

# A rolling bearing state evaluation method based on deep learning combined with Wiener process

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## ABSTRACT

As a key component of rotating parts, rolling bearings largely determine the operation safety of equipment. However, in practical applications, because the degradation trajectory of rolling bearings cannot be truly characterized, the existing model cannot accurately describe the degradation trajectory of rolling bearings, resulting in the running state of rolling bearings cannot be directly evaluated. Therefore, a method of rolling bearing state assessment based on deep learning combined with Wiener process is proposed in this paper. Firstly, a deep network model is constructed by deep learning to mine the degradation information of rolling bearings. Secondly, the mined degradation information is fused, and then the degradation indicator used to characterize the degraded trajectory of the rolling bearing is constructed. Then, based on Wiener process, the degradation model of rolling bearing is established to describe the degradation mode of rolling bearing. Finally, the constructed degradation indicator is input into the established degradation model to predict its RUL, and then the running state of the rolling bearing is evaluated.

## 1. INTRODUCTION

During the operation of mechanical equipment, due to the influence of many factors, mechanical equipment will inevitably degrade. This degradation process generally occurs first in components that produce relative motion, especially rolling bearings(Zhu et al. 2024). Therefore, in order to ensure that mechanical equipment always serves in a safe state, it is very necessary to evaluate the operating status of rolling bearings. The remaining useful life (RUL) prediction method has been recognized as a basic and effective method for state assessment of rolling bearings(Li et al. 2024). (If the RUL of the rolling bearing can be predicted, the current service status of the rolling bearing can be assessed) Currently, in the field of prediction of the RUL

of rolling bearings, scholars have proposed a series of life prediction methods of rolling bearings, but generally they can be divided into methods based on expert knowledge base, data-driven, physical models and hybrid methods(Wang et al. 2023).

The method based on expert knowledge base achieves prediction by comparing the similarity between the observed data and the previously defined fault database through expert system or fuzzy system(Qin et al. 2023). For example, Qin et al. proposed a two-stage RUL prediction method based on similarity, constructing a degradation indicator (DI) of bearings through a multi-head self-attention mechanism, and comparing the constructed DI with other bearing degradation indexes in the expert knowledge base, thereby realizing the prediction of the RUL of the bearing(Qin et al. 2023). Xia et al. proposed a hybrid Gaussian-evidence hidden Markov model that integrates expert knowledge and condition monitoring information to predict the RUL of bearings under the framework of belief function theory(Xiahou, Zeng, and Liu 2021). These methods often require special knowledge about the fault data, however obtaining this knowledge is expensive in practice. The data-driven method uses the historical status data of the equipment to extract characteristic information related to the status changes of the monitored object. Through statistical analysis, pattern recognition, machine learning and other technologies, it attempts to simulate the fuzzy functional relationship between sensor data and equipment status, and then realize the status assessment and RUL prediction of the monitored object(Li et al. 2022). For example, Cheng et al. extracted nonlinear features from bearing vibration signals and inputted them into convolutional neural networks to evaluate the health status of bearings, and combined them with relevant vector machines to predict the RUL of bearings(Cheng et al. 2021). Yoo et al. used continuous wavelet transform to convert bearing vibration signals into image signals and input them into convolutional neural networks for predicting the RUL of bearings(Yoo and Baek 2018). Ren et al. used deep self-coding neural networks to compress the time-frequency wavelet features of rolling bearings and predict the RUL of

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rolling bearings(Ren et al. 2018). However, these methods need to establish the state characterization function of the rolling bearing, and with the increase of the prediction time span, the characterization ability of the model decreases, and the prediction accuracy of the RUL decreases. The physical model method is based on the mathematical representation of the physical behavior during the degradation process to predict the degradation performance and RUL of the bearing. For example, Kogan et al. established a multi-body dynamics model of rolling bearings based on classical dynamics and kinematic equations to describe the health degradation process of rolling bearings under different faults and predict their RUL by fitting its degradation process(Kogan et al. 2015). Qian et al. improved the Paris-Erdogan model and constructed a multi-time scale degradation model to track the changes in the degradation rate of the bearing in different time periods to predict the RUL of the bearing(Qian, Yan, and Gao 2017). These methods can provide accurate prediction results, it still requires an in-depth understanding of the physical characteristics of the bearing and the prognosis of the bearing. The accuracy depends heavily on the accuracy of the physical model used. The hybrid prediction method is a RUL prediction method that combines the advantages of physical models and data drivers(Wang et al. 2020). Wang et al. constructed a new scalable two-stage linear/nonlinear composite model to describe various degradation behaviors of bearings through a hybrid data- and model-driven method, and predicted the RUL of bearings by using a long and short time memory network(Wang, Cui, and Wang 2022). Rezamand et al. defined the role of environmental conditions in the dynamics of bearing failure. They achieved the RUL prediction of faulty bearings through vibration signal recognition and fault dynamics analysis(Rezamand et al. 2021). The hybrid prediction method can effectively simulate the degradation process of rolling bearings. However, these methods complicate the algorithm and is limited by the physical behavior of the rolling bearing during the degradation process, which in turn leads to modeling difficulties.

Due to the limitations of different methods, the unclear exploration of the failure mechanism of rolling bearings, the lack of degradation data, and especially the neglect of historical operating data of rolling bearings in normal service, these methods cannot accurately evaluate the service status of rolling bearings. There are two reasons for this. First, the degradation characteristics used cannot accurately represent the degradation trajectory of rolling bearings; second, the degradation model used cannot map the failure mechanism of rolling bearings. Due to the powerful feature extraction ability of convolutional neural networks, by stacking multiple convolutional and pooling layers, more and more abstract and advanced features can be gradually extracted. This hierarchical feature extraction can better capture the degradation information of bearings, thereby improving the performance of the model. In addition, due to the excellent

non monotonic characteristics of the Wiener process, it can effectively describe the local fluctuation characteristics on the degradation path of bearings. Therefore, in order to overcome the limitations of the above methods, this paper proposes a rolling bearing state assessment method based on deep learning combined with Wiener process, starting from the construction of degradation indicators of rolling bearings and the failure mechanism mapping of the model. This method first constructs a degradation indicator extractor for the full- life cycle of rolling bearings based on one-dimensional convolutional neural. Secondly, a mapping model between its degradation trajectory and RUL is established based on the Wiener process. Then, using DI to estimate the unknown parameters in the model, the RUL prediction of the rolling bearing at different monitoring points is completed. Finally, the status evaluation of the rolling bearing is realized through the prediction results at the current moment.

## 2. METHOD PROPOSED

### 2.1. DI construction method

Convolutional neural network is a type of deep neural network, which consists of multiple neural network layers. Each layer consists of multiple neurons that are connected to the neurons in the previous layer. Convolutional neural networks usually contain three types of layers: convolutional layers, pooling layers, and fully connected layers. Because the dimensional convolutional neural network has good information mining and weight sharing capabilities(She and Jia 2019). Therefore, this paper constructs the bearing degradation index of the rolling shaft based on the one-dimensional convolutional neural network. The specific construction method is as follows:

Let  $[\mathbf{X}_1, \mathbf{X}_2 \cdots \mathbf{X}_{m-1}, \mathbf{X}_M]^T$  represent the full-life vibration signal of the M group of rolling bearings, and  $\mathbf{X}_i = [x_{i,1}, x_{i,2} \cdots x_{i,n-1}, x_{i,N}]^T$  be the full-life cycle signal of the  $i$ -th group, where N is the number of sampling times of the bearing. Therefore, the whole life vibration signals of the

group of rolling bearings can generate  $\sum_{i=1}^M N_i$  group of

samples. As shown in Figure 1, samples are input into the constructed one-dimensional convolutional neural network (1DCNN) in batches to perform convolution normalization and other operations. Finally, a neuron is connected to the output end to represent the current service status of the rolling bearing. In this way, the collected samples are sequentially input into the constructed one-dimensional convolutional neural network to obtain the degradation index that characterizes the degradation trajectory of the rolling bearing.

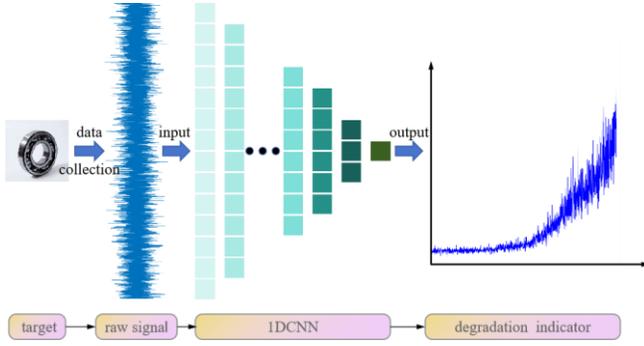


Figure1. DI construction process

## 2.2. State Assessment Method

The Wiener process has good statistical properties. Therefore, this paper establishes a degradation model of rolling bearings based on the Wiener process to describe its degradation state (Ta et al. 2023). The degradation process of the rolling bearing is described based on the Wiener process as shown in Equation (1), where  $y(t)$  represents the degradation state of the rolling bearing at time  $t$ , and  $y_0$  is the initial state of the rolling bearing.  $a$  is the drift coefficient, which represents the difference between similar rolling bearings and obeys the normal distribution  $N(\mu_a, \sigma_a^2)$ .  $t^b$  is the degradation trend term describing the severity of rolling bearing degradation, where  $b$  is a fixed coefficient.  $c$  is the diffusion coefficient, which represents the degree of fluctuation when the rolling bearing degrades, and  $B(t)$  is the standard Brownian motion (BM), which represents the inherent variability of the random degradation process over time. The fluctuation term describes the uncertainty when the rolling bearing degrades and obeys the normal distribution  $N(0, c^2 t)$ .

$$y(t) = y_0 + at^b + cB(t) \quad (1)$$

In order to ensure that rolling bearings always operate safely. Therefore, as shown in equation (2), the RUL  $l_k$  of the rolling bearing at time  $k$  is defined based on the first hitting time (Cheng et al. 2023), where  $\omega$  is the failure threshold.

$$l_k = \inf \{l : y(l+t_k) \geq \omega | y(t_k) = y_k\} \quad (2)$$

According to the characteristics of BM and the definition of the RUL of the above formula, the probability density function (PDF) of the RUL of the rolling bearing at any time is shown in Equation (3) (Si et al. 2012).

$$f(l_k) \cong \frac{1}{\sqrt{2\pi l_k^2 (\sigma_a^2 A(l_k)^2 + \sigma^2 l_k)}} \times \left( w(t_k) - B(l_k) \frac{w(t_k) \sigma_a^2 A(l_k) + \mu_a \sigma^2 l_k}{\sigma_a^2 A(l_k)^2 + \sigma^2 l_k} \right) \times \exp \left[ -\frac{(w(t_k) - \mu_a A(l_k))^2}{2(\sigma_a^2 A(l_k)^2 + \sigma^2 l_k)} \right] \quad (3)$$

where  $A(l_k) = (t_k + l_k)^b - t_k^b$ ,  $B(l_k) = A(l_k) - l_k b (t_k + l_k)^{b-1}$  and  $w(t_k) = w - y(t_k)$ . After obtaining the PDF of the RUL. As shown in equation (4), the pseudo life is first integrated and averaged, and then the RUL of the rolling bearing at time is obtained (Hu et al. 2020). Then use equation (5) to evaluate the service status of the bearing at the current moment,  $T_{past}$  represents the length of time the bearing has been in service relative to the current moment,  $BC_k$  represents the service status of the bearing at the current moment, and the closer  $BC_k$  is to 100%, the healthier the bearing is.

$$L_k = \int_0^\infty l_k f(l_k) dl_k \quad (4)$$

$$BC_k = \frac{L_k}{T_{past} + L_k} * 100\% \quad (5)$$

According to formula (3) and (4), if the RUL of the rolling bearing at the current time is obtained, the values of parameters  $\mu_a, \sigma_a^2, b$  and  $c^2$  need to be estimated. The parameters  $\mu_a, b, c^2$  can be obtained using the mapping model (1) as the fitting function. The parameter  $\sigma_a^2$  can be obtained by the maximum likelihood estimation method. According to the nature of Wiener process, sample  $y_{1:N} = \{y_1, y_2, \dots, y_N\}$  follows multivariate normal distribution, let  $\Lambda = [t_1^b, t_2^b, \dots, t_N^b]^T$ , then its mean and variance are shown in equation (6):

$$y \sim N(\mu_a \Lambda, \sigma_a^2 \Lambda \Lambda^T + c^2 \mathbf{Q}) \quad (6)$$

$$\mathbf{Q} = \left[ \min \{t_i, t_j\} \right]_{1 \leq i, j \leq N}$$

Obtain the PDF of the multivariate normal distribution according to Equation (6) and take the logarithm of both sides to obtain the likelihood function containing unknown parameters. Then use the likelihood function to partially derive the parameter  $\sigma_a^2$ , and make the equation equal to 0.

The solution expression for parameter  $\sigma_a^2$  is obtained as shown in Equation (7):

$$\sigma_a^2 = \frac{(y_{iM} - \mu_a \Lambda)^T Q^{-1} \Lambda \Lambda^T Q^{-1} (y_{iM} - \mu_a \Lambda) - c^2 \Lambda^T Q^{-1} \Lambda}{(\Lambda^T Q^{-1} \Lambda)^2} \quad (7)$$

**2.3. Method framework**

The proposed method is shown in Figure 2. This method first divides the obtained full-life data into  $\sum_{i=1}^M N_i$  samples according to the number of collections, and performs data processing on each sample to remove abnormal points and avoid interference with the DI construction model. Secondly, input the processed data into the constructed 1DCNN in batches to train the network until the network converges. Then, the trained network is used as the DI extractor of the rolling bearing, and the newly collected data is input into the DI extractor in sequence according to the number of sampling times, so as to obtain the DI describing the historical operating status of the rolling bearing. Then, use the historical DI data of the rolling bearing to estimate the unknown parameters in the mapping model, and bring them into equations (3) and (4) to obtain the RUL of the rolling bearing at the current moment. Finally, equation (5) is used to evaluate the current service status of the rolling bearing.

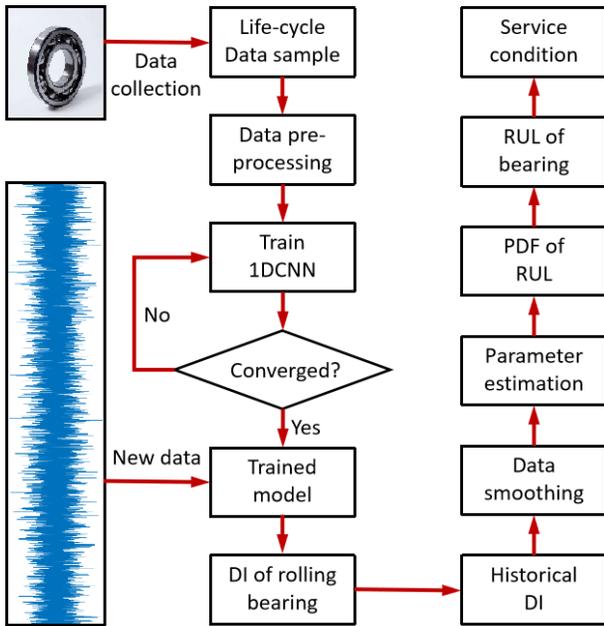


Figure2. Method framework

**3. EXPERIMENT**

In order to verify the effectiveness of the method, this paper uses two sets of public full-life rolling bearing data sets for verification. The constructed DI is quantitatively analyzed

using robustness (Rob), monotonicity (Mon), trendability (Tre) and comprehensive evaluation methods (Com)(Ta et al. 2023). If these four evaluation indicators are larger, it means that the constructed DI can better characterize the degradation trajectory of the bearing. Similarly, in order to analyze the prediction results from a quantitative perspective, this paper uses root mean square error (RMSE), adaptability ( $R^2$ ), mean absolute error (MAE) and cumulative relative accuracy (CAR) to analyze the prediction results. The smaller the RMSE and the MAE, the better the prediction effect; the larger  $R^2$  means the model has stronger adaptability; the greater the CAR, the better the prediction effect.

**3.1. Case 1**

Case 1 uses the full-life bearing data provided by the IEEE PHM 2012 Challenge to verify the method. Experimental data comes from PRONOSTIA experimental bench. This data set contains a total of 17 sets of accelerated degradation experimental data of rolling bearings, which were completed under three working conditions, as shown in Table 1. The operating conditions of the 17 sets of rolling bearings are shown in Table 2.

Table1. Operating conditions table

Condition number	Conditions 1	Conditions 2	Conditions 3
Rotating speed	1800 rpm	1650 rpm	1500 rpm
Apply load	4000 N	4200 N	5000

Table2. IEEE PHM 2012 Dataset

Data set	Conditions 1	Conditions 2	Conditions 3
Training set	Bearing1_1	Bearing2_1	Bearing3_1
	Bearing1_2	Bearing2_2	Bearing3_2
	Bearing1_3	Bearing2_3	Bearing3_3
Test set	Bearing1_4	Bearing2_4	
	Bearing1_5	Bearing2_5	
	Bearing1_6	Bearing2_6	
	Bearing1_7	Bearing2_7	

In this experiment, each group of bearings used two vibration sensors to collect data. The sampling frequency was 25.6kHz, the sampling interval was 10 seconds, and the duration of each sampling was 1 second. In this experiment, this paper uses Bearing1\_3 as a test sample, and the others as training samples to train the network, and continuously adjust the network parameters until the network converges. Bearing1\_3 data samples are input into the DI extractor successively, and the output DI are smoothed successively. The DI of Bearing1\_3 is shown in Figure 3. The constructed DI is compared with the 7 commonly used DI of rolling bearings. The comparison results are shown in Table 3 (Proposed method (M1), Degenerate angle (M2), Maximum value (M3), Mean absolute value (M4), Root mean square (M5) Root

amplitude (M6), Standard deviation (M7) Variance (M8)). It can be seen from the table that the DI constructed using the proposed method has good Tre, Rob and Mon. Because the range of these three evaluation indicators is between [0,1]. Therefore, the three of them are added to form a Com. Judging from the comprehensive indicator column in the table, the DI constructed in this paper is the best.

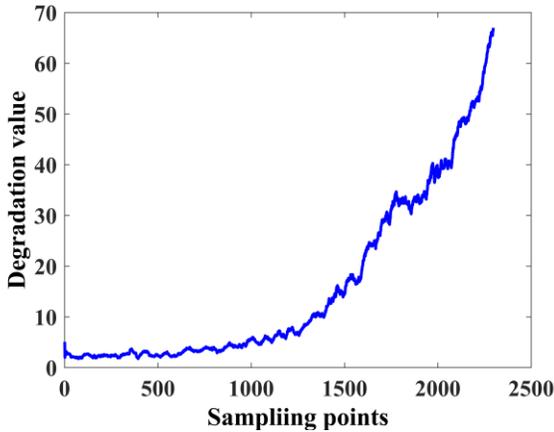


Figure3. Bearing1\_3 DI

Table3. Performance comparison of 8 DIs

	Rob	Mon	Tre	Com
M1	0.9932	0.8484	0.8867	2.7283
M2	0.9932	0.1276	0.4102	1.531
M3	0.9797	0.4599	0.7402	2.1798
M4	0.9737	0.3571	0.7402	2.0710
M5	0.7311	0.4207	0.8216	1.9734
M6	0.5934	0.0113	0.2156	0.8203
M7	0.9931	0.4233	0.8145	2.2309
M8	0.9909	0.4382	0.7979	2.2270

Bearing1\_3 conducted a total of 2375 samples in the experiment. In order to make the intervals between each condition monitoring (CM) point equal, this paper took the first 2300 samples as test samples, in which the monitoring interval was 100. Finally, Bearing1\_3 was monitored 23 times according to the service process of the bearing. The  $k$ -th CM point represents the service status of the bearing at time  $k$ , and the previous  $k$ -th CM point represents the historical service status of the bearing at time  $k$ . The constructed DIs are input into the PDF of the RUL in batches and the corresponding unknown parameters are estimated.

The obtained PDF of the RUL is shown in Figure 4. It can be seen from the figure that with more and more historical data, the PDF becomes more and more convergent, indicating that the credibility of the prediction is getting higher and higher.

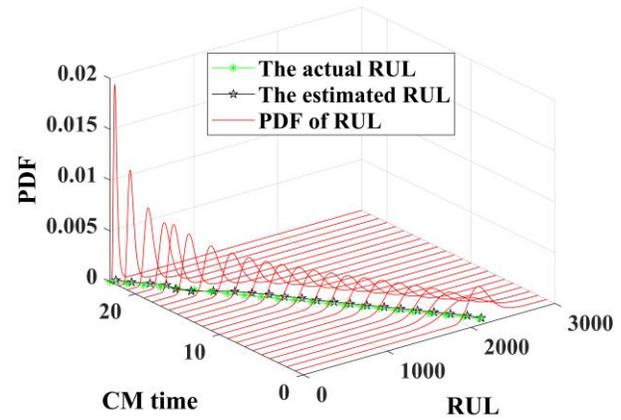


Figure4. PDF of RUL

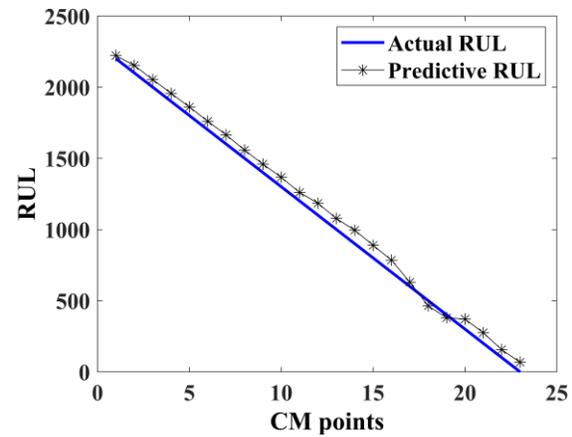


Figure5. Prediction results at different CM points

Table4. Quantitative analysis of prediction results

RMSE	R <sup>2</sup>	MAE	CAR
63.5707 (2.76%)	0.9908	60.5620 (2.63%)	0.8610

As can be seen from Figure 5, the prediction results of different CM points are close to the actual RUL of the rolling bearing Bearing1\_3. It can be seen from Table 4, the RMSE of the prediction result is only 2.76%, the MAE is 2.63%, R2 is close to 1, and the CAR is 86.10%. The above analysis results show that the method has good accuracy. In addition, Figure 6 shows the service status of the rolling bearing Bearing1\_3 at different CM points. It can be seen from the figure that the service performance of the rolling bearing

Bearing1\_3 gradually decreases as its service time becomes longer. It also illustrates the effectiveness of this method for evaluating the service status of rolling bearings.

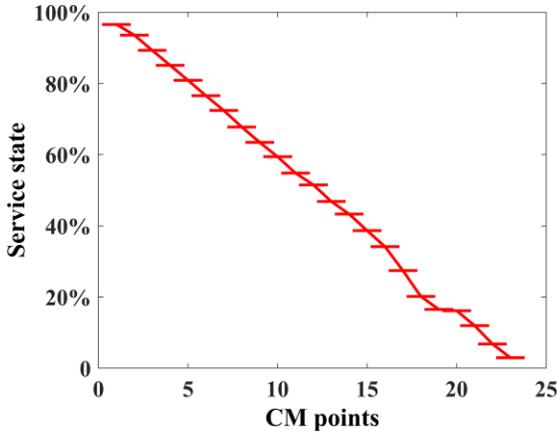


Figure6. Bearing1\_3 service status

### 3.2. Case 2

Case 2 uses the public data set of XJTU-SY for verification. This data set contains a total of 15 sets of full-life bearing data. The sampling frequency is 25.6 kHz, the sampling interval is 1min, and each sampling is 1.28 seconds long. In the same verification method as Case 1, 14 sets of bearings are used as training samples and 1 set is used as test samples. The test sample is Bearing 3\_1. The DI of Bearing 3\_1 obtained after the final test is shown in Figure 7. It can be seen from the figure that although the DI produces large local volatility, the overall Tre and Rob show good performance. In addition, the performance comparison of different DIs in Table 5 also proves that the DI constructed by this method has good representation performance.

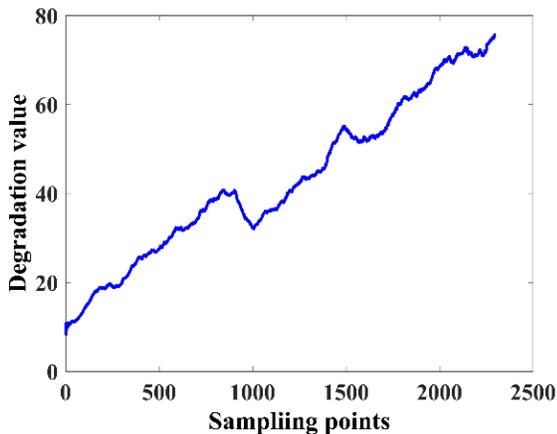


Figure7. Bearing1\_3 DI

Table5. Performance comparison of 8 DIs

	Rob	Mon	Tre	Com
M1	0.9431	0.7887	0.9530	2.6848
M2	0.9968	0.0292	0.1321	1.1581
M3	0.9919	0.0252	0.3321	1.3492
M4	0.9919	0.0996	0.3423	1.4338
M5	0.6331	0.0548	0.0941	0.7820
M6	0.5731	0.0236	0.1641	0.7608
M7	0.9960	0.1204	0.3419	1.4583
M8	0.9961	0.1064	0.3427	1.4452

Bearing 3\_1 took a total of 2538 samples. In order to keep the monitoring interval unchanged, the first 2500 sampling points were taken for verification, and a total of 25 times of monitoring were conducted. The RUL of PDF for each monitoring is shown in Figure 8. It can be seen from the figure that with more and more historical data, the PDF becomes more and more convergent, which shows that the credibility of the prediction is getting higher and higher. This leads to the same conclusion as Case 1.

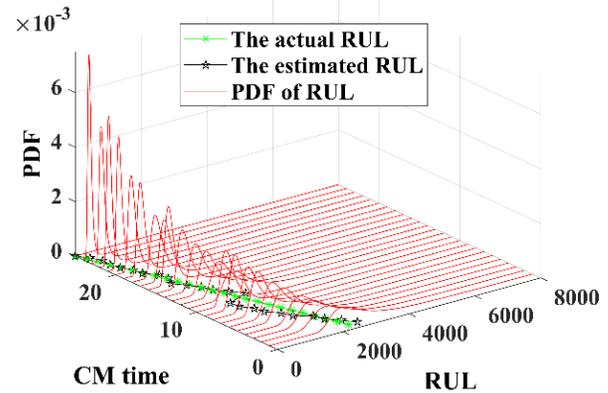


Figure8. PDF of RUL

Figure 9 shows the results of the actual life and predicted life of Bearing 3\_1 at different monitoring points. It can be seen from the figure that the deviation at some CM points is larger, and the deviation at some CM points is smaller. This is because the constructed DI has greater volatility at this CM point, which in turn leads to a greater deviation between the prediction results and the actual results. However, from the overall prediction effect, the prediction results are gradually closer to the actual prediction results. As can be seen from

Table 6, the RMSE of the prediction result is 9.72%, MAE is 7.10%, R2 is 0.8865, and CAR is 77.01%. The above analysis results show that the method has good accuracy. Figure 10 is the result of mapping the predicted RUL to service performance, and then determines the service status of the bearing. It can be seen from the figure that as the service time of the bearing increases, the performance of the bearing gradually decreases. Although there was a "recovery" during the period, this can be considered as the self-healing behavior of the bearing during service. Therefore, this method can well evaluate the service status of bearings.

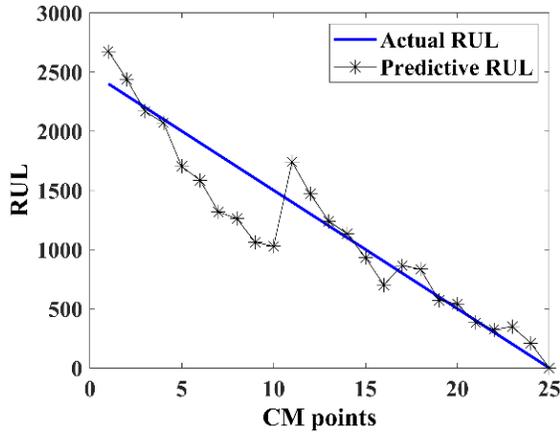


Figure9. Prediction results at different CM points

Table6. Quantitative analysis of prediction results

RMSE	R <sup>2</sup>	MAE	CAR
242.9127 (9.72%)	0.8865	177.4692 (7.10%)	0.7701

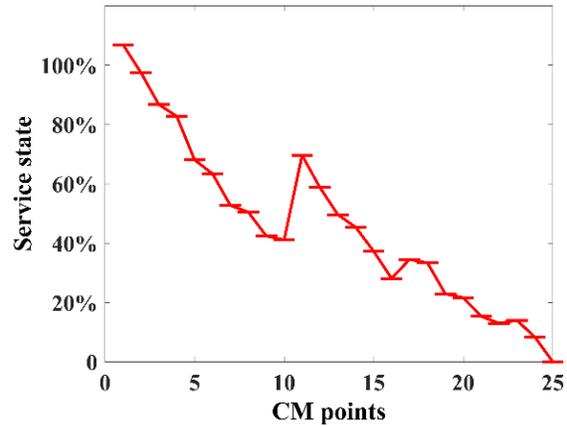


Figure10. Bearing1\_3 service status

#### 4. CONCLUSION

In order to evaluate the service status of rolling bearings, this paper proposes a rolling bearing status evaluation method based on deep learning combined with Wiener process. Since the existing DIs cannot characterize the degradation trajectory of rolling bearings. This paper uses a 1DCNN to extract the DIs of rolling bearings. Aiming at the problem of the RUL of rolling bearings, this paper constructs a degradation model of rolling bearings based on the Wiener process, and uses its PDF to estimate the RUL of rolling bearings. The RUL of the rolling bearing is mapped to its service status, thereby completing the service status assessment of the rolling bearing. This paper uses the IEEE PHM 2012 public data set to verify the method. The experimental results show that the extracted DI has good trend and monotonicity, and the service status assessment of the rolling bearing has good accuracy. However, the contribution of this paper is limited. From the verification results, the bearing prediction accuracy is largely determined by the constructed DI and the complexity of the model. Therefore, the follow-up work of this paper will start from mining the degradation information of bearings and establishing more complex prediction models to improve the prediction accuracy of bearings.

#### REFERENCES

Cheng, W., S. S. Xie, J. Xing, Z. L. Nie, X. F. Chen, Y. L. Liu, X. Liu, Q. Huang, and R. Y. Zhang. 2023. 'Interactive Hybrid Model for Remaining Useful Life Prediction with Uncertainty Quantification of Bearing in Nuclear Circulating Water Pump', *Ieee Transactions on Industrial Informatics*.

Cheng, Y. W., K. Hu, J. Wu, H. P. Zhu, and X. Y. Shao. 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.

Hu, C. H., H. Pei, X. S. Si, D. B. Du, Z. N. Pang, and X. Wang. 2020. 'A Prognostic Model Based on DBN and Diffusion Process for Degrading Bearing', *Ieee Transactions on Industrial Electronics*, 67: 8767-77.

Kogan, G., R. Klein, A. Kushnirsky, and J. Bortman. 2015. 'Toward a 3D dynamic model of a faulty duplex ball bearing', *Mechanical Systems and Signal Processing*, 54-55: 243-58.

- Li, T. M., X. S. Si, H. Pei, and L. Sun. 2022. 'Data-model interactive prognosis for multi-sensor monitored stochastic degrading devices', *Mechanical Systems and Signal Processing*, 167.
- Li, Y. J., Z. J. Wang, F. Li, Y. F. Li, X. H. Zhang, H. Shi, L. Dong, and W. B. Ren. 2024. 'An ensembled remaining useful life prediction method with data fusion and stage division', *Reliability Engineering & System Safety*, 242.
- Qian, Y. N., R. Q. Yan, and R. X. Gao. 2017. 'A multi-time scale approach to remaining useful life prediction in rolling bearing', *Mechanical Systems and Signal Processing*, 83: 549-67.
- Qin, Y., J. H. Yang, J. H. Zhou, H. Y. Pu, and Y. F. Mao. 2023. 'A new supervised multi-head self-attention autoencoder for health indicator construction and similarity-based machinery RUL prediction', *Advanced Engineering Informatics*, 56.
- Ren, L., Y. Q. Sun, J. Cui, and L. Zhang. 2018. 'Bearing remaining useful life prediction based on deep autoencoder and deep neural networks', *Journal of Manufacturing Systems*, 48: 71-77.
- Rezamand, M., M. Kordestani, M. E. Orchard, R. Carriveau, D. S. K. Ting, and M. Saif. 2021. 'Improved Remaining Useful Life Estimation of Wind Turbine Drivetrain Bearings Under Varying Operating Conditions', *Ieee Transactions on Industrial Informatics*, 17: 1742-52.
- She, D. M., and M. P. Jia. 2019. 'Wear indicator construction of rolling bearings based on multi-channel deep convolutional neural network with exponentially decaying learning rate', *Measurement*, 135: 368-75.
- Si, X. S., W. B. Wang, C. H. Hu, D. H. Zhou, and M. G. Pecht. 2012. 'Remaining Useful Life Estimation Based on a Nonlinear Diffusion Degradation Process', *Ieee Transactions on Reliability*, 61: 50-67.
- Ta, Y. T., Y. F. Li, W. A. Cai, Q. Q. Zhang, Z. J. Wang, L. Dong, and W. H. Du. 2023. 'Adaptive staged remaining useful life prediction method based on multi-sensor and multi-feature fusion', *Reliability Engineering & System Safety*, 231.
- Wang, B., Y. G. Lei, N. P. Li, and N. B. Li. 2020. 'A Hybrid Prognostics Approach for Estimating Remaining Useful Life of Rolling Element Bearings', *Ieee Transactions on Reliability*, 69: 401-12.
- Wang, X., L. L. Cui, and H. Q. Wang. 2022. 'Remaining Useful Life Prediction of Rolling Element Bearings Based on Hybrid Drive of Data and Model', *Ieee Sensors Journal*, 22: 16985-93.
- Wang, Z. J., Y. T. Ta, W. N. Cai, and Y. F. Li. 2023. 'Research on a remaining useful life prediction method for degradation angle identification two-stage degradation process', *Mechanical Systems and Signal Processing*, 184.
- Xiahou, T. F., Z. G. Zeng, and Y. Liu. 2021. 'Remaining Useful Life Prediction by Fusing Expert Knowledge and Condition Monitoring Information', *Ieee Transactions on Industrial Informatics*, 17: 2653-63.
- Yoo, Y., and J. G. Baek. 2018. 'A Novel Image Feature for the Remaining Useful Lifetime Prediction of Bearings Based on Continuous Wavelet Transform and Convolutional Neural Network', *Applied Sciences-Basel*, 8.
- Zhu, D., J. W. Lyu, Q. W. Gao, Y. X. Lu, and D. W. Zhao. 2024. 'Remaining useful life estimation of bearing using spatio-temporal convolutional transformer', *Measurement Science and Technology*, 35.