, Z., & Wang, G. (2020). A hybrid prognostics approach for estimating remaining useful life of wind turbine bearings. *Energy Reports*, *6*(1), 173–182. https://doi.org/10.1016/j.egyr.2020.11.265

Wang, S., Moan, T., & Jiang, Z. (2022). Influence of variability and uncertainty of wind and waves on fatigue damage of a floating wind turbine drivetrain. *Renewable Energy, 181*, 870–897. https://doi.org/10.1016/j.renene.2021.09.090

Wang, X. B., Zhang, X., Li, Z., & Wu, J. (2020). Ensemble extreme learning machines for compound-fault diagnosis of rotating machinery. *Knowledge-Based Systems, 188*, 105012. https://doi.org/10.1016/j.knosys.2019.105012

Wei, Z., Zhu, B., Yang, J., Perc, M., & Slavinec, M. (2019). Bifurcation analysis of two disc dynamos with viscous friction and multiple time delays. *Applied Mathematics and Computation*, *347*, 265–281. https://doi.org/10.1016/j.amc.2018.10.090

Xu, F., Huang, Z., Yang, F., Wang, D., & Tsui, K. L. (2020). Constructing a health indicator for roller bearings by using a stacked auto-encoder with an exponential function to eliminate concussion. *Applied Soft Computing Journal*, *89*, 106119. https://doi.org/10.1016/j.asoc.2020.106119

Xu, Z., Li, C., & Yang, Y. (2021). Fault diagnosis of rolling bearings using an Improved Multi-Scale Convolutional Neural Network with Feature Attention mechanism. *ISA Transactions*, *110*, 379–393. https://doi.org/10.1016/j.isatra.2020.10.054

Yang, C., Ma, J., Wang, X., Li, X., Li, Z., & Luo, T. (2022). A novel based-performance degradation indicator RUL prediction model and its application in rolling bearing. *ISA Transactions*, *121*, 349–364. https://doi.org/10.1016/j.isatra.2021.03.045

Zhai, Q., & Ye, Z. S. (2017). RUL Prediction of Deteriorating Products Using an Adaptive Wiener Process Model. *IEEE Transactions on Industrial Informatics*, *13*(6), 2911–2921.

https://doi.org/10.1109/TII.2017.2684821

Zhang, C., Song, D., Chen, Y., Feng, X., Lumezanu, C., Cheng, W., Ni, J., Zong, B., Chen, H., & Chawla, N. V. (2019). A deep neural network for unsupervised anomaly detection and diagnosis in multivariate time series data. *33rd AAAI Conference on Artificial Intelligence, AAAI 2019, 31st Innovative Applications of Artificial Intelligence Conference, IAAI 2019 and the 9th AAAI Symposium on Educational Advances in Artificial Intelligence, EAAI 2019, 1*, 1409–1416. https://doi.org/10.1609/aaai.v33i01.33011409

Zhao, B., Zhang, X., Zhan, Z., & Wu, Q. (2021). A robust construction of normalized CNN for online intelligent condition monitoring of rolling bearings considering variable working conditions and sources. *Measurement: Journal of the International Measurement Confederation, 174*(January 2020), 108973. https://doi.org/10.1016/j.measurement.2021.108973

Zhao, H., Chen, G., Hong, H., & Zhu, X. (2021). Remote Structural Health Monitoring for Industrial Wind Turbines Using Short-Range Doppler Radar. *IEEE Transactions on Instrumentation and Measurement*, *70*. https://doi.org/10.1109/TIM.2021.3053959

Zhao, R., Yan, R., Chen, Z., Mao, K., Wang, P., & Gao, R. X. (2019). Deep learning and its applications to machine health monitoring. *Mechanical Systems and Signal Processing, 115*, 213–237. https://doi.org/10.1016/j.ymssp.2018.05.050

Zhiyi, H., Haidong, S., Xiang, Z., Yu, Y., & Junsheng, C. (2020). An intelligent fault diagnosis method for rotor-bearing system using small labeled infrared thermal images and enhanced CNN transferred from CAE. *Advanced Engineering Informatics, 46*(August), 101150. https://doi.org/10.1016/j.aei.2020.101150

Zhou, F., Park, J. H., & Liu, Y. (2016). Differential feature based hierarchical PCA fault detection method for dynamic fault. *Neurocomputing*, *202*, 27–35. https://doi.org/10.1016/j.neucom.2016.03.007