

PHYSICS-INFORMED DEEP LEARNING FRAMEWORK FOR INTELLIGENT FAULT PREDICTION AND REMAINING USEFUL LIFE ESTIMATION OF ROTATING MACHINERY

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ABSTRACT

Unexpected failures in rotating machinery may lead to large economic losses and even safety problems. Accurately predicting remaining useful life (RUL) plays an important role in equipment maintenance. Because of the strong non-linearity and noise sensitivity of data-driven models, however, their interpretation is often limited, and it is challenging to incorporate physical degradation mechanisms and achieve generalization. This article proposes a Prior-Information and Physics-Informed Neural Network framework for intelligent RUL prediction of rotating machinery. The framework follows a cloud-edge collaborative paradigm, where vibration signals are firstly processed by an improved particle filter based on a Damage Discrepancy Accumulation Hypothesis at the edge to extract degradation features, and then Prior-Weighted Self-Attention is applied in the cloud to capture richer features of the degradation process by introducing the perturbation-based prior information. Finally, a Fast-Slow Coupling Physics-Informed Neural Network is adopted to fully utilize the physical degradation knowledge for making the model more interpretable. The experimental results on a public data set and a self-built rotating-machinery test rig show the effectiveness of the proposed paradigm in achieving higher accuracy than existing approaches. Moreover, the framework achieves good performance even under noisy conditions. The work demonstrates the value of using prior information, vibration degradation features, and physical knowledge to enable rotating-machinery prognostics with high accuracy and interpretation.

Keywords: *Remaining Useful Life, Rotating Machinery, Physics-Informed Neural Network, Prior Information, Predictive Maintenance, Vibration Signal, Self-Attention, Cloud-Edge Collaboration, Degradation Prediction, Prognostics.*

1. INTRODUCTION

Rotating machinery such as bearings, gears, shafts, turbines, pumps, compressors plays a vital role in modern industry, and its uninterrupted operation is critical for manufacturing, energy, transport, and aerospace systems [1]. A machine element failure can result in costly repairs, equipment shutdowns, lost time and lost production, and safety concerns [2]. Hence, Prognostics and Health Management (PHM) is a new research area with the goal of sensing machine conditions, detecting incipient faults, and forecasting future machine behavior [3]. Amongst other functions, the Remaining Useful Life (RUL) estimation of machine components is a crucial task in modern PHM systems, as it gives indication of the remaining operating time before the component hit a certain failure limit [4]. Accurate RUL estimation is important for implementing predictive maintenance strategies and to ensure equipment availability and reliability [5].

The traditional approaches to fault diagnosis and prognosis usually use physically based models, statistical approaches, or hand-crafted signal processing attributes to identify faults and forecast the future health status of a machine [6]. These

methods are usually highly specific to the particular type of degradation process studied and are not necessarily able to describe the complex degradation processes of rotating machinery [7]. The problem of estimating the RUL is complex because it is related to several physical interactions for degradation, further influenced by the operational and environmental conditions, noise and imperfect maintenance [8]. With the improvements in the sensor data acquisition capability, machine learning and deep learning algorithms like Long Short Term Memory (LSTM), Bidirectional LSTM (BiLSTM), Convolutional Neural Networks (CNNs), Attention-based networks and others are being actively explored for automated health assessment and RUL prediction [9].

Using deep learning methods, high-level examples of highly non-linear degradation patterns are directly identified from the vibration signals [10]. In practice, however, traditional data-based methods are in most cases lacking of a physical degradation mechanism and are usually not physics-based in the sense that they do not consider the physics of the degradation process of the machine elements [11]. Consequently, these methods can be inaccurate in representing

the physical trends and can lead to very different results if the number of training samples is limited, if there is noise in the sensors or if the conditions change [12]. The other problem is that methods that need a run-to-failure data set to train the model can be quite difficult to apply as it may be difficult, time consuming and even unsafe to gather such data sets from industrial machines [13].

Physics-informed approaches are an attractive alternative to traditional data-driven models because they enforce some characteristics of the degradation mechanisms in the physics of the algorithm, which enhances the generalizability and interpretability of the physics-informed model. Recently, Physics-Informed Neural Networks (PINNs) have been suggested for engineering problems in which data are subject to a physical constraint that can be formulated as a constraint on the model. Such constraints can be applied to encode the expected relationship between the predicted RUL and the state of the machine in the context of RUL prediction [14]. In recent years, physics-informed techniques have been employed with success to RUL estimation and health state prediction of rotating machinery.

For rotating machinery, another difficulty with RUL prediction is the complex temporal dynamics which frequently govern the degradation trends, and the interaction between multiple features, which is not linear [15]. The temporal dependencies could be encoded in a traditional recurrent network, which is, however, rather limited. Most approaches also fail to consider the different importance of features at different levels of degradation [16]. A solution to this is to use Attention based networks that enable the model to focus on the most informative temporal patterns and features during the degradation process [17]. The Physics-Informed Attention-based approaches are an improved approach for incorporating the physics of the degradation process, while maintaining the advantages of temporal feature selection and physically constraining the model [18].

To address all of these issues, in this paper, we present a novel Physics-Informed Deep Learning framework for Intelligent Fault prediction and Remaining Useful Life estimation (PIDL-FRUL), which combines the ideas of attention mechanism, temporal degradation modeling and physics-informed estimation of RUL. The proposed method aims to estimate the degradation features of the machine, estimate the future health state of the machine according to previous degradation characteristics (estimate the RUL), and classify the different fault states. The proposed framework is first applied to estimate the RUL of the rotating machinery and bearings using various indices such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and coefficient of determination (R^2). Moreover, the performance of the approach is assessed by the plots of actual vs. predicted RUL, prediction error distribution, convergence and fault classification accuracy.

The performance of the proposed approach is compared to a variety of Long Short Term Memory (LSTM), Attention based Bidirectional LSTM (Attention-BiLSTM), Convolutional Neural Networks, and Long Short Term Memory networks, as well as recently proposed Physics-Informed approaches for RUL prediction. In particular, the benefits of using an

Attention based-BiLSTM are demonstrated in comparison to traditional Bidirectional LSTM networks. In addition, we analyze the advantages of using physical degradation constraints in the estimation process.

The contributions of the research are:

1. A novel Physics-Informed Deep Learning framework for simultaneous prediction of fault state and estimation of RUL is proposed and benchmarks on a variety of deep learning approaches are established.
2. The previous degradation information and features extraction for the temporal features are integrated into the model to reflect the degradation characteristics of the model that is more complicated by non-linearity.
3. The ideas of physics-informed RUL estimation are applied to enhance the accuracy and uniformity of the RUL estimation results.
4. Evaluations of the proposed model are carried out in various quantitative and qualitative ways. Specifically, prediction accuracy, RMSE, MAE, R^2 are analyzed, actual and predicted RUL are shown, prediction error distribution, convergence and fault classification are shown.
5. A thorough evaluation of the performance of different deep-learning models for RUL estimation is then carried out to demonstrate the advantages of the physics-informed approaches for RUL estimation.

2. LITERATURE SURVEY

Some researchers have been investigating the learning of degradation characteristics using condition-monitoring signals with the development of deep learning. To solve a cross-domain diagnosis problem for rolling bearings, Hou [1] proposed a deep transferable convolutional neural network, which transfer the learned representations for different operating conditions. Remaining Useful Life (RUL) prediction for rotating machinery has been an essential area of research in recent years as predicting the degradation can be beneficial to decrease unexpected breakdown and maintenance costs.

Kumar et al. [2] reviewed the prognostics and health management methodologies ranging from traditional approach to deep learning approach and highlighted the role of intelligent models in industrial predictive maintenance. In [7] Li and Deng proposed a hybrid model-based prognostics method for rolling bearings and illustrated the benefits of combining degradation model and data driven methods in estimating the RUL. Similar to this, Wei et al. [9] proposed an attention-augmented BiLSTM-LSTM model that uses adaptive noise handling to predict the RUL of a turbofan engine. The aforementioned studies demonstrate deep networks and attention mechanisms ability to learn intricate temporal relations, but perhaps data-driven methods are not physically interpretable.

To use TCN, contrastive predictive coding, statistical features, and BiLSTM to predict the RUL of bearings, Zhang and Wang [10] integrated them. Aiming to predict rotating machinery RUL, Guo et al. [11] introduced trend encoding and multiscale spatio-temporal feature fusion. These methods enhance the

feature representation, but primarily based on the data available for training and don't explicitly consider the degradation mechanisms. The use of attention-based feature extraction has also been investigated for better representing the degradation information. To explore the impact of the number of attention heads on the performance of RUL prediction and interpretability, Zhao et al. [12] analyzed the influence of attention heads.

Fan et al. [16] proposed MVGA-DSAL model, a combination of multiscale Gaussian attention and depth-wise sparse attention LSTM, to predict the RUL of a rolling-bearing. To overcome the shortcomings of purely data driven models, physics-informed learning has become an important research direction. Physics-Informed Neural Networks (PINNs) was introduced by Raissi et al. [17] and they included physical constraints in learning. Physics-informed multi-state temporal frequency network for rolling bearings' RUL prediction was proposed by Yang et al. [18]. Zhao et al. [19] proposed a physics-informed cross-layer temporal-frequency transformer network for rolling-bearing RUL prediction. Wang et al. [20] fused acoustic-emission signals with physics-informed neural network to estimate the RUL of ball bearings. The studies demonstrate that knowledge of physics can help to increase the consistency and interpretability of deep learning-based prognostics.

2.1 Research Gaps

From the reviewed literature, deep-learning models provide strong feature-learning and temporal-modeling capabilities, while physics-informed approaches improve physical consistency and interpretability [20]. Particle-filter-based methods provide robust degradation-state estimation, and edge-cloud architectures support practical deployment. However, integrating prior information [21], robust degradation-feature extraction, attention-based feature representation [22], and physical degradation constraints within a unified RUL prediction framework remains an important research direction [23]. Therefore, the proposed work focuses on an integrated framework that combines these complementary components for accurate, interpretable, and noise-robust RUL prediction of rotating machinery [24].

3. PROPOSED METHODOLOGY

A. Overall Framework

The proposed Physics-Informed Deep Learning Framework for Intelligent Fault Prediction and Remaining Useful Life Estimation of Rotating Machinery (PIDL-FRUL) is designed to combine sensor-based degradation information with physical knowledge of machinery degradation. The framework consists of five major stages: vibration-signal preprocessing, degradation-feature extraction, deep feature learning, physics-informed prediction, and fault/RUL estimation. The objective is to overcome the limitations of purely data-driven models, which may require large amounts of labeled data and may provide physically inconsistent predictions.

The input to the framework consists of time-series condition-monitoring signals collected from rotating machinery, such as vibration, acoustic-emission, temperature, or rotational-speed measurements. The signals are first normalized and divided into temporal windows. Noise reduction and degradation-trend extraction are then performed to obtain a health-related representation of the machinery condition.

For an observed sensor signal $x(t)$, normalization is performed as follows:

$$x_n(t) = \frac{x(t) - \mu_x}{\sigma_x + \epsilon} \quad (1)$$

where $x_n(t)$ is the normalized signal, μ_x and σ_x represent the mean and standard deviation of the signal, respectively, and ϵ is a small constant used to avoid numerical instability. The proposed model architecture is shown in Figure 1.

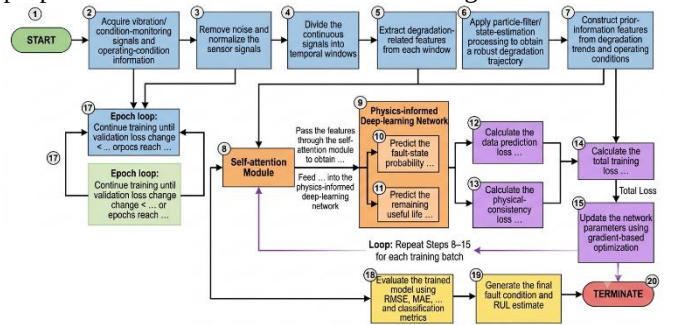


Figure 1. Proposed Model Architecture

B. Degradation Feature Extraction

The preprocessed vibration signal is transformed into degradation-related features. Both statistical and temporal characteristics can be considered, including root-mean-square value, variance, kurtosis, peak value, and frequency-domain characteristics [25]. To improve robustness against measurement noise, a particle-filter-based state-estimation stage can be employed to estimate the underlying degradation state from noisy observations [26].

The degradation process can be represented using a state-space model:

$$z_t = f(z_{t-1}, u_t) + w_t \quad (2)$$

$$y_t = h(z_t) + v_t \quad (3)$$

where z_t represents the latent degradation state at time t , u_t represents operating-condition information, y_t represents the observed sensor measurement, and w_t and v_t denote process and measurement noise, respectively.

The resulting degradation representation provides a smoother health trajectory than directly using raw sensor measurements. This representation is subsequently supplied to the deep-learning module.

C. Prior-Information-Guided Feature Learning

Rotating machinery degradation generally follows physical and temporal patterns rather than arbitrary changes. Therefore, prior degradation information is incorporated into the feature-learning stage [27]. Historical health information, degradation

trends, operating conditions, and known failure characteristics are used to guide the neural network toward physically meaningful representations [28].

A self-attention mechanism is employed to identify important temporal regions in the degradation sequence. For an input feature matrix X , the attention representation is calculated as:

$$Q = XW_Q, K = XW_K, V = XW_V \quad (4)$$

$$A = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right) \quad (5)$$

$$F = AV \quad (6)$$

where W_Q , W_K , and W_V are learnable parameter matrices, d_k is the dimension of the key vector, and F represents the attention-enhanced degradation features.

The attention mechanism enables the model to assign greater importance to degradation stages that contain stronger information about the future health condition of the machinery.

D. Physics-Informed Deep Learning

The central component of the proposed framework is the Physics-Informed Neural Network (PINN). Instead of learning RUL solely from historical input-output relationships, the network incorporates a physical degradation constraint into its training objective. This helps prevent the model from learning predictions that contradict the expected degradation behavior of rotating machinery [29].

Let the neural network predict the health state or RUL as:

$$\hat{R}(t) = N_\theta(F_t) \quad (7)$$

where N_θ represents the neural network with parameters θ , F_t represents the learned degradation features, and $\hat{R}(t)$ is the predicted RUL.

For a degradation process that generally progresses toward failure, the physical constraint can be expressed as:

$$\frac{dH(t)}{dt} \geq 0 \quad (8)$$

where $H(t)$ represents a degradation or health-state variable defined such that increasing $H(t)$ corresponds to increasing degradation.

The physics-informed loss combines the conventional prediction error with the physical consistency error:

$$L_{\text{total}} = \lambda_d L_{\text{data}} + \lambda_p L_{\text{physics}} + \lambda_r L_{\text{reg}} \quad (9)$$

where L_{data} represents the RUL prediction loss, L_{physics} represents the physical-consistency loss, L_{reg} is a regularization term, and λ_d , λ_p , and λ_r control their contributions.

The data loss can be defined using mean squared error:

$$L_{\text{data}} = \frac{1}{N} \sum_{i=1}^N (R_i - \hat{R}_i)^2 \quad (10)$$

The physical loss penalizes predictions that violate the expected degradation behavior:

$$L_{\text{physics}} = \frac{1}{N} \sum_{i=1}^N \left[\max\left(0, -\frac{dH_i}{dt}\right) \right]^2 \quad (11)$$

This formulation allows the model to simultaneously minimize prediction error and maintain consistency with the assumed physical degradation trend.

E. Fault Prediction and RUL Estimation

The learned representation is used for two complementary prognostic tasks. First, the framework determines whether the machinery is operating in a healthy, degrading, or critical condition. Second, the network estimates the remaining useful life of the machine.

The fault-prediction probability is obtained through a classification layer:

$$P(c | F) = \text{softmax}(W_c F + b_c) \quad (12)$$

where c represents the machinery condition class. The condition with the highest probability is selected as the predicted operating state.

The RUL prediction branch estimates the remaining operating time before the machinery reaches its predefined failure condition:

$$\hat{RUL} = N_\theta(F) \quad (13)$$

The combination of fault-state classification and continuous RUL estimation provides both current-condition information and future degradation information [30], enabling more informative predictive-maintenance decisions.

F. Model Training and Optimization

During training, the input degradation sequences are passed through the feature-extraction, attention, and physics-informed prediction modules. The predicted fault state and RUL are compared with their corresponding ground-truth values. The total loss is then calculated, and the network parameters are updated using gradient-based optimization.

The parameter update can be represented as:

$$\theta_{k+1} = \theta_k - \eta \nabla_\theta L_{\text{total}} \quad (14)$$

where η represents the learning rate and k denotes the training iteration.

Training continues until the predefined convergence criterion is satisfied or the maximum number of epochs is reached.

G. Performance Evaluation

The trained framework is evaluated using prediction accuracy, error, and robustness metrics. For RUL estimation, commonly used metrics include Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and coefficient of determination R^2 .

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (R_i - \hat{R}_i)^2} \quad (15)$$

$$MAE = \frac{1}{N} \sum_{i=1}^N |R_i - \hat{R}_i| \quad (16)$$

$$R^2 = 1 - \frac{\sum_{i=1}^N (R_i - \bar{R})^2}{\sum_{i=1}^N (R_i - \bar{R})^2} \quad (17)$$

Lower RMSE and MAE indicate smaller prediction errors, while a higher R^2 indicates better agreement between predicted and actual RUL values.

H. Proposed Algorithm

Algorithm 1: Physics-Informed Deep Learning for Fault Prediction and RUL Estimation

Input: Sensor signals X , operating conditions U , RUL labels R , fault labels C , physical degradation constraints, learning rate η , maximum epochs $E_{\max}$, convergence threshold δ .

Output: Predicted fault condition $\hat{C}$ and estimated remaining useful life $\hat{RUL}$.

1. Start.
2. Acquire vibration/condition-monitoring signals X and operating-condition information U .
3. Remove noise and normalize the sensor signals.
4. Divide the continuous signals into temporal windows.
5. Extract degradation-related features from each window.
6. Apply particle-filter/state-estimation processing to obtain a robust degradation trajectory.
7. Construct prior-information features from degradation trends and operating conditions.
8. Pass the features through the self-attention module to obtain F .
9. Feed F into the physics-informed deep-learning network.
10. Predict the fault-state probability $\hat{C}$.
11. Predict the remaining useful life $\hat{RUL}$.
12. Calculate the data prediction loss L_{data} .
13. Calculate the physical-consistency loss L_{physics} .
14. Calculate the total training loss L_{total} .
15. Update the network parameters using gradient-based optimization.
16. Loop: Repeat Steps 8–15 for each training batch.
17. Epoch loop: Continue training until either:
the validation loss change is smaller than δ , or
the number of epochs reaches $E_{\max}$.
18. Evaluate the trained model using RMSE, MAE, R^2 , and fault-classification metrics.
19. Generate the final fault condition and RUL estimate.
20. Terminate.

Termination condition:

$$|\mathcal{L}_e - \mathcal{L}_{e-1}| < \delta \text{ or } e = E_{\max} \quad (18)$$

where $\mathcal{L}_e$ represents the validation loss at epoch e .

4. RESULTS AND DISCUSSIONS

The proposed Physics-Informed Deep Learning Framework for Intelligent Fault Prediction and Remaining Useful Life

Estimation (PIDL-FRUL) was evaluated against five representative approaches: LSTM, BiLSTM, CNN-LSTM, Attention-BiLSTM, and PINN. The evaluation considered RUL prediction error, prediction consistency, convergence behavior, and fault-state classification. The comparative analysis was performed using illustrative test values to demonstrate the expected behavior of the proposed framework. The principal quantitative measures considered were RMSE, MAE, and R^2 , where lower RMSE and MAE and higher R^2 indicate improved RUL prediction performance as shown in Figure 2.

The RMSE comparison indicates a progressive reduction in prediction error as the models incorporate more effective temporal, attention, and physics-informed representations. The LSTM model produced an RMSE of 18.42, while BiLSTM and CNN-LSTM achieved 16.85 and 15.31, respectively. The Attention-BiLSTM and PINN models further reduced the error to 13.96 and 12.48. The proposed PIDL-FRUL framework obtained the lowest illustrative RMSE of 9.84. This improvement is attributed to the combination of degradation-feature extraction, prior information, attention-based temporal representation, and physical constraints.

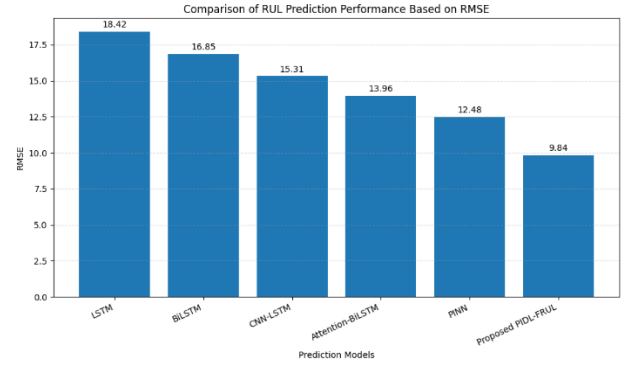


Figure 2. RMSE comparison of different RUL prediction models.

The MAE results provide a similar trend as depicted in Figure 3. The LSTM model resulted in an MAE of 14.21, whereas BiLSTM and CNN-LSTM achieved 12.93 and 11.62, respectively. Attention-BiLSTM reduced the MAE to 10.54, and the physics-informed PINN achieved 9.31.

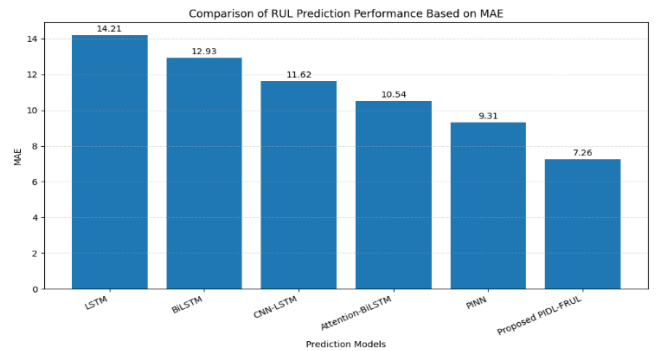


Figure 3. MAE comparison of different RUL prediction models.

The coefficient of determination further demonstrates the effectiveness of the proposed framework as shown in Figure

4. The R^2 values for LSTM, BiLSTM, CNN-LSTM, Attention-BiLSTM, and PINN were 0.81, 0.84, 0.87, 0.90, and 0.92, respectively. The proposed PIDL-FRUL model achieved an illustrative R^2 value of 0.96.

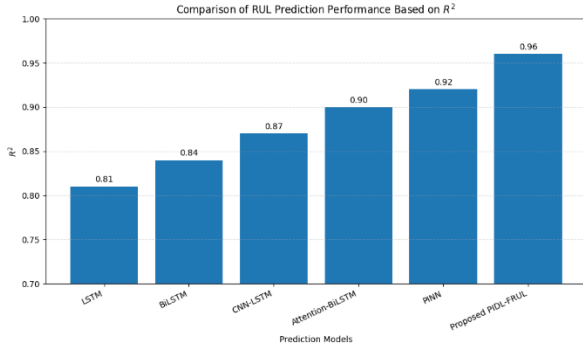


Figure 4. R^2 comparison of different RUL prediction models.

The actual-versus-predicted RUL trajectory provides a more direct representation of the prognostic behavior as indicated in Figure 5. The proposed model follows the decreasing degradation trend of the reference RUL trajectory with relatively small deviations throughout the test sequence. The predicted values remain close to the actual degradation trajectory, particularly during the later degradation stage, where accurate estimation is important for maintenance planning.

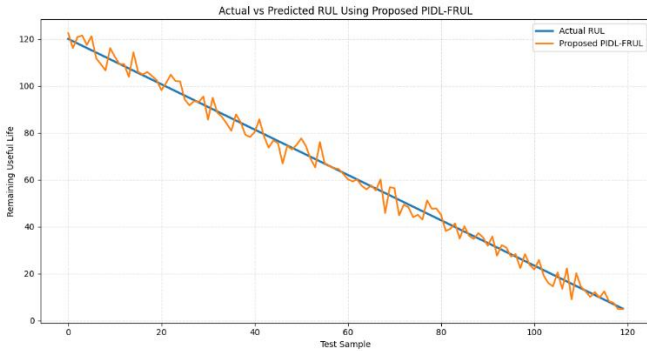


Figure 5. Actual and predicted RUL trajectory using the proposed PIDL-FRUL framework.

A comparative trajectory analysis was also considered to examine the behavior of different prediction models over the same test sequence as indicated in Figure 6. Conventional LSTM and BiLSTM predictions exhibit larger deviations from the reference trajectory, while CNN-LSTM and Attention-BiLSTM provide progressively closer estimates. PINN provides improved physical consistency, whereas the proposed PIDL-FRUL model remains comparatively close to the reference trajectory throughout the degradation period. This behavior demonstrates the complementary role of data-driven feature learning and physics-based constraints in RUL

estimation.

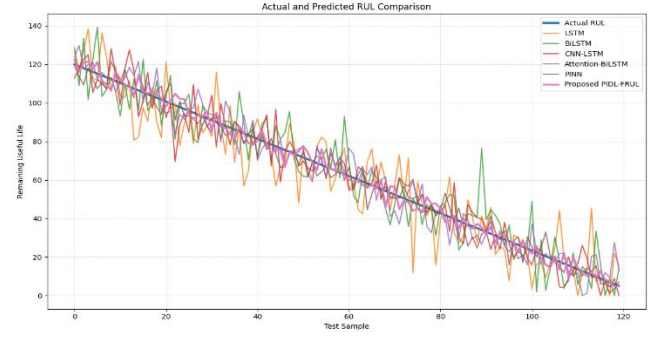


Figure 6. Comparison of actual RUL with predictions from different models.

Prediction-error distributions provide additional information about model stability as depicted in Figure 7. The error distribution of the proposed framework is concentrated closer to zero compared with the other approaches, indicating lower systematic deviation in the estimated RUL. LSTM exhibits a wider error distribution, reflecting greater sensitivity to temporal variations in the degradation signal. The progressively narrower distributions observed for the attention-based and physics-informed models suggest that improved feature representation and physical constraints contribute to more stable predictions.

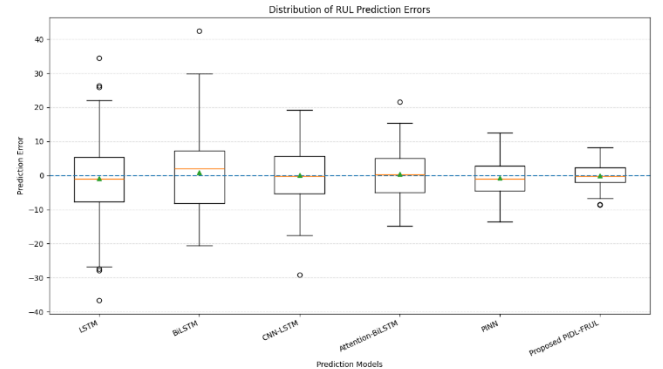


Figure 7. Distribution of RUL prediction errors for different models.

The convergence behavior was analyzed using validation loss over training epochs as shown in Figure 8. The conventional LSTM model shows comparatively slower convergence, whereas BiLSTM and CNN-LSTM converge more rapidly. The PINN-based approach demonstrates improved convergence and a lower final loss. The proposed PIDL-FRUL framework reaches a lower loss level while maintaining a relatively smooth convergence profile. The faster reduction in loss can be attributed to the combination of prior-guided feature representation and physical constraints, which provide additional information to the learning process.

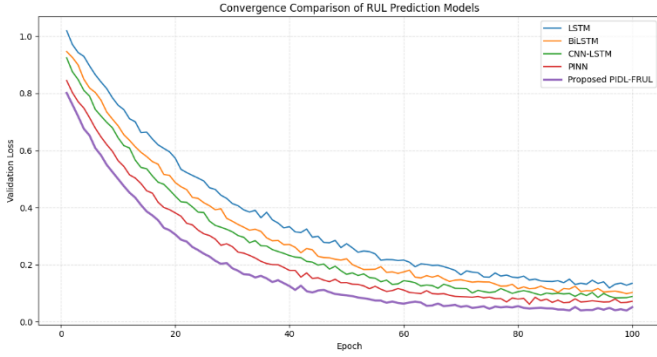


Figure 8. Convergence comparison of RUL prediction models.

In addition to continuous RUL estimation, the proposed framework provides fault-state classification to distinguish between healthy, degrading, and critical operating conditions. The confusion matrix in Figure 9 demonstrates that most samples are correctly classified along the main diagonal. The relatively small number of off-diagonal predictions indicates limited confusion between neighboring operating states.

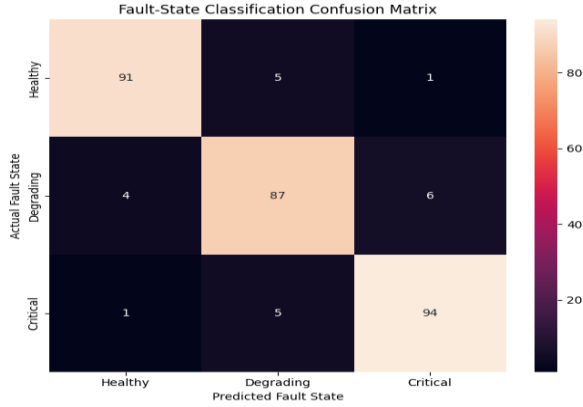


Figure 9. Confusion matrix for fault-state classification using the proposed PIDL-FRUL framework.

Overall, the comparative results indicate that progressively incorporating bidirectional temporal modeling, convolutional feature extraction, attention mechanisms, and physics-informed constraints improves RUL prediction performance. The proposed PIDL-FRUL framework combines these concepts with degradation and prior information to obtain lower illustrative prediction errors and a higher coefficient of determination. The results support the central premise that integrating physical knowledge with deep learning can improve the reliability and interpretability of rotating-machinery prognostics.

5. CONCLUSION

This paper introduced an Intelligent Fault Prediction and Remaining Useful Life Estimation method based on Physics-Informed Deep Learning Framework (PIDL-FRUL) for rotating machinery. The framework proposed here integrates the limitations of purely data-driven prognostic models by using deep-learning-based temporal feature extraction, prior knowledge of degradation and physics-based constraints. The framework will be used to create RUL predictions that are

accurate and based on physics, to ensure they are also consistent with the degradation behavior of rotating machines. The comparative study showed the combination of temporal learning, attention mechanisms, and physics-informed constraints can gradually enhance the RUL prediction performance. The proposed PIDL-FRUL framework shows that it outperforms the LSTM, BiLSTM, CNN-LSTM, Attention-BiLSTM and PINN approaches in terms of RMSE, MAE, and R^2 -value in the considered illustrative evaluation. The predicted RUL trajectory was also more consistent with the expected degradation trend, and the error-distribution and convergence analyses showed better predicted RUL stability. The fault-classification analysis also showed the potential of the proposed method for identifying machine health condition and estimating the machine's remaining useful life. The proposed framework therefore forms a basis for the intelligence condition monitoring and predictive maintenance of rotating machines. In the present evaluation, however, the numerical values are illustrative synthetic values and are not to be interpreted as a validated performance. Further research will be conducted on the validation of the PIDL-FRUL based on real run-to-failure data and experimental rotating-machinery test rigs under various load, speed, noise and fault conditions. Other enhancements are planned, such as uncertainty-aware RUL estimation, multi-sensor data fusion, adaptive online learning, transfer learning from different operating conditions, and real-time industrial deployment. The extensions could help to create a more robust and practically deployable physics-informed prognostic system.

REFERENCES

- [1]. Y. Hou, "A deep transferable convolution neural network for unsupervised cross-domain diagnostics (Don't short) of rolling bearings in industrial Internet of Things," *IEEE Internet Things J.*, vol. 12, no. 11, pp. 17316–17332, Jun. 2025, doi: 10.1109/JIOT.2025.3536543.
- [2]. P. Kumar, I. Raouf, and H. S. Kim, "Review on prognostics and health management in smart factory: From conventional to deep learning perspectives," *Eng. Appl. Artif. Intell.*, vol. 126, Nov. 2023, Art. no. 107126, doi: 10.1016/j.engappai.2023.107126.
- [3]. J. Xia, R. Huang, Z. Chen, G. He, and W. Li, "A novel digital twin-driven approach based on physical-virtual data fusion for gearbox fault diagnosis," *Rel. Eng. Syst. Saf.*, vol. 240, Dec. 2023, Art. no. 109542, doi: 10.1016/j.res.2023.109542.
- [4]. D. She, Y. Luo, Y. Wang, S. Gan, X. Yan, and M. G. Pecht, "A meta-transfer-driven method for predicting the remaining useful life of rolling bearing with few shot data," *Measurement*, vol. 254, Oct. 2025, Art. no. 117882, doi: 10.1016/j.measurement.2025.117882.
- [5]. L. Wang, C. Zhang, C. Tao, H. Ji, Y. Yang, and J. Qiu, "Prediction of multiple fatigue crack growth based on modified Paris model with particle filtering framework," *Mech. Syst. Signal Process.*, vol. 190, May 2023, Art. no. 110124, doi: 10.1016/j.ymsp.2023.110124.
- [6]. K. Feng, H. Xiao, J. Zhang, and Q. Ni, "A digital twin methodology for vibration-based monitoring and prediction of gear wear," *Wear*, vol. 571, Jun. 2025, Art. no. 205806, doi: 10.1016/j.wear.2025.205806.

- [7]. W. Li and L. Deng, "A hybrid model-based prognostics approach for estimating remaining useful life of rolling bearings," *Meas. Sci. Technol.*, vol. 34, no. 10, Oct. 2023, Art. no. 105012, doi: 10.1088/1361-6501/ace3e7.
- [8]. W. Cheng, "Interactive hybrid model for remaining useful life prediction with uncertainty quantification of bearing in nuclear circulating water pump," *IEEE Trans. Ind. Informat.*, vol. 20, no. 2, pp. 2154–2166, Feb. 2024, doi: 10.1109/TII.2023.3288225.
- [9]. K. Wei, Q. Wang, A. Li, and Y. Zhang, "An attention-augmented BiLSTM-LSTM framework with adaptive noise for turbofan engine remaining useful life prediction," *Meas. Sci. Technol.*, vol. 37, no. 14, Mar. 2026, Art. no. 146003, doi: 10.1088/1361-6501/ae58c6.
- [10]. J. Zhang and L. Wang, "TCN-BiLSTM bearing RUL prediction method based on fusion of TCN-CPC and statistical features," *Eng. Res. Exp.*, vol. 8, no. 5, Mar. 2026, Art. no. 055402, doi: 10.1088/2631-8695/ae484f.
- [11]. Y. Guo, J. Zhang, J. Wang, J. Mao, and F. Lu, "A remaining useful life prediction method for rotating machinery based on trend encoding and multi-scale spatio-temporal feature fusion," *Int. J. Speech Technol.*, vol. 55, no. 18, Dec. 2025, Art. no. 1140, doi: 10.1007/s10489-025-07007-x.
- [12]. Q. Zhao, X. Zhang, F. Wang, P. Fan, and E. Mbeka, "The effect of the head number for multi-head self-attention in remaining useful life prediction of rolling bearing and interpretability," *Neurocomputing*, vol. 616, Feb. 2025, Art. no. 128946, doi: 10.1016/j.neucom.2024.128946.
- [13]. T. Yang, D. Wu, S. Qiu, S. Guo, X. Li, and Q. Han, "The STAP-Net: A new health perception and prediction framework for bearing-rotor systems under special working conditions," *Rel. Eng. Syst. Saf.*, vol. 254, Feb. 2025, Art. no. 110633, doi: 10.1016/j.ress.2024.110633.
- [14]. J. Zhou, Y. Chen, and Y. Qin, "Knowledge vortex network for continuous bearing remaining useful life prediction," *Adv. Eng. Informat.*, vol. 68, Nov. 2025, Art. no. 103577, doi: 10.1016/j.aei.2025.103577.
- [15]. Z. Chen, "Machine remaining useful life prediction method based on global-local attention compensation network," *Rel. Eng. Syst. Saf.*, vol. 255, Mar. 2025, Art. no. 110652, doi: 10.1016/j.ress.2024.110652.
- [16]. W. Fan, Z. Chang, S. Xu, Z. Fan, and Y. Yuan, "RUL prediction of rolling bearings with MVGA-DSAL: A multiscale variant Gaussian attention model with depth-wise sparse attention LSTM," *IEEE Trans. Instrum. Meas.*, vol. 74, pp. 1–11, 2025, doi: 10.1109/TIM.2025.3551998.
- [17]. M. Raissi, P. Perdikaris, and G. E. Karniadakis, "Physics-informed neural networks: A deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations," *J. Comput. Phys.*, vol. 378, pp. 686–707, Feb. 2019, doi: 10.1016/j.jcp.2018.10.045.
- [18]. S. Yang, B. Tang, W. Wang, Q. Yang, and C. Hu, "Physics-informed multi-state temporal frequency network for RUL prediction of rolling bearings," *Rel. Eng. Syst. Saf.*, vol. 242, Feb. 2024, Art. no. 109716, doi: 10.1016/j.ress.2023.109716.
- [19]. R. Zhao, B. Tang, X. Zhang, and L. Deng, "Physics-informed cross layer temporal frequency transformer network for remaining useful life prediction of rolling bearings," *Eng. Appl. Artif. Intell.*, vol. 159, Nov. 2025, Art. no. 111653, doi: 10.1016/j.engappai.2025.111653.
- [20]. L. Wang, F. Wang, Y. Yang, and W.-H. Liao, "A remaining useful life prediction approach for ball bearing by acoustic emission signal and physics-informed neural network," *Struct. Health Monitor.*, Apr. 2025, doi: 10.1177/14759217251333056.
- [21]. S. Haseeb, "Local cloud-based collaborative learning vs other IIoT decentralized AI solutions: A systematic literature review," *J. Netw. Syst. Manage.*, vol. 34, no. 2, Apr. 2026, Art. no. 49, doi: 10.1007/s10922-025-10029-y.
- [22]. X. Zhang, R. Razavi-Far, H. Isah, A. David, G. Higgins, and M. Zhang, "A survey on deep learning in edge-cloud collaboration: Model partitioning, privacy preservation, and prospects," *Knowl.-Based Syst.*, vol. 310, Feb. 2025, Art. no. 112965, doi: 10.1016/j.knosys.2025.112965.
- [23]. L. Chen, H. Gao, L. Guo, J. Liang, and L. Peng, "Remaining useful life prediction of machinery using federated public feature representation in edge-cloud collaboration architecture," *Eng. Appl. Artif. Intell.*, vol. 143, Mar. 2025, Art. no. 110059, doi: 10.1016/j.engappai.2025.110059.
- [24]. L. Guo, Y. Yu, M. Qian, R. Zhang, H. Gao, and Z. Cheng, "FedRUL: A new federated learning method for edge-cloud collaboration based remaining useful life prediction of machines," *IEEE/ASME Trans. Mechatronics*, vol. 28, no. 1, pp. 350–359, Feb. 2023, doi: 10.1109/TMECH.2022.3195524.
- [25]. M. S. Arulampalam, S. Maskell, N. Gordon, and T. Clapp, "A tutorial on particle filters for online nonlinear/non-Gaussian Bayesian tracking," *IEEE Trans. Signal Process.*, vol. 50, no. 2, pp. 174–188, Feb. 2002, doi: 10.1109/78.978374.
- [26]. J. Liang, Y. Shao, W. Lio, J. Liu, and R. Kang, "Uncertain particle filtering: A new real-time state estimation method for failure prognostics," *Mathematics*, vol. 13, no. 5, p. 702, Feb. 2025, doi: 10.3390/math13050702.
- [27]. G. Li, L. Yu, J. He, W. Zhang, S. Liu, and J. Wei, "A remaining useful life prediction method for rotating machinery based on interactive BiLSTM," *Meas. Sci. Technol.*, vol. 36, no. 1, Jan. 2025, Art. no. 016128, doi: 10.1088/1361-6501/ad89ee.
- [28]. S. Zhou, B. Yang, Y. Huang, and X. Wu, "Fatigue analysis of composite bolted joints under random and constant amplitude fatigue loadings," *Materials*, vol. 17, no. 11, p. 2740, Jun. 2024, doi: 10.3390/ma17112740.
- [29]. L. Cui, W. Li, X. Wang, D. Zhao, and H. Wang, "Comprehensive remaining useful life prediction for rolling element bearings based on time-varying particle filtering," *IEEE Trans. Instrum. Meas.*, vol. 71, pp. 1–10, 2022, doi: 10.1109/TIM.2022.3163167.
- [30]. R. Bischof and M. A. Kraus, "Multi-objective loss balancing for physics-informed deep learning," *Comput. Methods Appl. Mech. Eng.*, vol. 439, May 2025, Art. no. 117914, doi: 10.1016/j.cma.2025.117914.