



OPEN Time-weighted kernel density for gearbox residual life prediction

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With improvements in industrial automation, the reliability of the gearbox, a key transmission device, has become increasingly crucial for the stable operation of an entire operating system. However, predicting the remaining useful life of the gearbox is challenging because of complex working environments and dynamic load changes. Several existing methods assume an inaccurate model structure and parameter estimation during life prediction, owing to the limited availability of similar fault sample data. In this study, we analyse the influence of kernel density estimation (KDE) based on time-varying distribution on the results of residual useful life prediction, considering the characteristics of such systems and the problems faced by current research methods. First, a time-varying KDE model with an incremental distribution of degradation features is established, and the influence of sample timing on KDE is introduced. Second, the exponential weighted moving average method is employed to predict the degraded samples, and recursive update was employed to reduce unnecessary double calculations during the estimation of the time-varying weight kernel density in the system operation process. Finally, the adaptability and effectiveness of the proposed method are verified using actual collected gearbox data. Research results indicate that the remaining useful life prediction outcomes of the method proposed in this paper are superior to those of the DGN model and the Ensemble model, as evidenced by its lower RMSE and MAE values.

Keywords Time-varying system, Kernel density estimation, Time-varying weight, Residual life prediction

The complexity and precision of mechanical systems have undergone continuous development; however, the probability and types of failures of these systems have also increased. In particular, a sudden failure of the gearbox, a critical transmission device, may interrupt the operation of the entire system, which can adversely affect production management and even endanger personal safety^{1,2}. Therefore, from the perspective of industrial big data, effective monitoring and evaluation of the remaining system life are essential³. Several studies have focused on predicting the remaining useful life (RUL) as the core of prognostics and health management⁴.

Various residual life prediction methods have been widely used, including methods based on physical mechanisms, expert prior knowledge, and data-driven approaches^{5–7}. Physical models^{8,9} are often challenging to establish for complex mechanical equipment, as the requisite expert knowledge is difficult to acquire^{10,11}. Therefore, data-driven life prediction methods are becoming increasingly prevalent. Yan et al.¹² utilised support vector machines to establish a degradation model for predicting the residual life. Yang et al.¹³ modelled the degradation state of components as a discrete semi-Markov process. Hu et al.¹⁴ reviewed residual life prediction models, such as regression, proportional risk, stochastic filter, and hidden Markov models, considering data-driven aspects. Several monotonous degradation processes that represent the development of wear or cracks in a system have been modelled as Gamma processes^{15–17}. However, these data-driven prediction methods typically make assumptions regarding the model structure^{18,19}, and a significant gap often exists between an actual process and assumption-based degradation models. The optimisation of parameter estimation may converge only to a local rather than the global minimum. Consequently, these prediction models cannot ensure final asymptotic convergence to the real sample model.

Moreover, actual monitored gearbox systems primarily operate under time-varying working conditions, with the distribution of their sample sequence tending to be unstable. Unlike time-invariant systems, the distribution rules of the degradation process constantly changes with time. Diyin et al.²⁰ described the dynamic condition as a uniform Markov chain and used the Bayesian method to update the signal parameters and residual life distribution of components. Li et al.²¹ proposed a probabilistic model to estimate the residual life for a degradation process within a specific region under dynamic time-varying operating conditions. Zhou et al.²² transformed the residual life prediction problem into a time-varying trajectory modelling problem and proposed a dynamic control network method to determine the RUL trajectory in a lifetime observation sequence. However, the

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Bellman equation in the Soft Actor-Critic (SAC) algorithm, an actor-critic reinforcement learning algorithm based on maximum entropy, may affect the prediction. Cao et al.²³ developed the time-domain convolution network residual self-attention mechanism, a new deep learning framework to predict the remaining service life of systems under different working conditions.

Long et al.²⁴ proposed a random hybrid system-based method to estimate the RUL based on the complexity and variability of degraded signals under time-varying operating conditions. The RUL under time-varying conditions can be predicted online by modelling the degraded signals and operating conditions of the components; however, the prediction accuracy continuously decreases with an increasing number of working conditions and the amount of calculations required. Furthermore, artificial neural networks require a large amount of high-quality observation data during training, which cannot be easily obtained. The “black box” characteristics of artificial intelligence technology can also reduce the transparency of intelligent learning methods. Additionally, the structure and parameters of neural network models must be formulated beforehand or initialised randomly. These issues cause bottlenecks in prediction performance, hindering artificial intelligence methods from accurately modelling the system mechanism of monitoring equipment.

The kernel density estimation (KDE) method is a data-driven method that makes no assumptions regarding data distribution. It is a non-parametric estimation method that analyses its distribution law based on the data^{25,26}. Xu et al.²⁷ employed KDE for life prediction using real-time degradation characteristic information to determine the prior distribution of parameters in real-time life predictions based on the Bayesian method. Jia et al.²⁸ proposed a new density extrapolation method for efficient reliability analysis. They used KDE and boundary correction to accurately identify the different shapes of target distribution. This method is suitable for calculating the probability density of cylinder failure events under a known number of failure cycles in a cylindrical sample. Zhang et al.²⁹ considered sudden changes in the wear process of a gearbox system and proposed a useful life prediction method based on KDE by detecting the point of sudden change. However, this model assumes that the degradation process remains stable and unchanged.

This study considers the range of issues presented and the time variability of most gearbox systems, and it has the following core components:

- (1) A method for predicting the RUL of a system is proposed by determining the degradation distribution from observed data.
- (2) Owing to the time variability of the degradation distribution, an RUL prediction model based on time-varying KDE is constructed.
- (3) Owing to the impact of the window width h on the estimation accuracy in KDE, an RUL prediction model based on adaptive h and time-varying KDE is constructed.
- (4) To avoid unnecessary repeated calculations of KDE when new observation data are added, a recursive update model based on adaptive h and time-varying KDE is constructed.

Time-varying KDE for the incremental distribution of degenerate features Modelling of time-varying KDE

The incremental distribution of the degenerate features in a time-varying system changes with time. Thus, the concept of time-varying weights was introduced to analyse the effect of time series on the KDE and life prediction accuracy of monitoring systems³⁰. Specifically, the closer the sample points are to the current moment, the better they reflect the running status of the current degenerate system over time. Conversely, the further a sample point is from the current moment, the less it influences the current running state. The time-varying weight factor was introduced based on the conventional KDE model to consider the influence of the time-varying weight. Thus, the time-varying weight KDE at time t is estimated as

$$\hat{f}_t(\Delta x) = \frac{1}{h} \sum_{i=1}^t K\left(\frac{\Delta x - \Delta X_i}{h}\right) w_{t,i}, \quad t = 1, 2, \dots, T' \quad (1)$$

Its corresponding cumulative distribution function is given as

$$\hat{F}_t(\Delta x) = \sum_{i=1}^t H\left(\frac{\Delta x - \Delta X_i}{h}\right) w_{t,i}, \quad t = 1, 2, \dots, T' \quad (2)$$

where $w_{t,i}$ denotes the time-varying weight factor, T' denotes the lifetime of the current monitoring equipment, K selects the most widely used Gaussian kernel, and h denotes the window width of the time-varying KDE.

Due to the uneven density distribution of the collected sample data, with the presence of regions of high density and low density, employing a fixed window width in a time-varying KDE model can lead to over-smoothing in high-density areas and under-smoothing in low-density regions. This can adversely affect the accuracy of the time-varying KDE and the prediction of remaining useful life. Therefore, to ensure that the time-varying kernel density estimation is closer to the actual values, by introducing a local window width factor $\lambda_i = \hat{f}(\Delta X_i)^{-\frac{1}{2}}$ to dynamically adjust the window size in response to changes in data density, the time-varying weighted KDE model based on an adaptive window width can be expressed as follows:

$$\hat{f}_t(\Delta x) = \sum_{i=1}^t \frac{1}{h_i} K\left(\frac{\Delta x - \Delta X_i}{h_i}\right) w_{t,i}, \quad t = 1, 2, \dots, T' \quad (3)$$

here h_i denotes the adaptive window width: $h_i = h_0 \cdot \lambda_i = h_0 \cdot \hat{f}(\Delta X_i)^{-\frac{1}{2}}$, where h_0 is the initial optimal window width of the sample dataset, obtained by minimising the integral mean squared error between the KDE and the actual density; $\hat{f}(\Delta X_i)$ is the KDE of the initial optimal window width²⁹.

Time-varying weight selection

In the KDE model with time-varying weights, $w_{t,i}$ denotes a time-varying weighting factor. Assuming that $w_{t,i}$ decreases exponentially with increasing interval between the sample data $\Delta X_i (i = 1, 2, \dots, t)$ and the current sample ΔX_t , $w_{t,i}$ can be defined as

$$w_{t,i} = (1 - \omega)\omega^{t-i}, \quad i = 1, 2, \dots, t \quad (4)$$

where ω denotes the forgetting factor and satisfies $0 \leq \omega < 1$. The interval between i and t reflects the interval between $\Delta x_i (i = 1, 2, \dots, t)$ and Δx_t . The smaller the interval, the larger the time-varying weight ($w_{t,i}$), and vice versa. The sum over $w_{t,i}$, denoted by s_t , can be expressed as

$$s_t = \sum_{i=1}^t w_{t,i} = \frac{(1 - \omega)\omega^{t-1} \left[1 - \left(\frac{1}{\omega} \right)^t \right]}{1 - \frac{1}{\omega}} = \frac{(1 - \omega)\omega^{t-1} \frac{\omega^t - 1}{\omega}}{\frac{\omega - 1}{\omega}} = 1 - \omega^t \quad (5)$$

Evidently, $w_{t,i}$ satisfies the sum of its weights when $t \rightarrow \infty$.

$$s_t = \sum_{i=1}^t w_{t,i} = 1 \quad (6)$$

Model parameter estimation

The current observable moment $t (t = 1, 2, \dots, T')$ and current known sample $\Delta X_i (i = 1, 2, \dots, t)$ obey the respective time-varying KDEs, $\hat{f}_i(\Delta x) (i = 1, 2, \dots, t)$. The unknown parameter ω in the model can be determined through maximum likelihood estimation. Substituting the known sample $\Delta X_i (i = 1, 2, \dots, t)$ into the time-varying KDE $\hat{f}_i(\Delta x) (i = 1, 2, \dots, T')$, the likelihood function, $L(\omega)$, of ω can be expressed as

$$L(\omega) = \prod_{i=1}^t \hat{f}_i(\Delta X_i) = \hat{f}_1(\Delta X_1) \cdot \hat{f}_2(\Delta X_2) \cdot \dots \cdot \hat{f}_t(\Delta X_t) \quad (t = 1, 2, \dots, T') \quad (7)$$

The log-likelihood function $l(\omega)$, which is normalised according to the sample size, can be expressed as

$$l(\omega) = \frac{1}{t} \sum_{i=1}^t \ln \hat{f}_i(\Delta X_i) = \frac{1}{t} \sum_{i=1}^t \ln \left[\sum_{j=1}^t \frac{1}{h_j} K \left(\frac{\Delta X_i - \Delta X_j}{h_j} \right) w_{i,j}(\omega) \right] \quad (t = 1, 2, \dots, T') \quad (8)$$

The derivative of $l(\omega)$ with respect to ω is set equal to 0, as follows:

$$\begin{cases} \frac{dl(\omega)}{d\omega} = 0 \\ 0 \leq \omega \leq 1 \end{cases} \quad (9)$$

here the value of ω can be obtained using the finite difference method, $\frac{dl(\omega)}{d\omega} = \frac{l(\omega + \Delta\omega) - l(\omega)}{\Delta\omega}$, to maximise the constraint.

Recursive update of time-varying KDE for degenerate feature increment

This study used real-time monitoring equipment wherein the number of samples continuously increased during the real-time operation process. Therefore, the time-varying weight, $w_{t,i}$, had to be recalculated and reallocated for each additional sample data. The time-varying KDE for known historical samples also had to be recalculated. In the time-varying weight KDE model, the introduction of a weight factor $w_{t,i}$ enabled the function $\hat{f}_t(\Delta x)$ to be updated efficiently through a recursive formula. This method significantly reduced the amount of redundant computation required for kernel density estimation in continuous monitoring systems, substantially enhanced the computational efficiency of the estimation process, and thus optimised the overall performance and efficiency of the system.

The time-varying weighted KDE $\hat{f}_t(\Delta x)$ at time $t (t = 1, 2, \dots, T')$ can be further expressed using Eq. (3) as follows:

$$\begin{aligned}\widehat{f}_t(\Delta x) &= \sum_{i=1}^t \frac{1}{h_i} K\left(\frac{\Delta x - \Delta X_i}{h_i}\right) w_{t,i} = \frac{1}{h_1} K\left(\frac{\Delta x - \Delta X_1}{h_1}\right) (1 - \omega)\omega^{t-1} \\ &+ \frac{1}{h_2} K\left(\frac{\Delta x - \Delta X_2}{h_2}\right) (1 - \omega)\omega^{t-2} + \cdots + \frac{1}{h_t} K\left(\frac{\Delta x - \Delta X_t}{h_t}\right) (1 - \omega)\end{aligned}\quad (10)$$

The time-varying weighted kernel density estimate $\widehat{f}_{t-1}(\Delta x)$ at time $t - 1$ is given as

$$\begin{aligned}\widehat{f}_{t-1}(\Delta x) &= \sum_{i=1}^{t-1} \frac{1}{h_i} K\left(\frac{\Delta x - \Delta X_i}{h_i}\right) w_{t-1,i} = \frac{1}{h_1} K\left(\frac{\Delta x - \Delta X_1}{h_1}\right) (1 - \omega)\omega^{t-2} \\ &+ \frac{1}{h_2} K\left(\frac{\Delta x - \Delta X_2}{h_2}\right) (1 - \omega)\omega^{t-3} + \cdots + \frac{1}{h_{t-1}} K\left(\frac{\Delta x - \Delta X_{t-1}}{h_{t-1}}\right) (1 - \omega)\end{aligned}\quad (11)$$

Accordingly,

$$\widehat{f}_t(\Delta x) = \omega \widehat{f}_{t-1}(\Delta x) + \frac{1}{h_t} K\left(\frac{\Delta x - \Delta X_t}{h_t}\right) (1 - \omega)\quad (12)$$

Equation (12) shows that the time-varying weighted KDE $\widehat{f}_t(\Delta x)$ at time t can be recursively obtained from $\widehat{f}_{t-1}(\Delta x)$ at time $t - 1$. This helps recursively update the time-varying KDE of the degenerate feature increment and reduce the amount of unnecessary repeated calculations when the time-varying weight KDE is solved in the continuous monitoring process.

Prediction of the degradation feature increment

In time-varying systems, the increment in the uncollected degenerate features must first be estimated to accurately predict the remaining life. Owing to the time series of the sample data, it is assumed that the closer a sample data instance is to the current sample, the better it can reflect the running state of the following samples, and vice versa. According to the exponentially weighted moving average method, which is a scheme used to weigh current and past sample data, the weights of sample data instances closer to the current time are larger and decrease as the time interval increases. Owing to its simplicity, this method has been extensively used in practical applications.

By setting t as the current time, the prediction model of the random time series ΔX_t at time t can be expressed as

$$\Delta X_t = \sum_{i=1}^{t-1} w'_{t,i} \Delta X_{t-i} + \varepsilon_t\quad (13)$$

where ε_t denotes white noise, which satisfies $E(\varepsilon_t) = 0$ and $E(\varepsilon_t^2) = \sigma_\varepsilon^2 > 0$; and $w'_{t,i}$ represents the exponential weight coefficient of sample ΔX_{t-i} , which satisfies

$$w'_{t,i} = (1 - \beta)\beta^{i-1}\quad (14)$$

where β represents the decay factor, which satisfies $0 \leq \beta < 1$; when $i \rightarrow \infty$, its weight sum is $s'_t = \sum_{i=1}^{\infty} w'_{t,i} = 1$.

Equation (14) can be further expressed as

$$\left(1 - \sum_{i=1}^{t-1} w'_{t,i} B^i\right) \Delta X_t = \varepsilon_t\quad (15)$$

where B denotes the backwards operator³¹.

Moreover,

$$1 - \sum_{i=1}^{t-1} w'_{t,i} B^i = 1 - \sum_{i=1}^{t-1} (1 - \beta)\beta^{i-1} B^i\quad (16)$$

When $t \rightarrow \infty$,

$$1 - \sum_{i=1}^{\infty} w'_{t,i} B^i = 1 - \sum_{i=1}^{\infty} (1 - \beta)\beta^{i-1} B^i = \frac{1 - B}{1 - \beta B}\quad (17)$$

Therefore,

$$\frac{1-B}{1-\beta B} \Delta X_t = \varepsilon_t \quad (18)$$

which can be written as

$$(1-B)\Delta X_t = (1-\beta B)\varepsilon_t \quad (19)$$

here,

$$W_t = \Delta X_t - \Delta X_{t-1} \quad (20)$$

When $t \rightarrow \infty$, the prediction model of a random time series ΔX_t becomes equivalent to

$$\begin{cases} W_t = \Delta X_t - \Delta X_{t-1} \\ W_t = \varepsilon_t - \beta \varepsilon_{t-1} \end{cases} \quad (21)$$

When both sides of $W_t = \varepsilon_t - \beta \varepsilon_{t-1}$ are multiplied by W_t , the following mathematical expression can be obtained:

$$\text{var}(W_t) = \sigma_\varepsilon^2(1 + \beta^2) \quad (22)$$

By multiplying the two sides of W_t by W_{t-1} and calculating the mathematical expectation, we obtain

$$\text{cov}(W_t, W_{t-1}) = -\beta \sigma_\varepsilon^2 \quad (23)$$

The correlation coefficient can then be obtained from Eqs. (22) and (23) as follows:

$$\rho_1 = \frac{\text{cov}(W_t, W_{t-1})}{\text{var}(W_t)} = \frac{-\beta}{1 + \beta^2} \quad (24)$$

As $0 \leq \beta < 1$, a parameter β can be defined as

$$\beta = \frac{-1 + \sqrt{1 - 4\rho_1^2}}{2\rho_1} \quad (25)$$

In actual monitoring systems, the number of samples collected is often limited. If $t(t = 1, 2, \dots, T')$ represents the current monitored time, the estimated value $\hat{\beta}$ of β in the exponential weighted moving average model can be obtained from the known sample $(\Delta X_1, \Delta X_2, \dots, \Delta X_t)$ as follows:

- Calculate $W_i = \Delta X_i - \Delta X_{i-1}$ ($i = 2, 3, \dots, t$)
- Calculate $\bar{W} = \frac{1}{t-1} \sum_{i=2}^t W_i$.
- Calculate $\hat{\tau}_0 = \frac{1}{t-1} \sum_{i=2}^t (W_i - \bar{W})^2$, $\hat{\tau}_1 = \frac{1}{t-2} \sum_{i=2}^{t-1} (W_i - \bar{W})((W_{i+1} - \bar{W}))$.

The correlation coefficient can then be expressed as

$$\hat{\rho}_1 = \frac{\hat{\tau}_1}{\hat{\tau}_0} \quad (26)$$

- The estimated value $\hat{\beta}$ of β is then expressed as

$$\hat{\beta} = \frac{-1 + \sqrt{1 - 4\hat{\rho}_1^2}}{2\hat{\rho}_1} \quad (27)$$

For a finite number of samples at time $t(t = 1, 2, \dots, T')$, the prediction model of the time series ΔX_t can be expressed as

$$\begin{aligned} \Delta X_t &= \sum_{i=1}^{t-1} w'_{t,i} \Delta X_{t-i} + \varepsilon_t = \sum_{i=1}^{t-1} (1 - \hat{\beta}) \hat{\beta}^{i-1} \Delta X_{t-i} + \varepsilon_t \\ &= (1 - \hat{\beta}) \hat{\beta}^0 \Delta X_{t-1} + (1 - \hat{\beta}) \hat{\beta}^1 \Delta X_{t-2} + \dots + (1 - \hat{\beta}) \hat{\beta}^{t-2} \Delta X_1 + \varepsilon_t \\ &= (1 - \hat{\beta}) \Delta X_{t-1} + (1 - \hat{\beta}) \hat{\beta} \Delta X_{t-2} + \dots + (1 - \hat{\beta}) \hat{\beta}^{t-2} \Delta X_1 + \varepsilon_t \end{aligned} \quad (28)$$

Accordingly, the predicted values of the incremental samples of the degraded features at any time after t can be obtained by using the time series prediction model of the known samples.

Time-varying KDE of degenerate eigenvalue distribution

Considering the time dependence, the time-varying KDEs change with the addition of degenerate feature increment samples. Assuming that the samples are collected once per unit time, the time-varying KDE can be obtained using the degenerate characteristic incremental samples at the initial time, which is denoted by $\hat{f}_1(\Delta x)$. The time-varying KDE for the degraded feature increment samples at the next time (denoted by $\hat{f}_2(\Delta x)$) can be obtained as the number of continuous monitoring samples increases. The time-varying KDE for the cumulative degradation quantity, $X_2 = \Delta X_1 + \Delta X_2$, at time $t = 2$ (denoted by $\hat{f}_2(x)$) can be expressed as the convolution of the time-varying KDE ($\hat{f}_1(\Delta x)$) of the degraded feature increment and $\hat{f}_2(\Delta x)$, expressed as

$$\hat{f}_2(x) = \hat{f}_1(\Delta x) * \hat{f}_2(\Delta x) \quad (29)$$

Accordingly, the time-varying weighted KDE (denoted by $\hat{f}_t(x)$) for the characteristic cumulative degradation, $X_t, t = 1, 2, \dots, T'$, at different times can be obtained as follows:

$$\hat{f}_t(x) = \hat{f}_1(\Delta x) * \hat{f}_2(\Delta x) * \dots * \hat{f}_t(\Delta x) \quad (30)$$

To reduce unnecessary redundant calculations, Eq. (30) can be expressed recursively as follows:

$$\begin{aligned} \hat{f}_t(x) &= \left[\hat{f}_1(\Delta x) * \hat{f}_2(\Delta x) * \dots * \hat{f}_{t-1}(\Delta x) \right] * \hat{f}_t(\Delta x) \\ &= \hat{f}_{t-1}(x) * \hat{f}_t(\Delta x) \end{aligned} \quad (31)$$

Essentially, the time-varying weight KDE $\hat{f}_t(x)$ of the characteristic degradation quantity X_t at a different time t can be obtained through recursion from the time-varying weight KDE of the characteristic degradation quantity X_{t-1} at time $t - 1$.

Real-time residual life prediction model based on time-varying KDE

Figure 1 depicts the prediction method flow based on the time-varying KDE.

We set t as the present monitoring moment and x_{th} as the failure threshold. When the cumulative feature degradation reaches x_{th} , the system is considered to have failed. Figure 2 depicts the change trend curve of the overall degradation characteristics of the degraded system. Let T be the RUL of the degenerate system at point t and $F_t(T)$ be the probability distribution function of the remaining life. $F_t(T)$ can then be expressed as

$$F_t(T) = p(X_{t+T} \geq x_{th}) = \int_{x_{th}}^{\infty} \hat{f}_{t+T}(x) dx \quad (32)$$

where $\hat{f}_{t+T}(x)$ denotes the probability density of the degenerate characteristic X_{t+T} at time $t + T$, which can be obtained from the convolution of the time-varying KDE $\hat{f}_i(\Delta x), i = 1, 2, \dots, t + T$, of the characteristic degradation increment at different historical times and can be expressed as

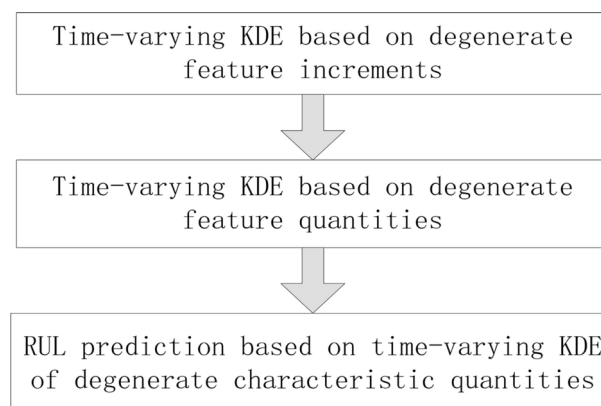


Fig. 1. Flowchart of residual life prediction.

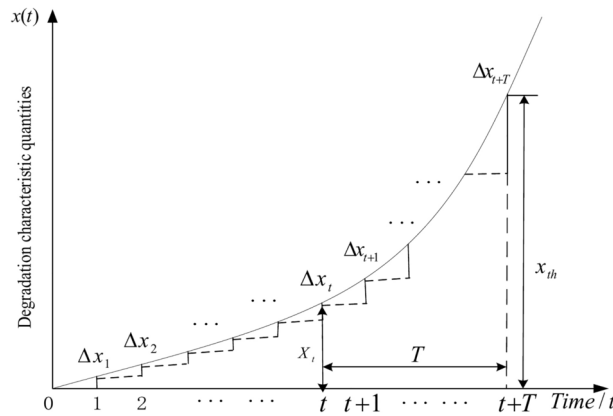


Fig. 2. Degradation characteristic curve and residual life prediction.

$$\hat{f}_{t+T}(x) = \hat{f}_1(\Delta x) * \hat{f}_2(\Delta x) * \dots * \hat{f}_t(\Delta x) * \dots * \hat{f}_{t+T}(\Delta x) \quad (33)$$

Equation (33) can be expressed recursively as follows:

$$\hat{f}_{t+T}(x) = \hat{f}_{t+T-1}(x) * \hat{f}_{t+T}(\Delta x) \quad (34)$$

Essentially, the probability density $\hat{f}_{t+T}(x)$ of the degenerate characteristic X_{t+T} at time $t + T$ can be obtained through the convolution of the probability density $\hat{f}_{t+T-1}(x)$ of the characteristic degradation quantity X_{t+T-1} at the previous time and the time-varying KDE $\hat{f}_{t+T}(\Delta x)$ of the characteristic degradation increment prediction value ΔX_{t+T} at time $t + T$.

Substituting Eq. (34) into Eq. (32), the probability density function $\hat{f}_t(T)$ of the RUL, which is estimated based on the time-varying kernel density, can be expressed as follows:

$$\begin{aligned} \hat{f}_t(T) &= \frac{dF_t(T)}{dt} \\ &= \frac{d \left[\int_0^{x_{th}} \hat{f}_1(\Delta x) * \hat{f}_2(\Delta x) * \dots * \hat{f}_t(\Delta x) * \hat{f}_{t+1}(\Delta x) * \dots * \hat{f}_{t+T}(\Delta x) d\Delta x \right]}{dt} \\ &= \frac{d \left[\int_0^{x_{th}} \hat{f}_{t+T-1}(x) * \hat{f}_{t+T}(\Delta x) d\Delta x \right]}{dt} \end{aligned} \quad (35)$$

Similarly, the real-time residual life can be predicted at any time after t .

Case analysis

To further verify the applicability of the proposed method, the RUL was predicted based on the data collected during gear fatigue. The data were derived from the test bench presented in Fig. 3, which depicts the positions of the main test gearbox and the accompanying test gearbox. The centre distance between the gearboxes was 15 cm. The monitored data collected during the test included temperature and vibration data. The gears were meshed using staggered teeth, as shown in Fig. 4. Figures 5 and 6 depict the specific installation positions of the vibration and temperature sensors. Table 1 lists the functions of the sensors installed at different positions.

The output torque of the monitored gear was 822.7 N m. Tooth breakage due to continuous gear wear under time-varying working conditions was defined as failure.

The root mean square (RMS) was used to accurately reflect the change in the degradation state during gear wear. By preprocessing the vibration signals received by the sensor (4)³², we extracted the RMS feature of the signal. The signal was sampled at a rate of 25.6 kHz, with a duration of 60 s and a sampling interval of 9 min, resulting in an RMS Monitoring Time (RMS-MT) curve, as shown in Fig. 7.

Figure 7 depicts the RMS characteristic curve representing the degradation state of the gear during the process from meshing to failure, and the specific description is presented in Table 2.

Prediction of the degradation feature increment

In a time-varying system, the degradation distribution of the sample series changes with time. Therefore, the degradation feature increment must first be predicted to predict the RUL of the degenerate system. Figure 8 depicts the mean curve of the degradation state obtained by the accumulation of the incremental values of



Fig. 3. Gear fatigue test bench.

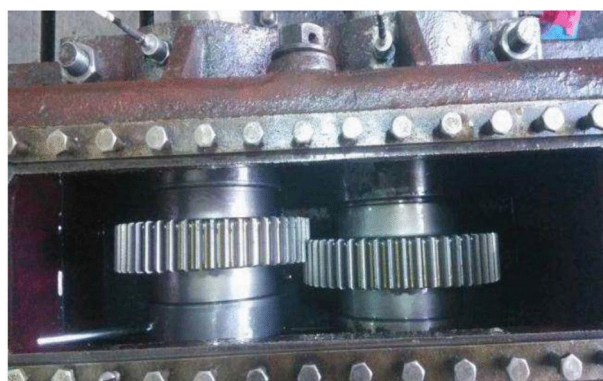


Fig. 4. Installation of the test gears.

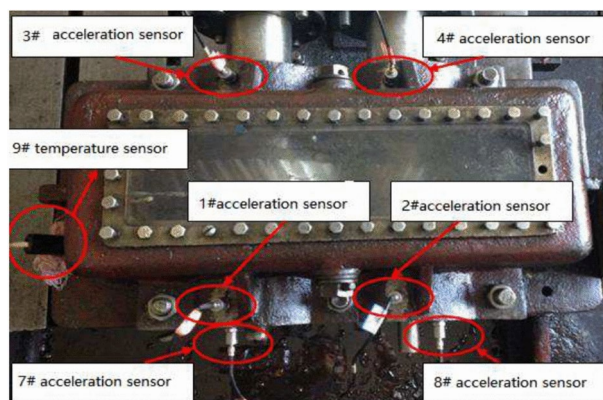


Fig. 5. Sensor locations in the main test box.

the degradation characteristics estimated using the exponential weighted moving average method when the monitored gear wear test was run for different periods.

Figure 8 depicts the difference between the degradation state prediction curves at different times. The predicted degradation characteristic curve at 70 h significantly deviates from the actual value, indicating a large error in the estimated degradation characteristic increment value. The monitoring information gradually increases with increasing monitoring time, and the degradation state prediction curve becomes closer to the actual degradation curve. Therefore, the error in the estimated degradation feature increment value gradually decreases. The dynamic changes in the gear wear degradation feature can be tracked and monitored effectively based on the estimated value of the degradation feature increment. Furthermore, the degradation feature

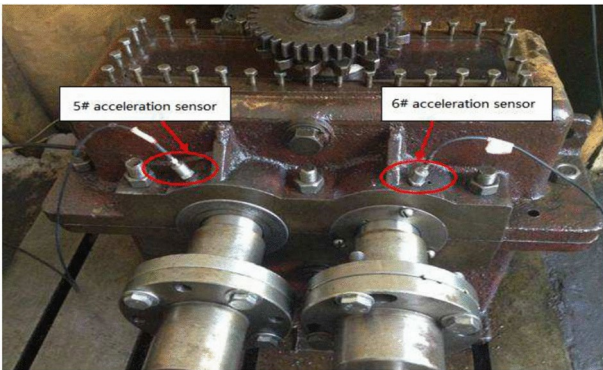


Fig. 6. Sensor locations in the accompanying test box.

Number	Sensor	Installation position	Function
(1)–(4)	Acceleration	Radial of the main test box bearing seat	Monitoring the vibration signal of the main test box
(5), (6)	Acceleration	Radial of the accompanying test box bearing seat	Monitoring the vibration signal of the accompanying test box
(7), (8)	Acceleration	Axial of the main test box bearing seat	Monitoring the vibration signal of the main test box
(9)	Acoustic	40 cm above the main test box	Monitoring the noise signal of the main test box
(10)	Acoustic	40 cm above the accompanying test box	Monitor the noise signal of the accompanying test box
(11)	Temperature	Inside the test gearbox	Monitoring the gearbox lubricating oil temperature signal

Table 1. Sensors installed at different positions.

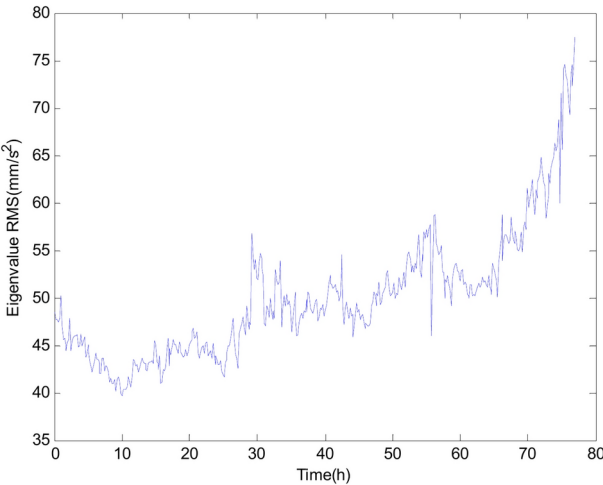
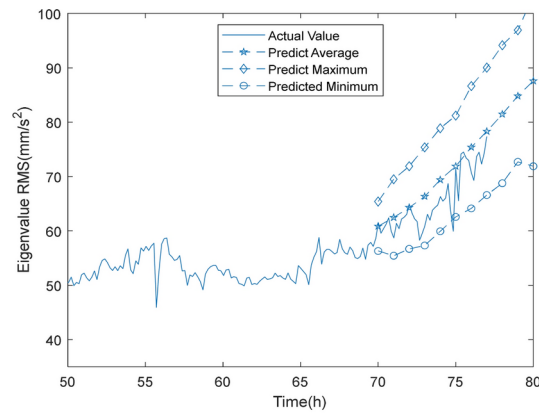


Fig. 7. RMS curve of the vibration signal eigenvalues.

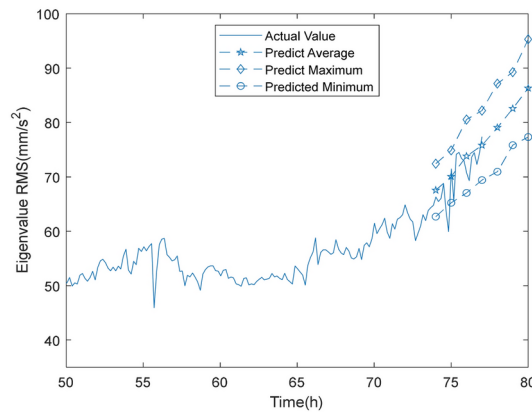
Monitoring time	RMS curve	Monitoring gear status
$t \in [0, 10] \text{ h}$	Showing a gradual decrease	Initial meshing stage
$t \in [10, 68] \text{ h}$	Showing a gradual increase	Normal fatigue wear stage
$t \in [68, 77] \text{ h}$	Starting to increase sharply	Fatigue and wear increase until the tooth is broken

Table 2. Gear status at different monitoring times.

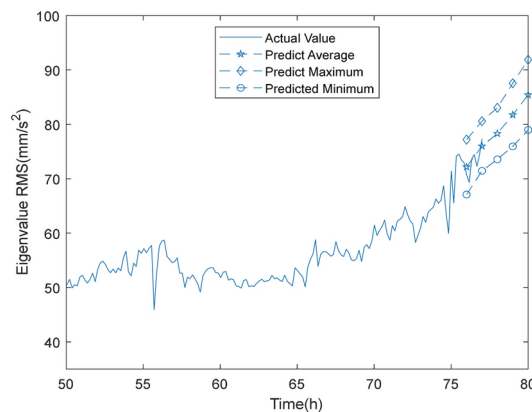
increment value estimated using the exponential weighted moving average method is closer to the actual degradation feature increment value.



(a) Degradation state prediction at 70 h.



(b) Degradation state prediction at 74 h.



(c) Degradation state prediction at 76 h.

Fig. 8. Comparison of the predicted degradation states at different instances.

Comparison of residual life prediction results for different window widths

The window width is adaptively selected based on the change in the sample density to improve the accuracy of the estimation of the degraded feature distribution owing to the random change in the sample density of the degraded features during the gear wear test. Essentially, the area with dense samples is estimated using a smaller window width, whereas the area with sparse samples is estimated using a larger window width.

Table 3 presents a comparison of the mean time to failure (MTTF)³³ results for fixed and adaptive smoothing window widths with time-varying KDE during the gear wear test for different running times.

$$MTTF = E(T) = \int_0^{\infty} t f_T(t) dt \quad (36)$$

Current moment (h)	Actual RUL (h)	Adaptive h time-varying KDE MTTF (h)	Relative error (%)	Fixed h time-varying KDE MTTF (h)	Relative error (%)
70	7.2	5.751	20.125	5.263	25.514
72	5.2	4.392	15.538	4.112	20.923
74	3.2	2.876	10.125	2.702	15.563
76	1.2	1.074	10.500	1.026	14.500

Table 3. Comparison of MTTF prediction results for fixed and adaptive smoothing window widths.

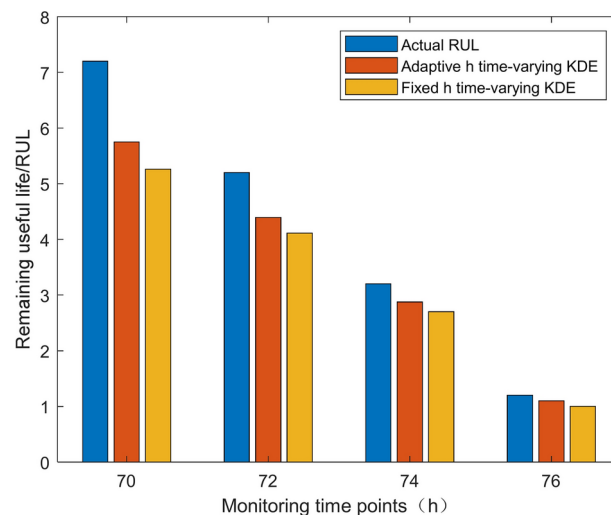


Fig. 9. Comparison of the prediction results for fixed and adaptive smoothing window widths.

Methods	Errors	
	RMSE	MAE
Adaptive h time-varying KDE	1.2307	0.9750
Fixed h time-varying KDE	1.4469	1.1978

Table 4. Comparison of the RMSE and MAE of the two methods for predicting the RUL.

A comparison of the data in Table 3 shows that the remaining useful life prediction using the adaptive window width kernel density method is more accurate than the method based on fixed window width kernel density estimation. Additionally, Table 3 also indicates that for datasets of different sizes, the accuracy of remaining useful life prediction using adaptive window width kernel density with large datasets shows a more significant improvement compared to using small datasets.

Figure 9 presents a comparison of the corresponding prediction results. Table 3 and Fig. 9 reveal that with increasing gear running time, the errors between the MTTF values predicted using the two window width methods and the actual remaining life decreased continuously. Furthermore, the MTTF predicted via the window width method used in this study was closer to the true value than that predicted by the fixed window width method, indicating that the uncertainty of the prediction results was reduced.

To demonstrate the advantages of the proposed method more directly, the root mean square error (RMSE) and mean absolute error (MAE) were introduced as measurement standards. Table 4 and Fig. 10 present a comparison of the RMSE and MAE of the remaining lives of various prediction methods. The smaller the standard value, the greater the accuracy of the prediction and the better the performance. The RMSE is expressed as follows:

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n \Delta_i^2} \quad (37)$$

The MAE is expressed as follows:

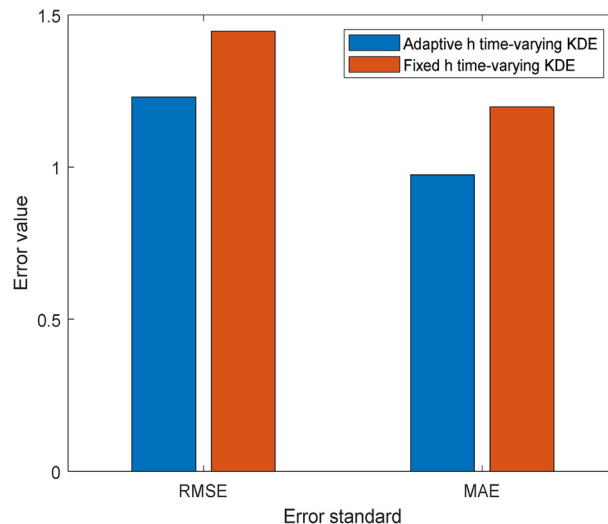


Fig. 10. Error comparison results of the two RUL prediction methods.

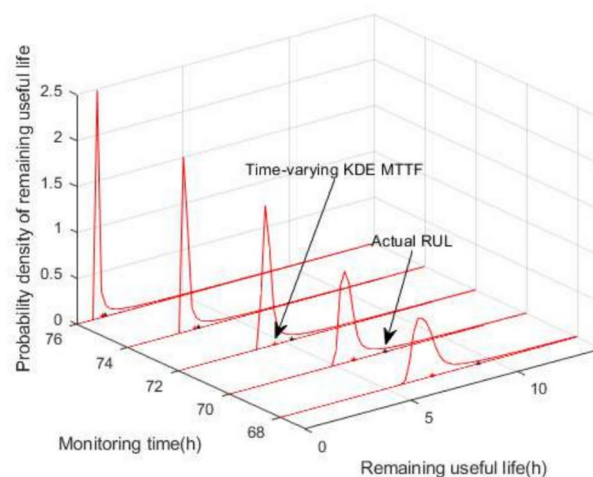


Fig. 11. RUL probability density comparison for different monitoring times.

$$MAE = \frac{1}{n} \sum_{i=1}^n \Delta_i \quad (38)$$

where i represents the monitoring time point and Δ_i denotes the absolute error between the average remaining life predicted at different and corresponding times.

Time-varying kernel density comparison of the probability density for real-time remaining life estimation

Figure 11 compares the MTTF predicted by the time-varying KDE and the actual RUL for different running times during actual gear operation.

Evidently, at the initial stage of gear wear, the error between the predicted and actual values of the real-time residual life was large owing to the limited number of known degradation samples. As the gear wear test continued, the sample data continued to increase, and the probability density curve of the predicted RUL narrowed, indicating that the variance and the uncertainty of life prediction continued to decrease. The predicted residual life became increasingly close to the actual residual life.

Comparison of time-varying KDE and DGN model-based RUL predictions

To verify the competitiveness of the proposed method, Table 5 and Fig. 12 present the results of two highly rated methods that were evaluated on the same dataset, in addition to the method suggested in the present study.

Current moment (h)	70	72	74	76
Actual RUL (h)	7.2	5.2	3.2	1.2
Proposed method's MTTF (h)	5.751	4.392	2.876	1.074
Relative error (%)	20.125	15.538	10.125	10.500
DGN ²² (h)	5.615	4.134	2.679	1.043
Relative error (%)	22.014	20.5	16.281	13.083
Ensemble model ³⁴ (h)	5.589	4.211	2.684	1.058
Relative error (%)	22.375	19.019	16.125	11.833

Table 5. Comparison of the results of the three models.

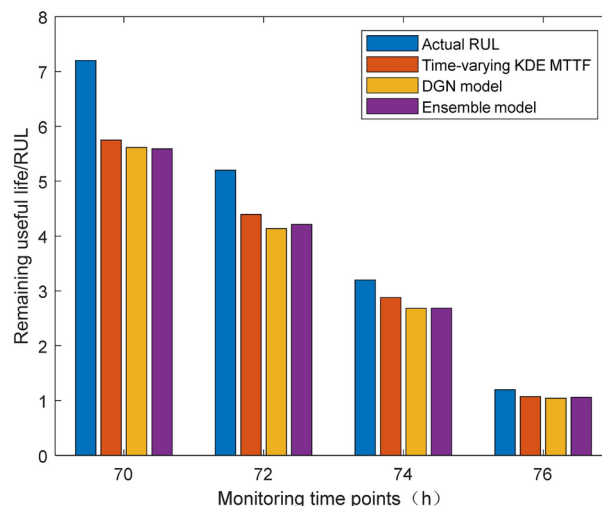


Fig. 12. Comparison of prediction results of the three models.

Methods	Error	
	RMSE	MAE
Time-varying KDE model	0.8475	0.6767
DGN model	0.9931	0.8323
Ensemble model	0.9823	0.8145

Table 6. Comparison of the prediction evaluation results of the three models.

As SAC in a previous study²² uses the Bellman equation to update the estimates of the state and action value functions, the improper setting of the discount factor in the Bellman equation under time-varying operating conditions results in poor generalisation of the algorithm under time-varying operating conditions. The ensemble model³⁴ in the process of training multiple base models, due to the inability to fully capture certain unique features in the data, coupled with the risk of overfitting in the process of model selection and parameter tuning, leads to unsatisfactory prediction effects of the ensemble model. The data shown in Table 5 and Fig. 12 indicate that although the method proposed in this study is not complex in theory, it still maintains a high level of accuracy, thus fully demonstrating the practical application effect and reliability of this method.

To thoroughly evaluate the predictive performance of our proposed method and compare it with two highly regarded methods, we conducted analyses using RMSE (Root Mean Square Error) and MAE (Mean Absolute Error). Tables 6 and Fig. 13 provide a detailed presentation of this comparison.

By contrasting the prediction errors of the three methods, we observed that our proposed method surpasses the DGN time-varying trajectory method and the integrated model in terms of prediction accuracy. Furthermore, the error observed between our proposed method and the actual values was significantly smaller, confirming its higher prediction accuracy and reliability.

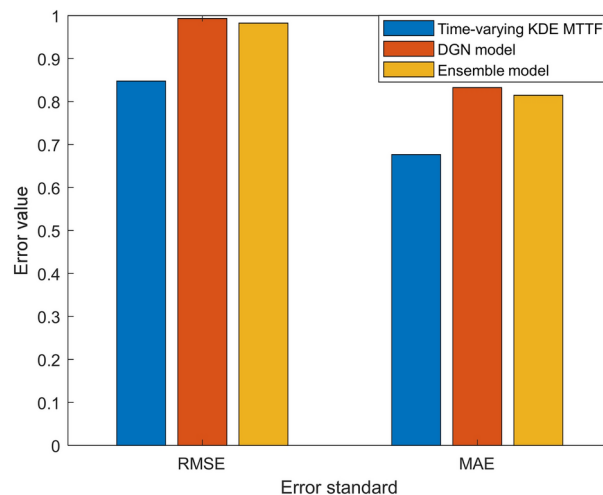


Fig. 13. Error comparison results of the three models.

Conclusion

In this study, different influence weights were assigned to samples at different times during KDE, and a remaining life prediction method based on time-varying weight KDE was proposed while considering the time variability of gearbox systems and time seriality of the sample data.

Because the system distribution changes with time, a time-varying weight was introduced in the proposed model based on the different impacts of the time series samples collected at different instances on the distribution in the time-varying system. The closer the samples were to the current time, the greater the influence on the distribution and the larger the weight to be assigned, and vice versa.

For samples that were not collected during continuous monitoring, the exponential weighted moving average method was employed to make predictions based on the past and current sample data. Additionally, as the proposed model was repeatedly implemented when the sample data continuously increased during the operation of the gearbox system, a real-time update model was established to effectively improve the computational efficiency. Finally, the rationality and competitiveness of the proposed model were verified through a gear wear test.

Owing to advancements in the manufacturing industry, single-component systems are no longer effective for mechanical equipment, and the interdependence between multiple components cannot be ignored. Therefore, in future works, we aim to analyse the prediction and health management of multi-component systems from the perspective of random correlations among gearbox system components.

Data availability

Data is provided within the manuscript file.

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Author contributions

Weizhen Zhang, Jianchao Zeng, and Hui Shi wrote the main manuscript text. All authors reviewed the manuscript.

Declarations

Competing interests

The authors declare no competing interests.

Additional information

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