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A Deep Temporal Learning Framework for Remaining Useful Life Prediction and Health State Assessment of Rotating Machinery

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ABSTRACT

Health state assessment and remaining useful life prediction are two key tasks for predictive maintenance of rotating machinery. To address limitations of existing studies—such as the separation of health assessment and lifetime prediction, insufficient modeling of temporal degradation features, and limited interpretability—this study proposes a deep temporal learning framework that jointly implements both tasks. The method takes raw monitoring signals as input, constructs temporal samples using a sliding window, and employs a shared temporal feature encoder to extract degradation representations. Based on these shared features, a health state assessment branch generates a continuous health indicator, while an RUL prediction branch estimates the remaining useful life, enabling collaborative modeling of the degradation process within a unified feature space. A multi-task joint loss is introduced to jointly optimize health state modeling and lifetime regression, enhancing the representation of local degradation patterns, long-term trends, and stage-wise characteristics. Experimental results on public run-to-failure datasets show that the proposed method produces health indicators with strong monotonicity, trendability, and robustness, and achieves superior prediction accuracy compared to several baselines. These findings verify the effectiveness of the proposed framework and highlight its potential for intelligent and predictive maintenance applications.

KEYWORDS

rotating machinery, deep temporal learning, remaining useful life prediction, health state assessment, health indicator

INTRODUCTION

Rotating machinery is one of the most critical classes of equipment in modern industrial systems and is widely used in aero-engines, rail transportation, wind power generation, petrochemical plants, and intelligent manufacturing [1, 2]. The operational reliability of such machinery is directly related to the safety, stability, and economic efficiency of the entire system [3]. Since key components such as bearings, gears, and rotors are often subjected to high speed, heavy load, and complex working conditions, performance degradation is inevitable and may ultimately lead to functional failure [4]. Traditional maintenance strategies, including scheduled maintenance and post-failure repair, usually suffer from high maintenance cost, excessive down-time, and inappropriate maintenance timing, making them increasingly inadequate for modern industry [5, 6]. Under this background, health state assessment and remaining useful life (RUL) prediction for rotating machinery have become two essential tasks for predictive maintenance and intelligent operation [7-9]. Health state assessment aims to characterize the degradation evolution of equipment throughout its life cycle, whereas RUL prediction further provides forward-looking support for maintenance scheduling and operational decision-making. Therefore, both tasks are of great significance for improving equipment availability and reducing operation and maintenance costs.

In recent years, with the rapid development of sensing technologies and artificial intelligence, data-driven approaches for rotating machinery health management have achieved remarkable progress [10]. In health state assessment, existing studies commonly focus on constructing health indicators, degradation features, or state classification models to describe the deterioration process of machinery [11]. In RUL prediction, deep learning models such as convolutional neural networks, recurrent neural networks, and attention-based architectures have been widely adopted to learn degradation information from monitoring signals and estimate the remaining lifetime. Although considerable improvements have been reported in prediction accuracy, several limitations still remain. First, many existing methods treat health state assessment and RUL prediction as two isolated tasks, without establishing a unified modeling framework, which restricts the sharing and enhancement of degradation representations across tasks. Second, the degradation of rotating machinery is inherently a temporal process with strong sequential dependency and stage-wise evolution, while some existing methods are still insufficient in jointly capturing local degradation patterns and long-term temporal dependencies. In addition, although end-to-end RUL prediction models may offer strong fitting capability, they often lack interpretability in terms of health evolution and are therefore limited in engineering applicability.

To address these issues, this study proposes a deep temporal learning framework for rotating machinery to jointly perform health state assessment and remaining useful life prediction. The proposed method takes raw monitoring signals or temporal samples as input and employs a shared temporal feature encoder to extract degradation representations, based on which a health state assessment branch and an RUL prediction branch are developed within a unified feature space. In this way, the degradation process of the equipment can be modeled in a collaborative manner. Such a joint learning strategy not only enhances the representation of local degradation characteristics and global temporal evolution trends, but also enables health state information to assist RUL prediction, thereby improving prediction accuracy and stability. Experiments will be conducted on public rotating machinery datasets, and the effectiveness of the proposed method will be systematically validated from the perspectives of health indicator construction, RUL prediction performance, ablation studies, and interpretability analysis.

RELATED WORK

Health state assessment of rotating machinery

Health state assessment is a fundamental component of predictive maintenance for rotating machinery. Its main objective is to characterize the full degradation evolution of equipment, from normal operation to performance deterioration and eventually to the stage close to failure, based on monitoring data. Traditional health assessment methods generally rely on handcrafted features extracted from the time domain, frequency domain, or time-frequency domain, such as root mean square, crest factor, kurtosis, spectral energy, and envelope-related features [12]. These features are further combined with principal component analysis, clustering analysis, or statistical modeling methods to construct health indicators or perform state classification. Such methods offer a certain degree of physical interpretability and have been widely adopted in early studies [13]. However, due to the complex operating environment of rotating machinery, significant working-condition variations, and strong noise interference, health indicators constructed from handcrafted features often suffer from limited robustness, poor monotonicity, and insufficient generalization capability, making them less effective in describing complicated degradation processes.

With the rapid development of deep learning, an increasing number of studies have turned to data-driven approaches for health state assessment. Compared with conventional methods, deep learning can automatically extract discriminative degradation features directly from raw monitoring signals, thereby reducing reliance on domain-specific manual feature engineering. Convolutional neural networks have been widely used to capture local impulsive characteristics and multi-scale degradation patterns, while autoencoders and their variants are commonly employed for unsupervised health representation learning and health indicator construction. Recurrent neural networks further enable the modeling of temporal evolution in machinery degradation by incorporating sequential context information. More recently, attention mechanisms and Transformer architectures have also been introduced to enhance the model's ability to focus on critical degradation stages and long-range dependencies. Overall, deep learning has provided a more flexible and efficient solution for health state assessment of rotating machinery. Nevertheless, how to construct health representations that simultaneously exhibit monotonicity, trendability, and robustness remains a key challenge in current research.

Data-driven RUL prediction methods

Remaining useful life prediction aims to estimate the time left before a machine reaches failure based on its current and historical operating conditions, and it is one of the central tasks in predictive maintenance. Existing RUL prediction approaches can generally be categorized into model-based methods, data-driven methods, and hybrid methods. Model-based methods rely on explicit degradation models or physical failure mechanisms and therefore require strong prior knowledge, which limits their applicability in scenarios involving complex operating conditions and multiple failure modes. By contrast, data-driven methods learn degradation patterns directly from historical monitoring data and have therefore attracted widespread attention in recent years. In particular, with the accumulation of large-scale industrial monitoring data, data-driven RUL prediction based on deep learning has become one of the dominant research directions in this field.

Among data-driven approaches, shallow machine learning models such as support vector regression, random forests, and Gaussian process regression were once widely adopted for lifetime prediction. However, these methods usually depend on manual feature extraction and have limited capability in representing highly nonlinear degradation processes. To improve the modeling of degradation information, researchers have introduced various deep learning architectures. Convolutional neural networks can automatically extract local degradation patterns from raw vibration signals or time-frequency representations. Recurrent neural networks and their variants, such as LSTM and GRU, are effective in modeling temporal dependencies in life evolution. Temporal convolutional networks enlarge the receptive field through dilated convolutions and thus show high efficiency in handling long sequential data. Transformer-based models and attention mechanisms further enhance the ability to capture global correlations and critical temporal information. In addition, some studies have attempted to combine convolutional networks with recurrent structures, attention mechanisms, or autoencoders in order to integrate the advantages of local feature extraction and long-term dynamic modeling. Although these methods have achieved promising prediction performance on several public datasets, their generalization capability and robustness still need further improvement when facing noise interference, varying operating conditions, and distribution shifts across samples.

Limitations of existing studies

Although substantial progress has been made in both health state assessment and RUL prediction of rotating machinery, several issues still remain from the perspective of practical engineering applications. First, many existing studies mainly focus on a single task, either health state assessment or RUL prediction, while only a limited number of works attempt to jointly model the degradation process from a unified perspective. Such task separation not only restricts the sharing of degradation features across different objectives, but also weakens the potential contribution of health state information to lifetime prediction. Second, the degradation of rotating machinery is inherently a temporal evolution process, which usually involves local abnormal impulses, long-term trend variations, and stage-wise transitions. However, some existing methods are still insufficient in temporal dependency modeling and therefore struggle to simultaneously capture local degradation patterns and global degradation evolution [14].

Moreover, although many end-to-end deep learning models have improved prediction accuracy, they often remain inadequate in terms of health evolution interpretation, degradation visualization, and engineering usability. In real-world maintenance systems, merely outputting an RUL value is often not sufficient for condition awareness and decision support. In practice, operators usually expect the model to also provide a clear description of health states or degradation trajectories. Meanwhile, degradation patterns often vary significantly across complex operating conditions and different machine instances, which imposes higher requirements on model robustness and generalization. Therefore, there is a strong need to develop a deep learning method that can collaboratively perform health state assessment and RUL prediction within a unified temporal feature space, so as to more fully exploit the temporal regularities of rotating machinery degradation and improve the accuracy, stability, and interpretability of the model [15].

PROBLEM FORMULATION

Signal representation and sample construction

In rotating machinery health monitoring scenarios, sensors usually collect vibration, temperature, current, acoustic emission, and other operational signals continuously. Among them, vibration signals are widely used for health state assessment and remaining useful life prediction because they are highly sensitive to early faults and degradation characteristics. Let the raw monitored time series be denoted as:

$$X = \{x_1, x_2, ..., x_T\} \tag{1}$$

where x_t represents the observation collected at time t , and T denotes the total sampling length over the entire life cycle. Since raw signals are usually high-dimensional and contaminated by noise, a sliding-window strategy is commonly adopted to construct samples for subsequent modeling. Specifically, a time window of length L moves along the original sequence with a step size S , thereby generating a set of temporal samples:

$$\mathcal{X} = \left\{X^{(1)}, X^{(2)}, ..., X^{(N)}\right\} \tag{2}$$

where N is the total number of samples, and the i -th sample is given by

$$X^{(i)} = \left\{x_i, x_{i+1}, ..., x_{i+L-1}\right\} \tag{3}$$

In this way, the continuous operational signal is transformed into local temporal segments that can be used for deep model training and inference. If the monitoring system contains multiple sensors, each sample can be further represented as a multivariate time series so as to preserve complementary information across different sensing channels.

To unify the subsequent health state assessment and RUL prediction tasks, each temporal sample is treated as an observation segment corresponding to a certain degradation stage, and is associated with relevant state description information. For samples located on a complete degradation trajectory, their labels may be derived from the failure time, health indicator construction rules, or manually defined state grading criteria. Consequently, the raw continuous monitoring data can be organized into a structured correspondence of “input sample–health state–remaining useful life,” which lays the foundation for joint modeling.

Health state assessment task

The purpose of health state assessment is to characterize the degradation level of equipment based on its historical and current monitoring data, and to represent its operating condition in the form of a continuous health indicator or discrete state label. Compared with simple fault identification, health state assessment focuses more on the progressive evolution of equipment performance over time, and can therefore provide a finer-grained description of the machine condition for lifetime prediction. In this study, a continuous health representation is adopted to characterize the equipment state. Specifically, for each sample, a health indicator h_i associated with the degradation level is learned as:

$$h_i = f_\theta(X^{(i)}) \tag{4}$$

where $f_\theta(\cdot)$ denotes the mapping function for health state assessment, θ denotes the learnable parameters, and h_i is the health indicator corresponding to the i -th sample. In general, the health indicator is expected to exhibit a relatively stable variation trend as degradation intensifies, so that it can effectively reflect the evolution of the machine from healthy operation to failure.

For rotating machinery, an effective health representation should satisfy at least the following requirements. First, it should possess good monotonicity, such that the overall variation trend can consistently reflect the degradation level. Second, it should exhibit strong trendability, so that degradation trajectories remain comparable across different samples or different machines. Third, it should have sufficient robustness to alleviate the influence of noise and operating-condition fluctuations on the assessment results. Therefore, in the problem setting of this study, the essence of the health state assessment task is to learn a low-dimensional health representation from temporal input samples that can stably characterize the degradation evolution pattern, thereby providing structured degradation information for subsequent lifetime prediction.

Since the public run-to-failure datasets used in this study do not provide manually annotated ground-truth health indicators, the reference health target is constructed according to the normalized degradation time ratio. Specifically, the initial healthy stage is assigned a health value close to 1, while the failure point is assigned a health value close to 0. For the i -th temporal sample, the reference health target is defined as

$$h_i = 1 - \frac{c_i}{C_f},$$

where c_i denotes the degradation cycle index corresponding to the i -th sample, and C_f denotes the failure cycle of the corresponding bearing. Therefore, the health target used in this study is a time-ratio-based weak label derived from run-to-failure information, rather than an expert-annotated health label.

RUL prediction task

The goal of remaining useful life prediction is to estimate the time left before functional failure based on the current and historical operating information of the equipment. Let the failure time of the machine be denoted by T_f . Then, the true remaining useful life at time t can be defined as:

$$RUL_t = T_f - t \tag{5}$$

For the i -th sample, let the corresponding RUL label be denoted as r_i . The RUL prediction task can then be formulated as learning a mapping from the input sample to the lifetime label:

$$\hat{r}_i = g_\phi(X^{(i)}) \tag{6}$$

where $g_\phi(\cdot)$ denotes the lifetime prediction model, ϕ denotes the model parameters, and $\hat{r}_i$ is the predicted remaining useful life. Since the degradation process of rotating machinery is usually characterized by strong nonlinearity, time-varying behavior, and stage-wise evolution, static observations at a single time point are often insufficient for accurate lifetime estimation. Therefore, the model needs to make full use of the dynamic degradation characteristics contained in the temporal samples.

Furthermore, since the health representation can reflect the degradation level of the machine from another perspective, this study regards health state information as an important auxiliary cue for RUL prediction. In the proposed framework, the health indicator is utilized through feature-level concatenation. Specifically, the learned health indicator is concatenated with the degradation feature extracted from the temporal encoder and then fed into the RUL regression branch. This design provides explicit degradation-state information to the RUL predictor without introducing an additional gating or attention mechanism. In other words, RUL prediction can be performed not only based on the raw temporal samples themselves, but also on the learned health representation, so that the prediction result is more consistent with the actual degradation process of the equipment. Accordingly, the lifetime prediction task can be further written as:

$$\hat{r}_i = g_\phi(X^{(i)}, h_i) \tag{7}$$

where h_i denotes the health representation generated by the health assessment branch. In implementation, h_i is fused with the temporal degradation feature by feature-level concatenation before being input into the RUL prediction branch. This formulation provides a clear interface for incorporating health-state information into lifetime estimation within the subsequent joint learning framework.

Joint learning objective

In traditional approaches, health state assessment and RUL prediction are usually treated as two independent tasks, with separate feature extraction and prediction models constructed for each of them. However, such a decoupled modeling strategy fails to fully exploit the intrinsic relationship between the two tasks at the degradation representation level. In fact, health state assessment focuses on representing and characterizing the degradation trajectory of the equipment, whereas RUL prediction aims to model the relationship between the degradation trajectory and the remaining lifetime. Both tasks fundamentally rely on accurate modeling of the temporal degradation pattern of the machine. Therefore, this study unifies the two tasks within the same deep temporal learning framework, where a shared temporal feature encoder is used to extract degradation representations, and two task-specific branches are designed for health assessment and lifetime prediction, respectively.

Let the degradation representation extracted by the shared encoder be denoted as z_i , which can be written as:

$$z_i = E(X^{(i)}) \tag{8}$$

where $E(\cdot)$ denotes the shared temporal feature encoder. Based on this shared representation, the health assessment branch outputs the health indicator:

$$\hat{h}_i = H(z_i) \tag{9}$$

and the RUL prediction branch produces the lifetime estimate:

$$u_i = [z_i; \hat{h}_i], \tag{10}$$

$$\hat{r}_i = R(u_i) \tag{11}$$

where $[z_i; \hat{h}_i]$ denotes feature-level concatenation, and $H(\cdot)$ and $R(\cdot)$ denote the health assessment branch and the RUL prediction branch, respectively. To achieve joint optimization, the overall loss function is defined as:

$$\mathcal{L} = \lambda_1 \mathcal{L}_{health} + \lambda_2 \mathcal{L}_{rul} + \lambda_3 \mathcal{L}_{reg} \tag{12}$$

where $\mathcal{L}_{health}$ denotes the health assessment loss, $\mathcal{L}_{rul}$ denotes the RUL prediction loss, $\mathcal{L}_{reg}$ is the regularization term, and λ_1 , λ_2 , and λ_3 are the corresponding weighting coefficients. Through such a joint learning strategy, the model can simultaneously learn health evolution patterns and lifetime degradation patterns within a unified feature space, thereby improving both state representation capability and lifetime prediction performance in rotating machinery health management tasks.

PROPOSED METHOD

Overall framework

To simultaneously achieve health state assessment and remaining useful life prediction for rotating machinery, this study proposes a unified deep temporal learning framework. As illustrated in the overall architecture, the proposed framework consists of four major components: a data preprocessing layer, a temporal feature encoding layer, a health state assessment branch, and an RUL prediction branch. For the input raw monitoring signals, sliding-window segmentation is first performed to construct temporal samples, followed by preprocessing operations such as normalization to generate standardized input sequences. These samples are then fed into a shared temporal feature encoder to extract deep representations that reflect the degradation process of the equipment. Based on these shared representations, the health assessment branch further maps the degradation features into a continuous health indicator, while the RUL prediction branch outputs the estimated remaining useful life under the joint guidance of the shared features and the learned health representation.

The core idea of this framework lies in enabling cross-task information flow between health state assessment and RUL prediction through shared temporal representations. The shared temporal encoder, the health assessment branch, and the RUL prediction branch are synchronously optimized under the unified objective function, so that the learned features can support both condition characterization and lifetime estimation. On the other hand, RUL prediction imposes an additional lifetime-regression-oriented constraint on these degradation features, allowing the shared feature space to possess both state representation capability and lifetime discrimination ability. Therefore, the proposed framework is not a simple serial combination of two tasks, but rather a collaborative optimization scheme for health state assessment and lifetime prediction within a unified degradation representation space, thereby improving model accuracy, stability, and interpretability.

From a functional perspective, the framework has two notable characteristics. First, the shared temporal encoder is able to capture both local degradation patterns and global evolutionary trends, thereby making fuller use of the dynamic information hidden in the complex degradation process of rotating machinery. Second, the health indicator generated by the health assessment branch provides additional degradation priors for lifetime prediction, making the predicted RUL more consistent with the actual degradation behavior of the equipment. Based on this design, the proposed method can simultaneously describe health evolution and estimate remaining useful life within a unified architecture, offering an effective modeling paradigm for intelligent health management of rotating machinery.

Data preprocessing and temporal sample generation

In rotating machinery monitoring signals, the raw data are usually characterized by high sampling frequency, long observation duration, and significant disturbance from complex operating conditions and environmental noise. As a result, the original signals often exhibit high dimensionality, redundancy, and strong fluctuations. Therefore, appropriate preprocessing is necessary before feeding the data into the deep model, so as to improve sample quality and enhance the effectiveness of subsequent feature learning. In this study, the raw signals are first normalized to reduce the influence of differences in scale and amplitude across samples. Let the raw sample be denoted by $X^{(i)}$, and its normalized form be denoted by $\tilde{X}^{(i)}$. Then,

$$\tilde{X}^{(i)} = \frac{X^{(i)} - \mu}{\sigma} \tag{13}$$

where μ and σ denote the mean and standard deviation of the training samples, respectively. Through this operation, the model can focus more on the degradation patterns themselves rather than being disturbed by the absolute amplitude variations in the raw signal.

During sample construction, a sliding-window strategy is adopted to divide the continuous monitoring signal into multiple local temporal segments. Let the window length be L and the stride be S . Then, a set of temporal samples can be generated from the complete life-cycle sequence. Each sample preserves local degradation characteristics, while temporal continuity is maintained across adjacent windows, thereby providing a basis for sequential modeling. For run-to-failure samples with complete failure information, the corresponding RUL labels are assigned according to the temporal position of each sample, and continuous health descriptions are constructed based on the degradation evolution process. If multiple sensor channels are available, the signals from different channels are synchronously aligned along the time dimension and fed into the model in the form of multivariate temporal sequences, so as to preserve complementary information from different monitoring perspectives.

To further enhance the model's ability to perceive temporal degradation patterns, the generated window samples are organized into an input form suitable for sequential learning. Specifically, each sample not only represents a local observation near a certain time point, but also carries short-term degradation information at that stage, while the ordering among samples reflects the global life-cycle evolution trend of the equipment. Through this "local window + sequential association" sample generation strategy, the model can simultaneously focus on local abnormal impulses and degradation details, as well as learn the long-term dependency structure in lifetime evolution, thereby laying the data foundation for joint health state assessment and RUL prediction.

Deep temporal feature learning module

The temporal feature learning module is the core of the proposed method. Its objective is to extract deep degradation representations from raw monitoring samples that can simultaneously reflect local degradation patterns and global temporal evolution trends. Since rotating machinery degradation signals usually contain both short-term dynamic features, such as local impulses and frequency modulation, and long-term progressive performance deterioration patterns, a single type of network is often insufficient to capture both aspects effectively. Therefore, this study designs a shared deep temporal feature encoder to hierarchically model the input samples and learn more discriminative and temporally consistent degradation representations.

Specifically, a one-dimensional convolutional structure is first employed to extract local features from the input sequence. The convolutional layers can capture impulsive components, local waveform variations, and short-term degradation patterns through local receptive fields, and can progressively form multi-scale representations through layer stacking. Let the input sample be $\tilde{X}^{(i)}$. The convolutional feature can then be expressed as:

$$F_i = \mathrm{CNN}\ (\tilde{X}^{(i)}) \tag{14}$$

where F_i denotes the local temporal feature extracted by the convolutional module. Compared with conventional handcrafted feature extraction, this process can automatically learn local structural information related to degradation directly from the raw signal, thereby reducing reliance on prior expert knowledge.

After obtaining the local convolutional features, a temporal modeling unit is further introduced to capture long-term dependencies and stage-wise evolutionary trends in the degradation process. To this end, BiLSTM, GRU, TCN, or attention-enhanced temporal structures can be employed to model the local feature sequence. Let the temporal modeling unit be denoted as $\mathcal{T}(\cdot)$. Then, the shared degradation representation can be written as:

$$z_i = \mathcal{T}(F_i) \tag{15}$$

Here, z_i denotes the deep degradation representation of the i -th sample. This representation contains not only local degradation pattern information, but also contextual dependencies across time steps, thereby offering a more complete description of the equipment degradation state. Compared with methods relying only on convolution or only on recurrent structures, the hybrid temporal encoder adopted in this study can simultaneously enhance local feature perception and global trend modeling, thus providing more reliable shared representations for subsequent health state assessment and RUL prediction.

To further improve feature quality, two aspects are emphasized in the temporal feature learning process. First, the learned degradation representation should maintain temporal consistency with health evolution, meaning that adjacent degradation stages should exhibit smooth transitions in the feature space. Second, the shared representation should contain sufficient degradation-discriminative information to support the collaborative optimization of both health state assessment and lifetime prediction. This feature contains not only local degradation pattern information, but also contextual dependencies across time steps, thereby offering a more complete description of the equipment condition.

Health state assessment branch

After obtaining the shared degradation representation z_i , the proposed framework first uses a health state assessment branch to quantify the current degradation level of the equipment. Unlike conventional approaches that only perform fault classification, this study focuses on the continuous degradation evolution throughout the full life cycle of the equipment. Therefore, the health assessment task is formulated as a continuous health indicator learning problem. Specifically, the health assessment branch transforms the shared features into a low-dimensional health representation through several fully connected mapping layers and outputs the corresponding health indicator $\hat{h}_i$ for each sample:

$$\hat{h}_i = H(z_i) \tag{16}$$

where $H(\cdot)$ denotes the health state assessment branch. This health indicator is used to characterize the degradation process of the equipment from healthy operation to failure proximity, and its variation trend is expected to remain as consistent as possible with the true degradation evolution.

To make the constructed health indicator more physically meaningful and practically useful, this study emphasizes monotonicity, trendability, and robustness in health state modeling. Monotonicity means that the health indicator should vary consistently with the degradation process without excessive meaningless oscillations. Trendability requires that degradation trajectories preserve a consistent evolutionary direction across different samples or machines. Robustness means that the health indicator should suppress abnormal fluctuations caused by noise disturbance and operating-condition variation. Under these requirements, the health assessment branch outputs not only an intermediate variable for condition description, but also more structured and interpretable degradation information for subsequent lifetime prediction.

From the perspective of joint modeling, the health assessment branch plays a dual role in the proposed framework. On the one hand, it maps abstract deep degradation features into interpretable health representations, allowing the degradation process of the equipment to be observed and analyzed in the form of continuous trajectories. On the other hand, the generated health indicator is further used as auxiliary information for the RUL prediction branch, thereby strengthening the model's understanding of lifetime evolution. Therefore, the health assessment branch not only performs health evolution description, but also serves as a degradation-prior constraint to some extent.

RUL prediction branch

Based on the shared degradation representation and the learned health indicator, the proposed framework further constructs an RUL prediction branch to estimate the remaining useful life of the equipment. Different from methods that directly regress the lifetime value only from raw features, this study introduces health state information into the lifetime prediction process, enabling the model to estimate RUL under a more explicit degradation-semantic constraint. Specifically, the shared degradation representation z_i and the corresponding health indicator $\hat{h}_i$ are first concatenated at the feature level to form a fused representation $u_i = [z_i; \hat{h}_i]$. The fused representation is then fed into the RUL regression branch to output the predicted lifetime value:

$$u_i = [z_i; \hat{h}_i] \tag{17}$$

$$\hat{r}_i = R(u_i) \tag{18}$$

where $R(\cdot)$ denotes the RUL prediction branch and $\hat{r}_i$ is the predicted remaining useful life of the i -th sample. This design allows lifetime prediction to rely not only on implicit feature learning, but also on the explicit degradation description provided by the health state assessment branch.

Since the lifetime degradation process of rotating machinery is usually highly nonlinear and stage-dependent, the RUL prediction branch needs to have strong regression capability. To this end, a regression head composed of several fully connected layers is adopted to perform nonlinear mapping on the input features, and the difference between the predicted and true lifetime labels is constrained through the loss function. Compared with conventional single-task RUL prediction, the proposed lifetime prediction branch receives auxiliary supervision from health state modeling within the shared feature space, and is therefore more likely to learn a lifetime mapping that is consistent with the actual degradation level of the equipment. This design is beneficial not only for improving prediction accuracy, but also for enhancing the smoothness and consistency of lifetime estimation over the full life cycle.

Furthermore, placing health state assessment and lifetime prediction within the same framework also improves the model’s sensitivity to degradation stage transitions. When the equipment moves from an early stable stage to a clearly deteriorating stage, the health indicator changes accordingly, and the RUL prediction branch can make use of this change to dynamically adjust the prediction results. Therefore, the RUL prediction branch is not an isolated regressor, but rather an essential component of the joint degradation modeling framework together with the health assessment branch.

Loss function and optimization

To jointly optimize health state assessment and RUL prediction, this study constructs a multi-task loss function to train the entire framework in an end-to-end manner. Let the health indicator output by the health assessment branch be $\hat{h}_i$, with its corresponding reference health target denoted by h_i . Let the lifetime estimate produced by the RUL prediction branch be $\hat{r}_i$, and its ground-truth label be r_i . Then, the health assessment loss can be defined as:

$$\mathcal{L}_{health} = \frac{1}{N}\sum_{i=1}^{N}(h_i - \hat{h}_i)^2 \tag{19}$$

and the RUL prediction loss can be defined as:

$$\mathcal{L}_{rul} = \frac{1}{N}\sum_{i=1}^{N}(r_i - \hat{r}_i)^2 \tag{20}$$

Here, $\mathcal{L}_{health}$ is used to constrain the consistency between the learned health indicator and the target health description, whereas $\mathcal{L}_{rul}$ minimizes the prediction error of remaining useful life.

Considering that the XJTU-SY and PRONOSTIA datasets do not provide standard manually annotated health labels, the health target h_i used in $\mathcal{L}_{health}$ is generated from the normalized degradation time ratio, as described in the problem formulation. Therefore, $\mathcal{L}_{health}$ should be understood as a weakly supervised health-indicator learning loss based on run-to-failure life-cycle information rather than a loss based on expert health annotations. In addition, a degradation-regularity-based monotonicity constraint is introduced to further improve the physical consistency of the learned health indicator. For example, a monotonicity constraint can be used to encourage the health indicator to evolve steadily along the degradation direction:

$$\mathcal{L}_{mono} = \frac{1}{N-1}\sum_{i=1}^{N-1}\max(0, \hat{h}_{i+1} - \hat{h}_i) \tag{21}$$

which suppresses abnormal fluctuations that contradict the degradation direction. In addition, smoothness or regularization constraints can be introduced to improve the robustness of the learned health representation. By combining the above terms, the overall loss function of the proposed method can be written as:

$$\mathcal{L} = \lambda_1\mathcal{L}_{health} + \lambda_2\mathcal{L}_{rul} + \lambda_3\mathcal{L}_{mono} + \lambda_4\mathcal{L}_{reg} \tag{22}$$

where λ_1 , λ_2 , λ_3 , and λ_4 are weighting coefficients, and $\mathcal{L}_{reg}$ denotes the parameter regularization term.

During model optimization, the entire framework is trained end-to-end through gradient backpropagation using Adam or a similar optimizer to iteratively update the network parameters. The shared temporal encoder, the health assessment branch, and the RUL prediction branch are synchronously optimized under the unified objective function, so that the learned features can serve both health evolution description and lifetime estimation. Through such a multi-task collaborative optimization strategy, the model can better exploit the temporal regularities hidden in the degradation process of rotating machinery, thereby improving accuracy, stability, and interpretability.

EXPERIMENTAL SETUP

To evaluate the effectiveness of the proposed deep temporal learning framework for rotating machinery health state assessment and remaining useful life prediction, the experiments are designed from four aspects, namely datasets, evaluation metrics, baseline methods, and implementation details. The overall experimental pipeline is illustrated in Fig. 1. First, continuous run-to-failure signals are collected from public rotating machinery datasets, and temporal samples are generated using a sliding-window strategy. Then, the samples are divided into training, validation, and test sets for model training and parameter selection. Finally, the model is evaluated from both the health assessment perspective and the RUL prediction perspective, and compared with several representative baseline methods.

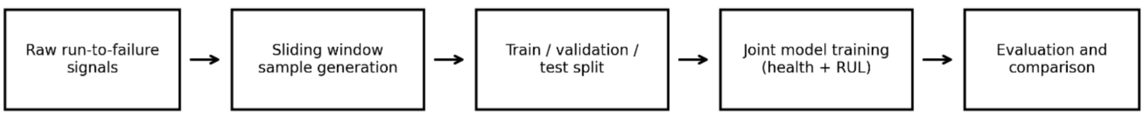

Figure 1.Experimental pipeline for health assessment and RUL prediction

As shown in Figure 1, the experimental design emphasizes the idea of unified input, joint training, and dual-task evaluation. Different from conventional setups that focus only on lifetime prediction, the present study evaluates not only the regression accuracy of RUL estimation, but also the quality of health state representation, thereby providing a more comprehensive assessment of the model’s degradation modeling capability.

Datasets

Two representative public bearing run-to-failure datasets are adopted in this study, namely the XJTU-SY bearing dataset and the PRONOSTIA bearing dataset. The XJTU-SY dataset contains multiple full-life vibration sequences collected under different operating conditions, which makes it suitable for investigating complex degradation trajectories and individual differences among bearings. The PRONOSTIA dataset is a widely used benchmark in RUL research and is therefore suitable for fair comparison with existing methods. Experiments on these two datasets make it possible to evaluate the applicability and robustness of the proposed method under different degradation scenarios.

During sample construction, fixed-length sliding windows are used to segment the continuous vibration signals, and each sample is associated with both a health-state description and an RUL label. For the RUL task, labels are assigned according to the temporal distance between the sample position and the failure time. For the health assessment task, continuous health representations or corresponding constraint targets are constructed based on the degradation evolution order. Specifically, the reference health target of each sample is calculated using the normalized time-to-failure ratio, with the beginning of the run-to-failure sequence assigned a value close to 1 and the failure point assigned a value close to 0. This setting ensures that the same input sample can simultaneously serve both health assessment and lifetime prediction tasks.

Evaluation metrics

To comprehensively evaluate model performance, metrics are selected from both the health assessment perspective and the RUL prediction perspective. These two groups of metrics are related but not equivalent. The health-indicator metrics, including Monotonicity, Trendability, and Robustness, evaluate whether the learned health indicator can provide a stable and physically meaningful description of the degradation process. In contrast, MAE, RMSE, and Score directly measure the numerical accuracy of RUL estimation. In the proposed architecture, a more monotonic and robust health indicator is expected to provide more reliable degradation-state information to the RUL branch, which may contribute to lower prediction errors. However, good health-indicator quality does not necessarily guarantee optimal RUL accuracy, because the final RUL prediction also depends on the temporal encoder and regression mapping. Therefore, the two groups of metrics are used in a complementary manner. For the RUL prediction task, Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Score are used to quantify the accuracy of lifetime estimation. For the health assessment task, Monotonicity, Trendability, and Robustness are adopted to evaluate the quality of the constructed health indicator. The former group mainly reflects the deviation between predicted and true remaining lifetime, whereas the latter group measures whether the health indicator can stably, continuously, and consistently characterize the degradation process.

Such a dual-perspective metric design is consistent with the joint modeling objective of this study. In other words, the proposed method is expected not only to accurately predict the remaining useful life of the equipment, but also to learn health representations with meaningful degradation interpretability, thereby improving the credibility and engineering usability of the method.

Baseline methods

To validate the effectiveness of the proposed method, several representative baseline models are selected for comparison, including traditional machine learning methods, pure temporal deep learning methods, and hybrid temporal deep learning methods. The traditional machine learning baselines mainly include Support Vector Regression (SVR) and Random Forest (RF), which are used to reflect the performance level of hand-crafted-feature-based modeling. Pure temporal deep learning methods include LSTM and GRU, which are used to evaluate sequential modeling capability. Hybrid deep learning methods include CNN-LSTM, TCN, and Transformer-based models, which are used to compare local feature extraction and global temporal modeling ability.

These baselines cover multiple levels ranging from traditional methods to advanced deep learning models, and therefore provide a relatively comprehensive basis for analyzing the superiority of the proposed method. Through such hierarchical comparison, it becomes possible to further examine whether the joint modeling of health state assessment and RUL prediction can bring stable and significant performance improvement.

Implementation details

In implementation, temporal samples are generated using a sliding-window strategy and are divided into training, validation, and test sets according to complete degradation trajectories in order to avoid information leakage. The models are trained using the Adam optimizer, with an initial learning rate of 1×10^{-3} , a batch size of 64, and a maximum of 100 training epochs. To improve training stability and reduce the risk of overfitting, early stopping, dropout, and L_2 regularization are adopted during training. For deep learning models, normalized temporal samples are directly used as inputs, whereas for traditional machine learning methods, unified statistical features are extracted before model training.

Overall, the experimental setup in this section provides a consistent and reliable basis for the subsequent result analysis. Through standardized comparison on public datasets, the proposed method can be systematically evaluated in terms of both health state assessment and remaining useful life prediction.

RESULTS AND DISCUSSION

This section systematically evaluates the proposed method from four aspects, namely health state assessment results, RUL prediction results, ablation study, and feature visualization with interpretability analysis. Different from conventional studies that focus only on lifetime prediction accuracy, the present work evaluates not only the performance in terms of MAE, RMSE, and Score, but also the quality of the constructed health indicator in terms of monotonicity, trendability, and robustness. The former reflects the accuracy of lifetime estimation, whereas the latter reflects the consistency and interpretability of the learned degradation trajectory. These two perspectives complement each other: a reliable health indicator can help stabilize RUL prediction, while RUL prediction accuracy further verifies whether the learned degradation representation is useful for prognostic decision-making. Such a dual-perspective evaluation provides a more comprehensive understanding of the superiority of the proposed joint framework in degradation process modeling.

Health assessment results

Figure 2 presents the health indicator trajectories generated by different methods. It can be observed that the handcrafted health indicator exhibits noticeable local fluctuations during the degradation process. Such fluctuations become particularly evident in the middle and late degradation stages, indicating that traditional feature-based methods are less effective in stably characterizing performance deterioration under complex operating conditions. By comparison, the LSTM-based health indicator is able to capture the overall degradation tendency to some extent, but its curve still contains non-negligible oscillations. In contrast, the health indicator generated by the proposed method shows a much smoother and more continuously decreasing trend, which is more consistent with the actual degradation evolution of the equipment. This suggests that the proposed model can extract degradation-relevant representations from raw temporal signals more effectively.

Figure 2. Health indicator trajectories generated by different methods

To quantitatively compare the health assessment capability of different methods, Table 1 reports the results in terms of Monotonicity, Trendability, and Robustness. It can be seen that the proposed method achieves the best performance on all three health-indicator-related metrics. In particular, the significantly higher Mon value indicates that the constructed health indicator is more consistent with the overall degradation evolution. The improvement in Tre suggests that the method is able to preserve more consistent degradation trends across different samples, while the increase in Rob demonstrates stronger resistance to local noise and fluctuation. These results show that the proposed method not only produces a health representation that can be used for subsequent lifetime prediction, but also yields a degradation trajectory with strong engineering interpretability.

Table 1. Health assessment performance comparison

Method	Mon	Tre	Rob
Handcrafted HI	0.71	0.68	0.74
LSTM-based HI	0.82	0.79	0.83
CNN-LSTM	0.85	0.81	0.86
Transformer	0.86	0.83	0.85
Proposed	0.92	0.89	0.91

By jointly considering Figure 2 and Table 1, it can be found that the superiority of the proposed method in health assessment mainly comes from two aspects. First, the shared temporal encoder can simultaneously capture local degradation patterns and global evolution trends, thereby reducing random oscillations in the health indicator. Second, the joint learning mechanism imposes an additional degradation-semantic constraint through the RUL branch on the health branch, making the generated health trajectory more consistent with the actual lifetime evolution process. Therefore, the improvement in health assessment is reflected not only in smoother curves, but also in statistically more consistent degradation representations. Since the learned health indicator is further used as auxiliary degradation information in the RUL branch, improvements in Mon, Tre, and Rob are expected to contribute to more stable lifetime estimation, although the final RUL error is still determined jointly by the shared encoder and the regression branch.

RUL prediction results

To validate the effectiveness of the proposed method in remaining useful life prediction, Figure 3 shows the RUL prediction curves on a representative test bearing. As can be seen, CNN-LSTM is able to track the overall downward trend of the lifetime, but still exhibits noticeable early or late deviations in the middle and late degradation stages. In contrast, the prediction curve of the proposed method is much closer to the true RUL trajectory, and it maintains relatively high fitting accuracy even in the rapid degradation stage. This indicates that, with the introduction of health state information, the model becomes more sensitive to degradation stage transitions and can therefore improve the stability and accuracy of lifetime estimation in the later stage of degradation.

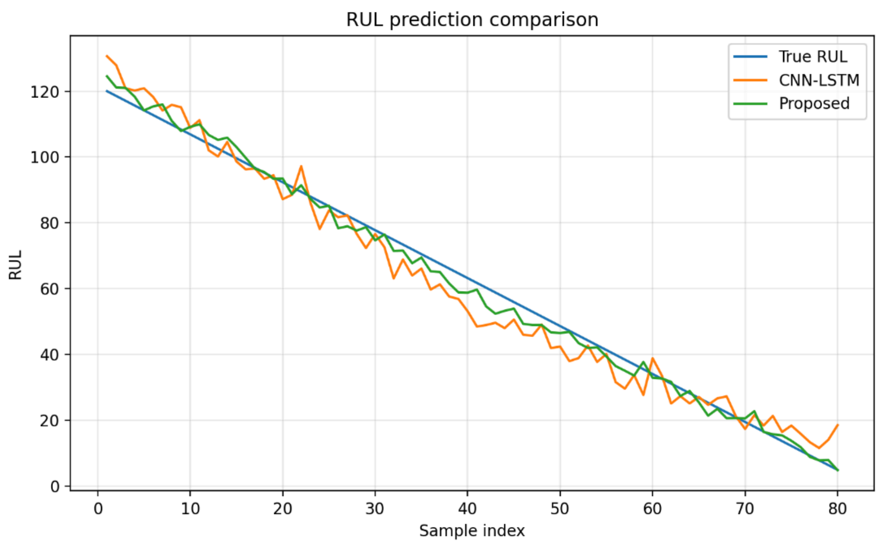

Figure 3. RUL prediction comparison on a representative test bearing

Table 2 summarizes the RUL prediction performance of different methods on the two public datasets. It can be seen that the proposed method achieves the lowest MAE, RMSE, and Score on both XJTU-SY and PRONOSTIA. Compared with traditional machine learning methods, deep learning models generally show stronger lifetime prediction capability, indicating the clear advantage of automatic degradation representation learning in modeling complex rotating machinery degradation processes. Further comparison among deep learning methods reveals that pure temporal models such as LSTM and GRU can exploit sequential dependencies, but still lag behind hybrid deep models because they lack explicit local degradation pattern modeling. By contrast, the proposed method integrates shared temporal encoding with health-state-assisted constraints, leading to better prediction accuracy on both datasets.

Table 2. RUL prediction performance comparison on two datasets

Dataset	Method	MAE	RMSE	Score
XJTU-SY	SVR	18.4	23.1	0.312
XJTU-SY	RF	16.9	21.7	0.287
XJTU-SY	LSTM	13.7	17.5	0.236
XJTU-SY	GRU	13.1	16.9	0.228
XJTU-SY	CNN-LSTM	10.8	14.2	0.181
XJTU-SY	TCN	10.2	13.6	0.174
XJTU-SY	Transformer	9.8	13.0	0.169
XJTU-SY	Proposed	8.7	11.9	0.148
PRONOSTIA	SVR	20.1	24.8	0.336
PRONOSTIA	RF	18.6	23.3	0.314
PRONOSTIA	LSTM	15.4	19.6	0.259
PRONOSTIA	GRU	14.8	18.7	0.247
PRONOSTIA	CNN-LSTM	12.1	15.8	0.196
PRONOSTIA	TCN	11.6	15.1	0.189
PRONOSTIA	Transformer	10.9	14.3	0.178
PRONOSTIA	Proposed	9.5	12.8	0.156

It is worth noting that the performance gain of the proposed method on both datasets is not reflected merely in lower average error, but also in smoother prediction curves, fewer abnormal deviations, and better stability in the later degradation stage. These results indicate that joint health assessment and RUL prediction is not simply an additional auxiliary branch, but rather a mechanism that enhances the model's understanding of degradation patterns within a shared feature space. Particularly in the rapid lifetime-decreasing region, the health indicator provides additional degradation priors, enabling the model to respond more accurately to critical degradation stages.

Ablation study

To further verify the effectiveness of each key component in the proposed framework, an ablation study is conducted on the XJTU-SY dataset, and the results are shown in Fig. 4 and Table 3. Specifically, the health assessment branch, the temporal modeling unit, and the monotonicity constraint are removed one by one to examine their contributions to the final RUL prediction performance. In addition, a single-task RUL baseline is constructed using the same temporal encoder as the proposed model, but without the health assessment output, health loss, or monotonicity constraint, so as to directly examine whether the joint optimization strategy improves RUL prediction beyond the effect of model capacity.

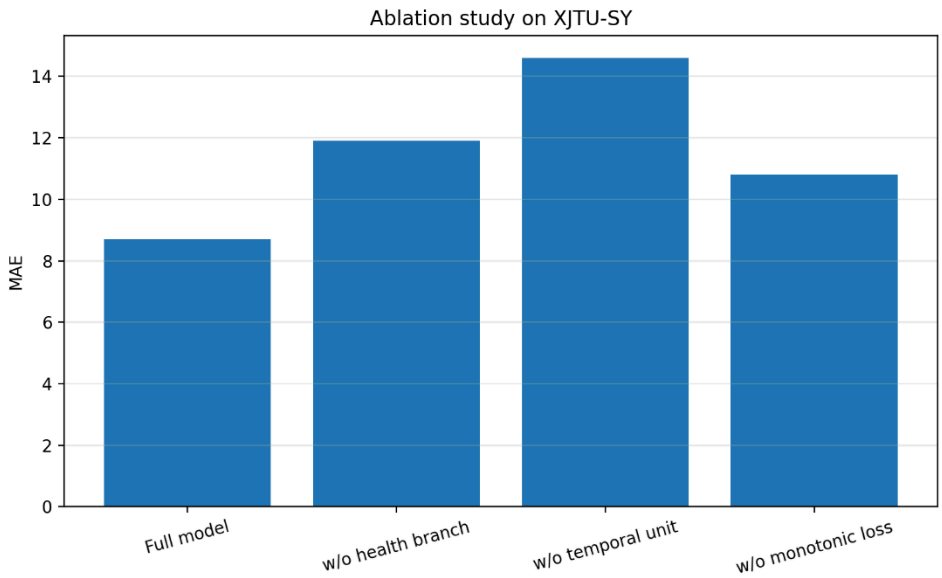

Figure 4. Ablation study of different modules on the XJTU-SY dataset

As shown in Figure 4, the full model achieves the best MAE performance, whereas removing any key component leads to a noticeable increase in prediction error. Among them, the performance degradation is most significant when the temporal modeling unit is removed, indicating that long-range temporal dependency modeling plays a decisive role in understanding the degradation process. Removing the health assessment branch also leads to a substantial performance drop, which confirms that health-state information provides effective assistance for RUL prediction. By contrast, removing the monotonicity constraint results in a relatively smaller but still evident performance reduction, suggesting that this constraint contributes to model stability and health representation quality.

Table 3. Ablation results of the proposed framework on XJTU-SY

Variant	MAE	RMSE	Mon
Full model	8.7	11.9	0.92
Single-task RUL model	10.6	13.7	-
w/o health branch	11.9	15.4	0.81
w/o temporal unit	14.6	18.8	0.77
w/o monotonic loss	10.8	13.9	0.85

Table 3 further quantitatively confirms the trend observed in Fig. 4. The full model achieves the best results in terms of MAE and RMSE, and also produces the highest Mon value among models with health-indicator outputs. Compared with the single-task RUL baseline using the same temporal encoder, the full model obtains lower prediction errors, indicating that the improvement is not merely caused by increased model capacity, but is closely related to the health-state-assisted joint optimization strategy. When the health branch is removed, the Mon value decreases substantially, showing that the model becomes weaker in continuous degradation trajectory modeling. When the temporal unit is removed, both MAE and RMSE deteriorate markedly, confirming that the absence of long-term dependency modeling leads to distorted lifetime estimation. When the monotonicity constraint is removed, the model still preserves the basic temporal learning capability, but the continuity and interpretability of the health indicator are weakened. These findings suggest that the components of the proposed framework are not simply stacked together, but instead interact with each other in a mutually reinforcing manner within the joint modeling paradigm.

To further distinguish the contribution of joint learning from the effect of increased model capacity, an additional single-task RUL baseline is introduced. This baseline adopts the same temporal feature encoder and RUL regression head as the proposed method, but removes the health assessment output and optimizes only the RUL loss. Therefore, the comparison between this baseline and the full model directly reflects the contribution of health-state-assisted joint optimization.

Visualization and interpretability analysis

To further investigate whether the learned degradation representations exhibit good separability and interpretability, Figure 5 presents a two-dimensional visualization of the shared features under different degradation stages. It can be observed that samples corresponding to the healthy state, degradation state, and near-failure state form relatively clear clusters in the feature space, while also showing a progressive arrangement along a certain direction. This indicates that the learned shared degradation representation preserves strong state-structural information in a low-dimensional space, which is beneficial for both subsequent health assessment and lifetime prediction.

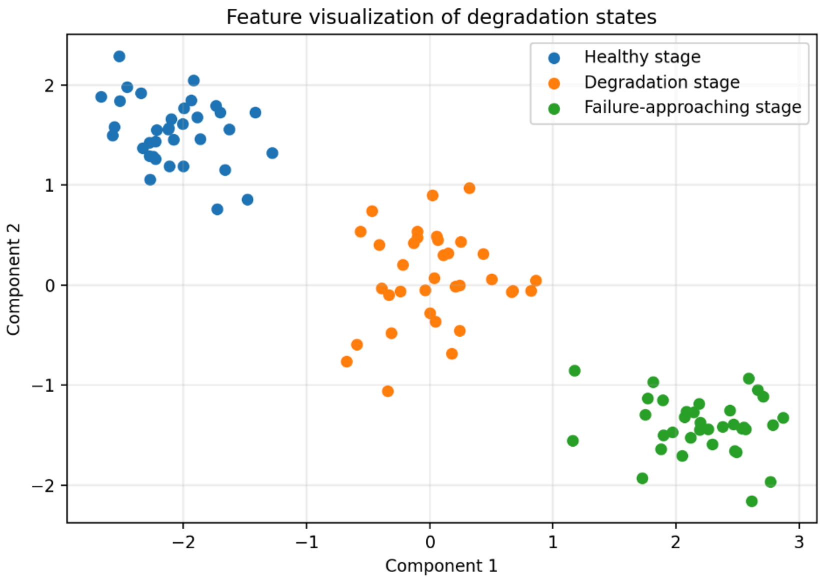

Figure 5. Visualization of learned degradation features in different health stages

This feature distribution has two important implications. First, the relatively clear separation among different degradation stages indicates that the model can effectively distinguish health state differences, rather than merely outputting lifetime values in a black-box manner. Second, the samples exhibit a relatively continuous migration trend from the healthy region to the near-failure region, suggesting that the learned representation is consistent with the degradation process. This observation is consistent with the previously reported health indicator curves and ablation results, jointly demonstrating that the proposed framework improves not only prediction accuracy but also the interpretability of degradation modeling.

Overall, the above results show that the proposed method achieves clear advantages in health state assessment, RUL prediction, module effectiveness validation, and feature interpretability analysis. The underlying reason is that the shared temporal encoder improves the modeling of complex degradation dynamics, the health assessment branch enhances the continuity and physical meaning of degradation representation, and the RUL branch further constrains the feature space from the perspective of lifetime regression, thereby achieving collaborative optimization of health representation and lifetime prediction. These findings indicate that the proposed joint deep temporal learning framework can more fully exploit the temporal regularities hidden in the full-life degradation process of rotating machinery and provide more reliable technical support for intelligent health management.

CONCLUSIONS

This study proposed a unified deep temporal learning framework for two key tasks in rotating machinery health management, namely health state assessment and remaining useful life (RUL) prediction. By taking raw monitoring signals as input, the proposed method employs a shared temporal feature encoder to extract degradation representations and builds a health state assessment branch together with an RUL prediction branch within a unified feature space, thereby enabling joint modeling of the equipment degradation process. Compared with conventional approaches that handle health assessment and lifetime prediction separately, the proposed framework can simultaneously exploit health evolution information and lifetime degradation information, thus improving the capability of characterizing complex degradation patterns. Experimental results on public rotating machinery run-to-failure datasets demonstrated that the proposed method can generate health indicators with desirable monotonicity, trendability, and robustness, while also achieving superior RUL prediction performance in terms of MAE, RMSE, and Score. The ablation and visualization analyses further verified the effectiveness of the main modules and showed that the learned representations exhibit clear stage separability and degradation continuity. These results confirm the feasibility and effectiveness of the proposed unified framework for joint condition assessment and RUL estimation.

Nevertheless, several limitations should also be acknowledged. First, the proposed method was mainly validated on public benchmark datasets, and its robustness under more complex industrial scenarios, such as variable operating conditions, strong noise interference, and cross-machine transfer settings, still requires further verification. Second, the current framework primarily relies on single-source monitoring signals, which may limit its ability to capture more comprehensive degradation characteristics in practical applications. Third, although the model shows good predictive performance, its uncertainty awareness and online adaptation capability remain limited, which may affect reliability in real-time deployment.

Future work can be extended in several directions. It would be valuable to further investigate the generalization capability of the model under complex working conditions and cross-domain scenarios. In addition, multi-source heterogeneous sensing information, such as vibration, temperature, current, and acoustic emission signals, can be integrated to achieve more comprehensive degradation feature fusion. Moreover, uncertainty quantification and online updating mechanisms can be incorporated to improve the reliability and adaptability of the framework in practical industrial environments. Overall, this study provides a promising perspective for jointly modeling health state assessment and RUL prediction of rotating machinery, and lays a foundation for future research on intelligent operation and predictive maintenance.

Author Contributions

Conceptualization – Zihao Xia; methodology – Zihao Xia; formal analysis – Zihao Xia; investigation – Zihao Xia; resources – Zihao Xia; writing-original draft preparation – Zihao Xia; writing-review and editing – Zihao Xia; visualization – Zihao Xia; supervision – Zihao Xia. All authors have read and agreed to the published version of the manuscript.

Conflicts of Interest

The author declares no conflict of interest.

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