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Remaining Useful Life Estimation of Bearings Using Vibration Signal Processing Based on Continuous Wavelet Transform and LSTM Deep Learning Network

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ABSTRACT

This study introduces a predictive model for estimating the remaining useful life (RUL) of bearings, leveraging a deep learning approach based on Long Short-Term Memory (LSTM) networks and Continuous Wavelet Transform (CWT). The vibration signal data, which is essential for condition monitoring, were sourced from a well-established dataset. To enhance the model's ability to capture time-frequency features, each vibration signal was processed using CWT, resulting in scalogram representations. These scalograms were then fed into the LSTM network to create an accurate RUL prediction model. The performance of the proposed LSTM-based deep learning model was thoroughly assessed by comparing it with three conventional artificial neural network (ANN) models, each trained using a different algorithm: Trainbr, Trainlm, and Trainscg. The results demonstrated that the LSTM model significantly outperformed the traditional ANN models, yielding a Root Mean Square Error (RMSE) of 0.18 and a Mean Absolute Percentage Error (MAPE) of 0.0103. In contrast, the three ANN models resulted in much higher average RMSE and MAPE values of 12.4377 and 1.5557, respectively. These findings confirm the superiority of the LSTM-based model for RUL estimation in bearing health monitoring and its potential for real-world industrial applications.

1. INTRODUCTION

Rotating machinery refers to mechanical systems whose primary functions depend on rotational motion. These machines are widely used across various industries such as power generation, petrochemicals, port transportation, automotive manufacturing, aerospace, and many others. Once such equipment fails, the malfunctioning of rotating machinery significantly disrupts normal operations, potentially leading to severe shutdowns, financial losses, and even human casualties. Therefore, online monitoring and fault diagnosis of rotating machinery have become essential aspects of system design and maintenance strategies [1].

Various diagnostic techniques such as oil analysis, temperature monitoring, acoustic emission detection, and vibration analysis serve as primary tools for fault detection and diagnosis. Among these, vibration signal analysis is

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more accessible in terms of data acquisition compared to other methods [2], and thus, it has been widely employed in the field of rotating machinery diagnostics. Traditional approaches to vibration signal analysis typically begin by extracting fault-related features using methods like Wavelet Transform [3], Empirical Mode Decomposition (EMD) [4], Ensemble EMD [5], Empirical Wavelet Transform [6], or Variational Mode Decomposition (VMD) [7], followed by pattern recognition techniques for fault classification. However, these methods often require extensive prior domain knowledge and face limitations when applied to large-scale datasets.

Machine learning has emerged as a promising solution to overcome such limitations. The goal of machine learning is to simulate the human brain by creating a neural network structure capable of learning. When processing various types of signals, machine learning techniques extract, transform, classify, and describe features—offering strong self-learning capabilities that enable the discovery of data relationships and the automatic extraction of useful information. This makes machine learning particularly effective in handling complex fault diagnosis problems and has attracted significant attention from researchers [8].

In the domain of condition monitoring and fault detection of rolling-element bearings, numerous studies have integrated feature extraction techniques with machine learning algorithms. For instance, Seryasat et al. (2010) in two separate studies, first extracted effective features using Fast Fourier Transform (FFT), wavelet energy entropy, and Root Mean Square (RMS) to perform multi-fault diagnosis of bearings [9]; then, in a subsequent study, they used time-domain features and a multi-class Support Vector Machine (MSVM) to improve classification accuracy [10]. Additionally, Seryasat et al. (2014) combined Discrete Wavelet Transform (DWT) with an SVM neural network to effectively identify faults, achieving promising results in real-world environments [11]. In another study, which was later retracted for scientific reasons, Intrinsic Mode Functions (IMF), Hilbert Marginal Spectrum, and MSVM were used for signal analysis and classification [12]. Furthermore, Seryasat et al. (2013) proposed an efficient and rapid approach using Principal Component Analysis (PCA) for dimensionality reduction combined with SVM for fault detection, enabling precise identification of faults in noisy datasets [13]. Collectively, these studies highlight the importance of selecting appropriate features and classification models to enhance the accuracy of bearing fault diagnosis systems.

The present study aims to implement a deep learning-based approach for fault detection and remaining useful life (RUL) estimation of bearings using vibration signal analysis.

2. DATASET DESCRIPTION

In this study, we employed the dataset used in [14], which consists of data collected from four ball bearings mounted on a single shaft. The shaft is connected to an electric motor via a pulley-belt system, operating at a constant speed of 2000 revolutions per minute (RPM). A static radial load of 6000 pounds was applied to the shaft using a spring-based loading mechanism. The bearings under test were of type ZA-2115.

3. VIBRATION SIGNAL ACQUISITION

To capture the vibrations of the bearing assembly, accelerometer sensors were utilized. Specifically, an ICP-type quartz accelerometer (model PCB 353B33) was mounted perpendicularly on the outer casing of the bearings. The vibration data acquisition began at the start of the motor operation, under load, and continued until the bearing failure occurred. The sampling frequency for the accelerometer sensors was set at 20 kHz.

The system operation began on February 12, 2004, at 10:32:39 AM, and the failure event was recorded on February 19, 2004, at 06:22:39 AM. During this period, Bearing No. 1 experienced a failure characterized by a localized defect on the outer race. A total of 984 vibration signals were recorded throughout the experiment, and these raw vibration signals were utilized as the primary dataset in this study. Each signal was captured over a duration of 10 minutes.

4. BEARING LIFE ESTIMATION

The shaft was rotating at a constant speed of 2000 RPM. Given that one vibration signal was recorded every 10 minutes, and a total of 984 signals were obtained, the effective operating cycles of the bearing were computed using the following relation:

$$C = (\frac{2000}{60})^{rps} \times (10 * 60)^{s} \times 984 = 19680000 \tag{1}$$

Based on the above calculation, the bearing under study experienced failure and ceased operation after 19,680,000 operational cycles.

5. SIGNAL PROCESSING

The Continuous Wavelet Transform (CWT) is a signal analysis technique used to examine and interpret non-stationary and non-periodic signals. In this method, the input signal is decomposed using a set of basic wavelet functions, which act as short-duration wave-like oscillations. This approach facilitates the detection and analysis of various signal components over time and is recognized as a powerful tool in fields such as signal processing, imaging, and pattern recognition [15].

Similar to the Fourier Transform, the CWT uses inner products to measure the similarity between a signal and an analyzing function. In the Fourier Transform, the analyzing functions are complex exponentials. The coefficients of the Short-Time Fourier Transform (STFT), denoted as F(ω, τ), represent the correlation between the signal and a sinusoid with angular frequency ω within a specific time window centered at τ.

In contrast, the CWT utilizes a wavelet function ψ as the basis for analysis. The transform compares the input signal with scaled and translated versions of this wavelet. The stretching or compressing of the wavelet function is referred to as dilation or scaling, which aligns with the physical concept of scale. By comparing the signal to the wavelet at different scales and positions, a two-dimensional function is obtained. If the wavelet is complex-valued, the resulting CWT is also a complex-valued function of scale and position. For real-valued signals and wavelets, the CWT yields real-valued results.

For a given scale parameter a > 0 and translation parameter b, the Continuous Wavelet Transform of a signal x(t) is defined as follows [15]:

$$C(a,b;f(t),\psi(t)) = \int_{-\infty}^{\infty} f(t)\frac{1}{a}\psi^{*}\left(\frac{t-b}{a}\right)dt \tag{2}$$

In the above equation, the symbol *** denotes the complex conjugate. Not only do the scale and translation parameters affect the CWT coefficients, but the choice of the wavelet function also has a significant impact on the results. In this study, each vibration signal was processed using the Continuous Wavelet Transform. The output of this process was visualized as a scalogram spectrum [16].

A scalogram is an analytical representation in which the input signal is decomposed into various frequency components. It is particularly suitable for the analysis of non-stationary and aperiodic signals. In a scalogram, the energy distribution of the signal is displayed over both frequency and time domains. The wavelet transform, as a signal analysis method, enables the decomposition of a signal into both frequency and time components. It shows the signal's energy levels across different frequencies and time intervals. This makes wavelet-based analysis highly effective and stable for dealing with asymmetric and non-linear signals.

Through the use of scalograms and wavelet transforms, underlying patterns and structural features within a signal can be identified and examined in greater detail. These methods find applications in numerous scientific and technical fields, including signal processing, data analysis, and medical imaging [16].

6. DEEP LEARNING AND BEARING FAULT DIAGNOSIS

To better understand the functioning of recurrent neural networks (RNNs), it is useful to revisit the structure of traditional feedforward neural networks. In feedforward networks, each neuron in a hidden layer connects to neurons in the previous and next layers. The output of a neuron is propagated forward only and cannot loop back to the same layer or any preceding one hence the term feedforward.

Recurrent neural networks, in contrast, allow for feedback connections. The output of a neuron can be used as input not only for the next layer but also for the same or a previous layer. This design is more biologically inspired and closer to how the human brain functions compared to feedforward architectures [17].

In this study, a Long Short-Term Memory (LSTM) network a specialized form of RNN was implemented to estimate the remaining useful life (RUL) of the bearing [18].

7. EVALUATION METRICS

To evaluate the accuracy of the proposed RUL estimation model, two widely used performance indicators were adopted: the Mean Absolute Percentage Error (MAPE) and the Root Mean Square Error (RMSE), normalized over the prediction range. These metrics are crucial for assessing the predictive power and robustness of models used in bearing lifetime estimation tasks [19].

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{3}$$

$$\mathrm{MAPE} = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \tag{4}$$

Where,

- y_i is the actual (true) value
- $\hat{y}_i$ is the predicted value
- n is the number of observations

8. RESULTS AND DISCUSSION

The vibrational behavior of the bearing assembly mounted on a common shaft over the time interval from startup to the failure of the first bearing is illustrated in Figure 1. The vibration signals are labeled as A, B, C, and D. Analysis of the vibrational behavior of each bearing reveals that the oscillatory pattern of each signal remains within a specific amplitude range. However, for bearing number one, a gradual increase in the amplitude of the oscillation is observed, and as the failure point approaches, this amplitude rises sharply. The peak amplitude in the final stage of degradation exceeded the healthy-state amplitude by more than tenfold. A similar trend of amplitude increase was observed in the other bearings as well; however, for bearing number two, the increase was relatively subtle and less discernible.

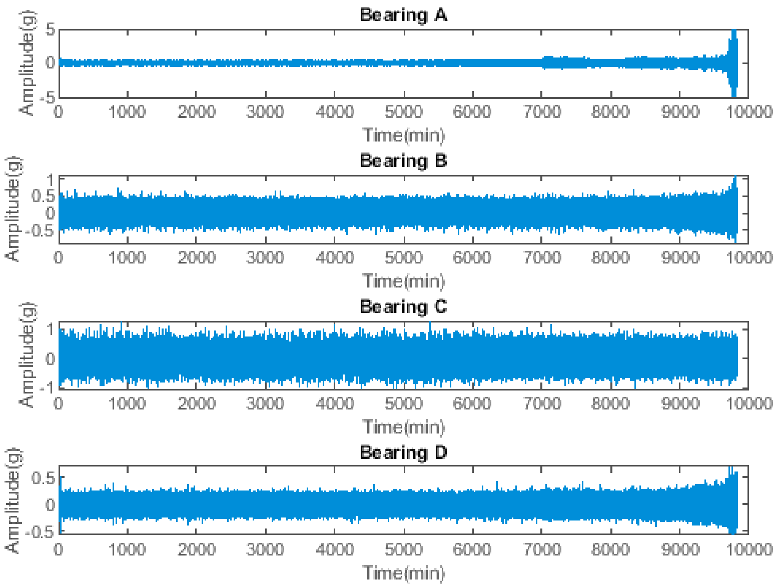

Fig. 1. Vibration signals of bearings A, B, C, and D from startup to the failure occurrence in bearing A.

Overall, the results in this section show that as the operating time of the bearing increases, its components deteriorate, which in turn affects the intensity of the vibrations produced. The symptoms of this degradation are manifested as an increase in amplitude and disruption of harmonic oscillations in the vibration signal. Additionally, as signs of failure appear in the bearing, the friction between the rotating components increases, leading to a rise in the amplitude of oscillation, which is the intensity of the vibrations. Therefore, monitoring the vibrational behavior of bearings is a critical tool for estimating their remaining useful life. Figures 2 and 3 display the scalogram output from the continuous wavelet transform for the bearing in its healthy and faulty states. A comparison of the visual appearance of these two scalograms reveals significant differences across various bands. The variation in scale intensity in the healthy spectrum is much smaller compared to the faulty spectrum, which is attributed to frequency changes occurring during the bearing's failure. Moreover, the intensity of the frequency spectrum energy during bearing failure is noticeably higher than in the healthy state. This phenomenon is visible in the change of the scalogram's color from blue to red. The comparison of images confirms that the scalogram spectrum is a suitable tool for classification, fault detection, and the estimation of the bearing's remaining life.

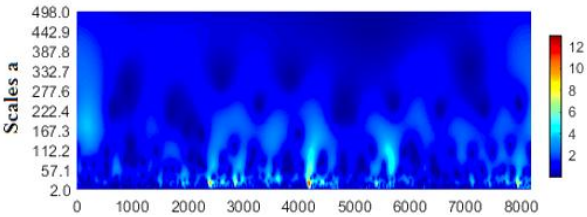

Fig. 2. Extracted scalogram of the vibration signal from the bearing in the healthy state.

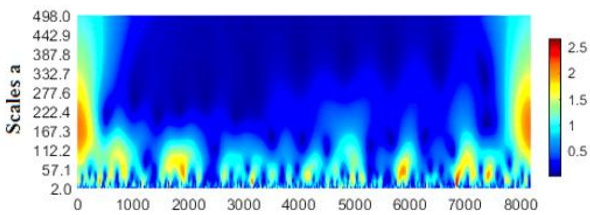

Fig. 3. Extracted scalogram of the vibration signal from the bearing in the failure state

The total operating time of the bearing was 19,680,000 cycles, and the entire dataset consisted of 984 data points. After applying the signal processing steps, these data were converted into scalogram spectra. As mentioned in Chapter 3, to estimate the remaining useful life of the bearing, the deep learning LSTM network was used. Figure 4 presents the initial specifications of the deep learning model for estimating the remaining life of the bearing. The changes in RMSE values and the model's error values for different training iterations are shown in Figure 5. The entire training and evaluation process of the deep learning model for estimating the inertia constant consisted of 140 iterations. The error convergence was achieved at the 31st iteration. The lowest RMSE value obtained for remaining life estimation was 0.18, and the minimum calculated MAPE for this model was 0.0103.

1	'sequenceinput'	Sequence Input	Sequence input with 1 dimensions
2	'lstm'	LSTM	LSTM with 500 hidden units
3	'fc_1'	Fully Connected	500 fully connected layer
4	'dropout'	Dropout	10% dropout
5	'fc_2'	Fully Connected	90 fully connected layer
6	'regressionoutput'	Regression Output	mean-squared-error with response 'Response'

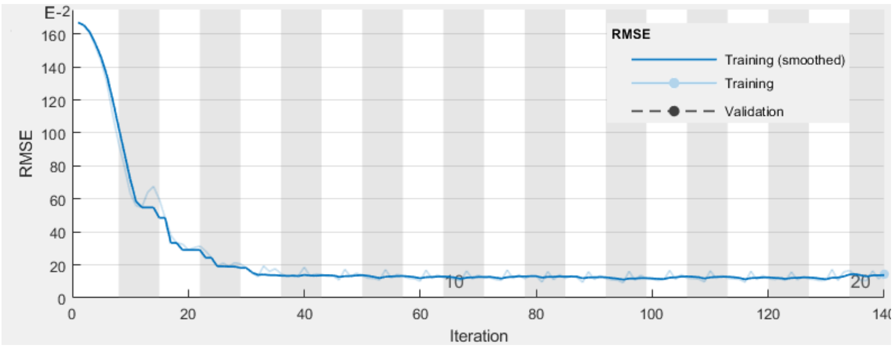

Fig. 4. Initial Specifications of the Deep Learning Model

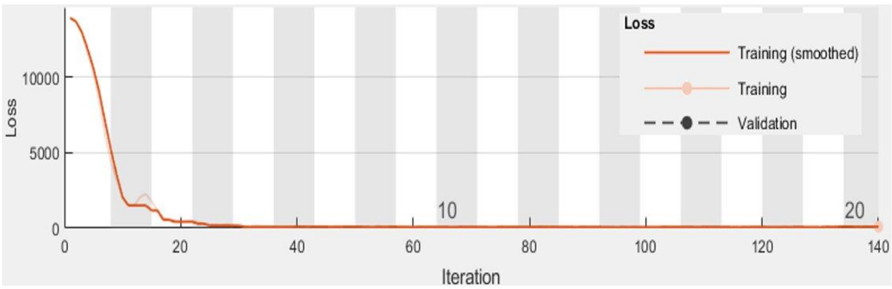

Fig. 5. Changes in RMSE and Model Error for Remaining Life Prediction of Bearings

To compare the results of the deep learning model and validate its findings, an Artificial Neural Network (ANN) model was also developed for the prediction of bearing remaining life. In Figure 6, the correlation between the actual and predicted results by the ANN model is shown for the activation functions Trainscg, Trainlm, and Trainbr. Additionally, Table 1 presents the evaluation metrics for the three ANN models mentioned above. The analysis of the ANN results revealed that the highest accuracy in predicting bearing remaining life was achieved by the ANN model with the Trainbr activation function. Comparing the results of the deep learning model with those of various neural network models indicates that the LSTM approach exhibits a significantly lower error in predicting bearing remaining life and demonstrates much higher efficiency compared to the traditional ANN model. Table 2 presents the results from similar studies that have utilized the dataset from this research. The comparison of results shows that the RMSE value obtained in the present study was significantly higher than that in the research by Kundu, Darpe, and Kulkarni [22], highlighting the superior accuracy of the proposed method in predicting bearing remaining life. On average, the accuracy of this model in predicting bearing remaining life was approximately 18% higher compared to the studies presented in Table 2.

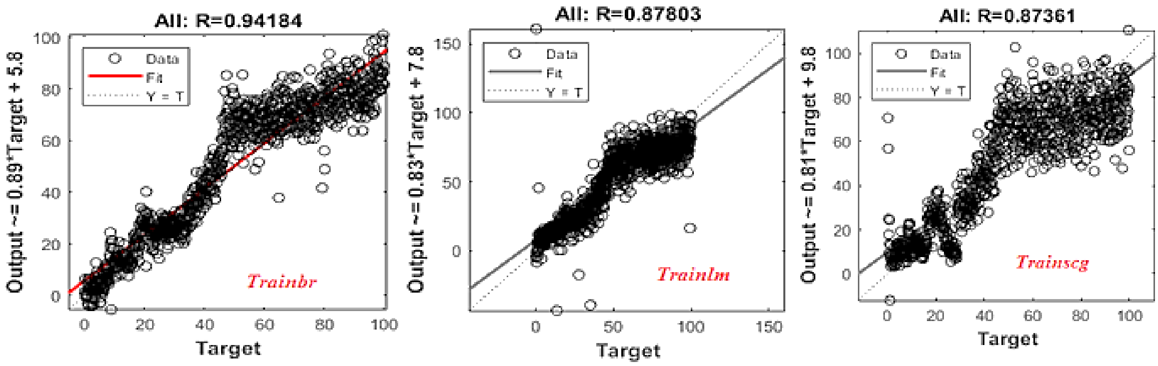

Fig. 6. Correlation between Actual and Predicted Results

Table 1. Evaluation Metrics for Bearing Life Estimation Model

MAPE	RMSE	Activation Function Type
1.5430	14.1161	Trainscg
2.6349	13.9613	Trainlm
0.4893	9.23561	Trainbr
0.0103	0.18	LSTM Model

Table 2. Comparison of the Current Study's Results with Similar Studies

Method	RMSE	Reference
Support Vector Regression	0.2573	[20]
Accelerated Weibull Failure Time Regression	1.0115	[22]
Deep Learning	0.3797	[21]
Proposed Method	0.18	--

9. CONCLUSION

An analysis of the vibration signals obtained from the operation of the dataset showed that as time progressed and the bearing became worn, the vibrational behavior of the bearing underwent significant changes. Specifically, over time, the amplitude of the vibration signal increased, with this increase observed gradually. Ultimately, the results revealed that as the time approached the failure point of the bearing, the vibration amplitude increased sharply and with a steep slope, such that at the moment of bearing failure, the vibration signal amplitude was more than ten times greater than that during normal operation. The LSTM deep learning model was implemented to estimate the bearing's remaining life, and this model converged well to the final error. The minimum RMSE and MAPE values obtained for this model were 0.18 and 0.0103, respectively.

Declaration

We acknowledge that we used ChatGPT to enhance the academic writing of our manuscript while ensuring the originality and integrity of our work.

Transparency Statement

The data supporting this study are available upon reasonable request to the corresponding author, subject to ethical and confidentiality considerations.

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Declaration of Interest

The authors declare that they have no competing interests.

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