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Research Article

A Hybrid Method to Predict the Remaining Useful Life of Scroll Wheel of Control Rod Drive Mechanism

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As one of the rotating components in the reluctance motor type control rod drive mechanism (CRDM), the life of the scroll wheel is closely related to the service life of the CRDM. In addition, the prediction of the remaining useful life of the scroll wheel helps to optimize the maintenance process of the CRDM. This paper proposes a hybrid method to predict its remaining useful life when the available degradation data are rare and the failure threshold cannot be accurately defined. First, the particle filtering algorithm, whose state transfer equation is established on the segmental damage physical model, is used to predict the degradation state of the scroll wheel. Second, the proportional hazard model for the relationship between the scroll wheel damage characteristics and reliability model is established to predict the remaining useful life of it. The proposed method focuses on the establishment of segmental damage physical model and the clustering analysis of damage characteristics extracted from vibration signals, which can be used to predict the remaining useful life of the scroll wheel. In addition, the results provide an opportunity for the condition-based preventive maintenance of the CRDM.

1. Introduction

As an important part of the reactor control system and safety protection system, the control rod drive mechanism (CRDM) is vital to the reliable operation of the reactor. The CRDM drives the control rod to move up and down to achieve the start-stop and power regulation of the reactor. The life of the CRDM directly affects the reliability of the power regulation of the reactor. While the impact of degradation on the life of the CRDM is expected to be avoided by high-quality design, unanticipated component degradation has become a problem that cannot be ignored. The research about CRDM has received increasing attention in recent years. By using the fault tree method, Ramesh and Usha [1] investigated the reliability of a single CRDM in a fast breeder test reactor. Lin et al. [2] developed an internal calculation program for the solid fuel thorium molten salt reactor system to solve the dynamic problem of rod dropping. Caylor et al. [3] proposed a control rod diagnosis method for CRDM condition monitoring, which combined optimized system testing and online monitoring to improve the performance of the CRDM. Oluwasegun and Jung [4] proposed a conceptual framework of digital twin technology for predicting CRDM performance by using coil current data. However, the above studies focused on the performance evaluation of the CRDM and there are few research studies about how to predict the remaining useful life of the CRDM.

Because of its importance to reactor safety, the CRDM is subjected to the Maintenance Rule and must undergo periodic surveillance and testing [5]. Operators typically perform detailed performance testing of the CRDM during planned plant shutdowns. Nonetheless, unexpected failures of the CRDM can occur that cannot be detected in advance through planned maintenance [4]. The main reasons are that the failure phenomena that occur during the operation of the reactor are different from those during the planned shutdown and the uncertainty that causes failure to happen is introduced by the degradation of the CRDM. Moreover, once the CRDM failed (such as a rod drop accident), the activities to investigate the root causes and re-establish normal operation can consume a lot of resources. If the failure is caused by mechanical part (such as the scroll wheel), its repair will consume more time and resources. Therefore, this triggers the need for condition monitoring and remaining useful life prediction of the CRDM. Ling et al. [6] investigated the relationship between the latch, stepping stress, and friction stress in the magnetic lifting CRDM to establish the latch life model by using an approximate model. Song et al. [7] investigated the thermal aging mechanism of coils and estimated the relevant parameters and confidence intervals by using the Arrhenius lognormal regression model and the Arrhenius Weibull regression model, respectively. Hertz [8] obtained the latch's wear mechanism by reproducing and observing the wear process and predicted the latch's service life based on it. In general, the research studies on the remaining useful life of the CRDM are still in the preliminary stage and most of them are about the magnetic lifting CRDM, and the studies about the reluctance motor type CRDM are rare.

The reluctance motor type CRDM drives the rotor by injecting magnetic flux into the stator coil, which causes the rotation of the scroll wheel. Then, the scroll wheel drives the lead screw and the control rod to move up and down in the guide barrel [9], as shown in Figure 1 [10]. As one of the rotating parts in the CRDM, the performance of the scroll wheel will gradually deteriorate under the influence of operational and environmental stresses, which is a potential risk for the CRDM. Therefore, it is urgent to evaluate the performance of the scroll wheel and to predict its remaining useful life. There are many methods to evaluate the states of rotating components, which can be divided into physical model-based methods [11, 12] and data-driven methods [13, 14]. The physical model-based methods, which are unable to adjust the relevant model parameters by using monitoring data, entail developing a physical model of the degradation process. Then, the component's life is predicted based on this model. The data-driven methods directly use the damage characteristics extracted from monitoring data to build a damage prediction model and then adjust the model parameters using real-time monitoring data. However, the data-driven method requires a large amount of data to train the model in order to achieve higher prediction accuracy. In addition, the accuracy and authenticity of the data directly limit their application.

Numerous research studies have been conducted to improve the prediction accuracy of the data-driven model. Recently, Ding et al. [15] proposed a modified auto-regression degradation trend estimation methodology that constructed weak-stationary degradation indicators from time and frequency domains to predict the future degradation trend of rolling and slewing bearings. In order to deal with few-shot prognostics under unlabeled historical data, Ding and Jia [16] established a creative link between big historical data, abstracting and refining prior degradation knowledge and limited on-site condition data by using an unsupervised meta gated recurrent unit. In addition, they

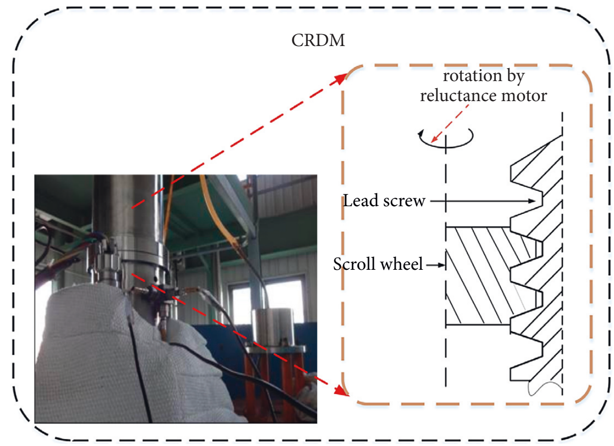

FIGURE 1: The sketch of the reluctance motor type CRDM.

also proposed a dynamic structure–adaptive symbolic approach that tracked the real-time condition of machinery in service and helped to visualize and quantify degradation through the evolving structures of life models [17]. However, there are two main problems when evaluating the remaining useful life of the scroll wheel: One is how to predict the state of the scroll wheel when the available historical data and operational data are rare; the other is how to predict the service life of the scroll wheel when the failure threshold cannot be accurately defined. The hybrid methods not only avoid the limitation that the data-driven methods cannot explain the physical relationship between the damage states and extracted features but also solve the problem of using the physical model alone that is difficult to dynamically adjust model parameters in time. In addition, the hybrid methods have been widely used in the prediction of the remaining useful life of rotating machinery, such as bearings [18], gears [19], planetary gearboxes [20], fans [21], etc.

Therefore, this paper proposes a hybrid method based on the particle filtering (PF) algorithm and proportional hazard model to tackle the above problems. The particle filtering algorithm is used to predict the states of the scroll wheel. Instead of using the empirical exponential degradation model, a segmental damage model of the scroll wheel developed using the multi-time scale model is used as the state transfer equation of the PF algorithm in this paper. In addition, the calculation process is dynamic because the state transfer equation changes according to the comparison of the predicted damage characteristics and the segmental threshold value. Then, the proportional hazard model is used to establish the relationship between the degradation characteristics and the reliability model when the scroll wheel's failure threshold cannot be accurately defined due to the rare referential experiences.

The remainder of the paper is organized as follows. The segmental damage physical model of the scroll wheel developed using the multi-time scale model is proposed in Section 2. Section 3 establishes the framework to predict the remaining useful life of the scroll wheel based on the proposed method. In Section 4, the damage characteristics of the scroll wheel are classified by the k-means algorithm, and the

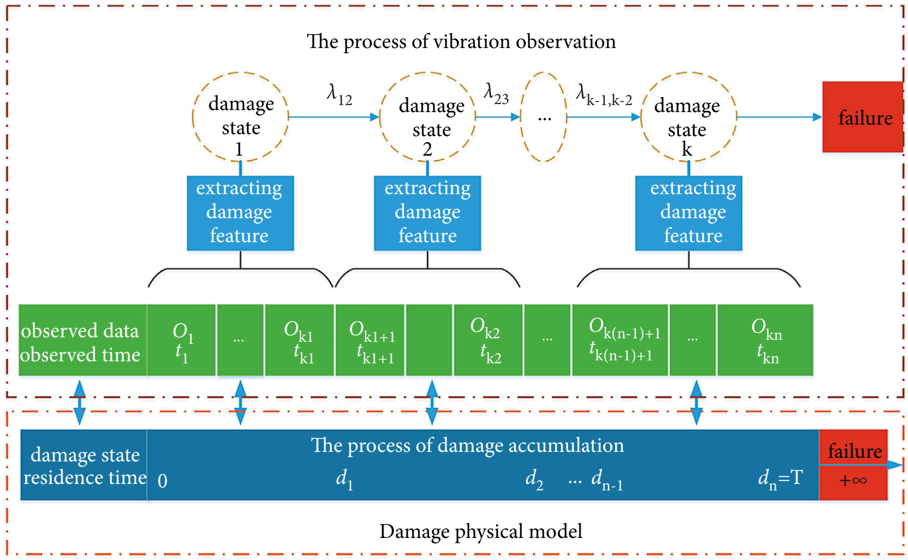

Figure 2: The relationship between the equipment observation process and damage process.

remaining useful life of it is predicted on the basis of the framework proposed in Section 3. Finally, Section 5 summarizes the research findings.

2. Establishing the Physical Degradation Model of Scroll Wheel

The vibration data of the scroll wheel implies a wealth of degradation state information. The relationship between the vibration observation process and the damage process is depicted in Figure 2. As shown in Figure 2, the remaining useful life prediction for the scroll wheel consists of two main steps. First, the valid and stable features should be extracted from the monitoring signal to accurately reflect the current state of the scroll wheel. Second, the extracted features are used to develop an accurate physical model to predict the degradation state and remaining useful life of the scroll wheel.

In Figure 2, the vibration monitoring process of the scroll wheel reflects its dynamic characteristics at fast time scales, and the physical damage model of the scroll wheel used as the PF algorithmic state transfer equation reflects its dynamic characteristics at slow time scales. According to the dynamic system theory, the performance degradation process of the scroll wheel can be regarded as the coupling of the vibration process at fast time scales and the damage process at slow time scales [22, 23]. The phase space warping algorithm proposed by Chelidze et al. [22] is an efficient method that can be used in the multi-time scale modeling process. The phase space warping algorithm could establish a linear relationship between the tracking metrics and the actual physical damage by constructing tracking metrics through the phase space changes of the monitored vibration data. At present, the phase space warping algorithm has been applied to system fault identification [24], degradation tracking of simulated bearing signals [25, 26], degradation tracking of electromechanical system [27, 28], etc. In this paper, the phase space warping method is also used to calculate the damage value of the scroll wheel based on the vibration signals (see references [18, 22, 23] for details).

Qian et al. [18] pointed out that a dynamic system with coupled fast and slow time scales subsystems can be expressed as follows:

$$\dot{X} = f(X, \mu(\phi), t), \tag{1}$$

$$\dot{\phi} = \varepsilon g(\phi, X, t), \tag{2}$$

where $X \in R^n$ denotes the system's fast variable, which can be observed via sensors, such as vibration signals. $\phi \in R^m$ represents the slow variable in the damage evolution process. $f(\bullet)$ and $g(\bullet)$ denote the system's fast-changing and slow-changing functions, respectively. $\mu(\bullet)$ represents a function of the damage variable ϕ. t represents the time, and ε is a small ratio constant that is used to differentiate between fast and slow time scales.

Assume that at the initial time $t = t_0$, $\phi = \phi_0$. The fast time scale variable X is a function of $\mu(\phi_0)$. The fast time scale equation can be simplified as follows:

$$X_0 = F(X_0, \mu(\phi_0), t_0) = F(\mu(\phi_0)). \tag{3}$$

In equation (3), $F(\cdot)$ is the function connecting X and $\mu(\phi)$. Then, at any time $t\,(t > t_0)$, the state variable of the fast time scale system is $X_t = F(\mu(\phi_t))$. Substituting it into equation (2) to get the following equation:

$$\dot{\phi} = \varepsilon g(\phi, F(\mu(\phi)), t). \tag{4}$$

Defining slow time scale $\tau = \varepsilon t$, the slow time equation of damage evolution is further simplified as

$$\dot{\phi} = g(\phi, F(\mu(\phi))). \tag{5}$$

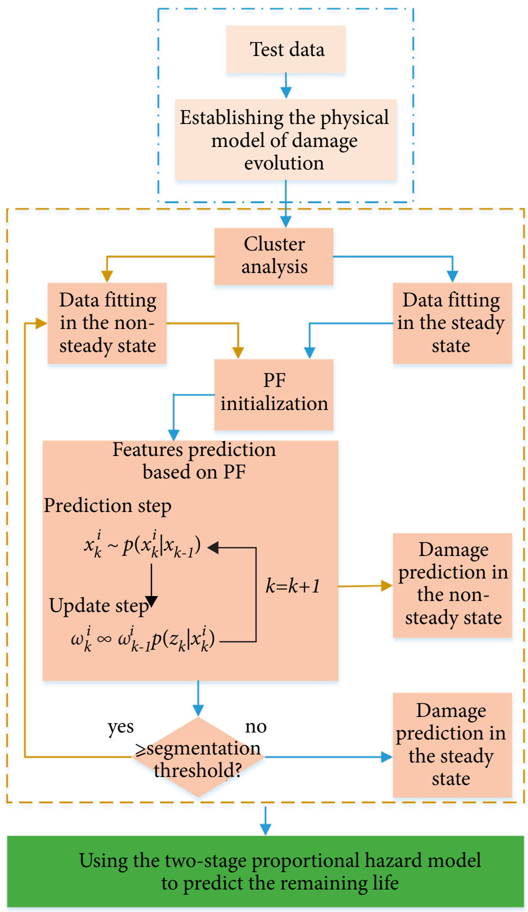

Figure 3: The framework to predict the remaining useful life of the scroll wheel.

The left side of equation (5) is the derivative with respect to τ, which is a time scale that varies slowly. As can be seen from equation (5), the damage evolution rate is determined by the damage state. Based on the qualitative analysis of various damage evolution processes, Cusumano Chatterjee [28] assumed that the damage evolution function can be represented as follows:

$$\frac{\mathrm{d}\phi}{\mathrm{d}\tau} = a(\phi - \phi_0)^b. \tag{6}$$

Assuming that the degradation process of rotating machinery can be divided into a steady-state process and an unsteady-state process, and the initial damage of the rotating machinery is 0, the equation of the damage variable obtained by piecewise integration of the above equation is as follows:

$$\phi = \begin{cases} \left[a_1(1-b_1)\tau\right]^{1/1-b_1}, & b_1 \neq 1,\ \tau \in [0, t_1], \\ \left[a_2(1-b_2)(\tau - t_1)\right]^{1/1-b_2}, & b_2 \neq 1,\ \tau \in (t_1, \infty), \end{cases} \tag{7}$$

where t_1 is the demarcation point between the various stages of degradation. When $b_1 = 1$ and $b_2 = 1$, the damage evolution mechanism is identical to the widely used exponential model.

3. The Remaining Useful Life Prediction Framework Based on the Proposed Method

This paper focuses on the prediction of the remaining useful life of the scroll wheel using vibration signals on the basis of a hybrid method. It consists of three main steps, as shown in Figure 3. In Figure 3, this paper arbitrarily divides the performance degradation process of the scroll wheel into a steady-state process and a non-steady-state process.

First, the damage characteristics are categorized by the k-means algorithm [29]. According to the results of cluster analysis, the physical models of damage at different degradation stages are obtained when they are fitted separately using the damage characteristics of different degradation stages. Then, the obtained damage models are used as the state transfer equations of the PF algorithm.

Second, the PF algorithm is used to predict the damage characteristics. The data-driven model based on Bayesian estimation provides a rigorous mathematical solution framework for the long-term prediction of dynamic systems [30]. Both Kalman filtering and extended Kalman filtering are approximations of Bayesian estimations and cannot deal with signals with severe nonlinearity, while the PF algorithm solves the problem very well. The PF algorithm is a Monte Carlo simulation-based Bayesian state estimation algorithm [31]. Given a set of time-varying state x_t and observation sequence y_t, the state space model can be defined as follows.

Equation of state:

$$x_t = f_t(x_{t-1}, \omega_t). \tag{8}$$

Observation equation:

$$y_t = h_t(x_t, v_t), \tag{9}$$

where $t = 1, 2, \ldots$ is a discrete time series. $f_t\colon R_x^n \times R_\omega^n \longrightarrow R_x^n$ is a state transfer function. $h_t\colon R_x^n \times R_v^n \longrightarrow R_y^n$ is a state observation function. ω_t and v_t denote the process noise and observation noise, respectively. n_x and n_ω denote the dimensions of the state vector and process noise vector, respectively. n_y and n_v denote the dimensions of the observation vector and the observation noise vector, respectively. From a Bayesian perspective, the posterior probability distribution contains all the information necessary for state estimation. The recursive equations for state posterior probability estimation using Bayesian theory are as follows.

Equation of prediction:

$$p(x_t|y_{1:\,t-1}) = \int p(x_t|x_{t-1})p(x_{t-1}|y_{1:\,t-1})\mathrm{d}x_{t-1}. \tag{10}$$

Equation of update:

$$p(x_t|y_{1:\,t-1}) = \frac{p(y_t|x_t)p(x_t|y_{1:\,t-1})}{p(y_t|y_{1:\,t-1})}, \tag{11}$$

where $p(x_t|x_{t-1})$ is defined by the state equation. $p(y_t|x_t)$ is defined by the observation model. $p(y_t|y_{1:\,t-1})$ is the normalization function, which has the following definition:

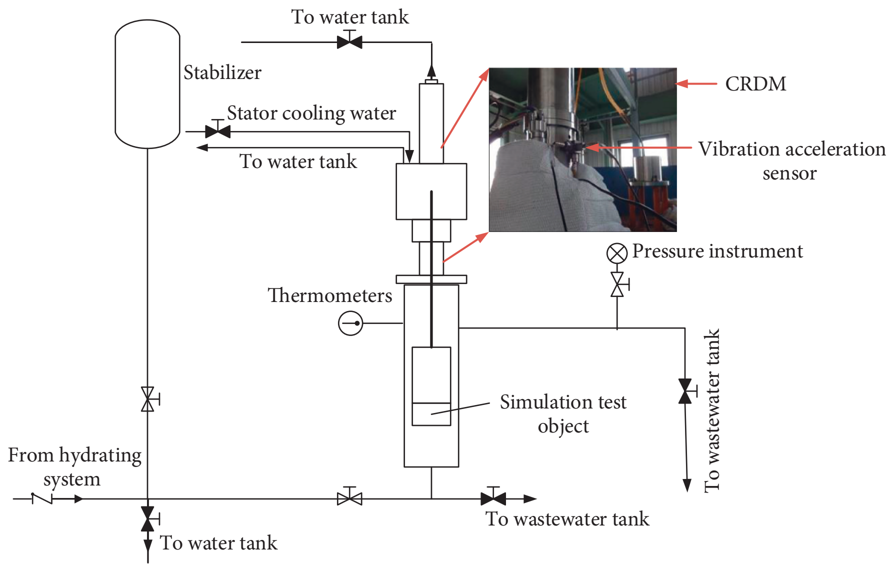

FIGURE 4: Schematic diagram of the CRDM full life test device.

$$p(y_t|y_{1:t-1}) = \int p(y_t|x_t)p(x_t|y_{1:t-1})\mathrm{d}x_t. \quad (12)$$

Since the preceding calculation requires a large number of high-dimensional integration operations and the process is complicated, the Monte Carlo method is used to solve the problem.

Finally, the remaining useful life of the scroll wheel is predicted using the two-interval proportional hazard model. Considering the difficulty of defining the failure threshold in practice, this paper employs a two-interval proportional hazard model [32] to predict the remaining useful life of the scroll wheel. The following equation describes the proportional hazard model with time-varying covariates:

$$\lambda(t; Z(t)) = \lambda_0(t)\exp(Z(t)\beta), \quad (13)$$

where $\lambda(t; Z(t))$ is the failure rate function, $\lambda_0(t)$ is the basis failure rate function, and $Z(t)$ is a covariate affecting the system's failure probability at time t. In addition, in this paper, the damage characteristics extracted from vibration signals are used as covariates. β is the regression parameter.

In practice, the Weibull distribution is often used as the basis failure rate function for the proportional hazard model, as shown in

$$\lambda(t; Z(t)) = \left[\frac{\gamma}{\eta}\left(\frac{t}{\eta}\right)^{\gamma-1}\right]\exp(Z(t)\beta), \quad (14)$$

where $\gamma > 0$ and $\eta > 0$ denote the shape and scale parameters of the Weibull distribution, respectively.

Theoretically, the calculation of the parameters like γ, η, β can be estimated as $\hat{\theta} = \{\hat{\gamma}, \hat{\eta}, \hat{\beta}\}$ by the maximum likelihood method. However, in practical applications, it is difficult to estimate the parameter directly. In this paper, the Newton–Raphson iterative method is used to solve the problem. The two-interval proportional hazard model is similar to the traditional proportional hazard model, except that the parameters for different degradation stages are estimated using data from the corresponding stages.

When the values of $\hat{\gamma}, \hat{\eta}, \hat{\beta}$ are obtained, the component's reliability over time t can be calculated by combining the component's covariate from the beginning to the current time t, as shown in

$$R(t; Z(t)) = \exp - \int_0^t \left[\frac{\hat{\gamma}}{\hat{\eta}}\left(\frac{\nu}{\hat{\eta}}\right)^{\hat{\gamma}-1}\right]\exp\left(\left(Z(\nu)'\hat{\beta}\right)\mathrm{d}\nu\right), \quad (15)$$

where $Z(\nu)'$ is the predicted covariate value at timeν.The scroll wheel's remaining useful life can be calculated as follows:

$$\begin{aligned} RUL(t; Z(t)) &= E[T - t|T \geq t] \\ &= \int_0^{\infty} \exp\left(-\int_t^{t+\tau} \lambda(\nu; Z(\nu)')\mathrm{d}\nu\right)\mathrm{d}\tau \\ &= \int_0^{\infty} \exp - \int_t^{t+\tau} \left[\frac{\hat{\gamma}}{\hat{\eta}}\left(\frac{\nu}{\hat{\eta}}\right)^{\hat{\gamma}-1}\right]\exp\left(\left(Z(\nu)'\hat{\beta}\right)\mathrm{d}\nu\right)\mathrm{d}\tau. \end{aligned} \quad (16)$$

4. The Remaining Useful Life of Scroll Wheel

The reluctance motor type CRDM is used intensely, making it more susceptible to performance degradation. The accelerated life test of the CRDM is carried out to analyze the aging-related degradation caused by the wear damage of the scroll wheel [9]. Figure 4 that is reproduced from the work of Zhu et al. depicts the test device's schematic diagram. The test devices mainly include the CRDM, a stator cooling water system (to ensure the temperature of the stator coil is within the specified range during operation), a water replenishment system (to ensure the water inventory in the entire test system), and a pressure stabilization system (maintaining the

Table 1: The normalized damage characteristics of the scroll wheel.

Time (day)	Normalized damage characteristics
6	0
6.5	0.0030
7	0.0039
7.5	0.0050
8	0.0058
8.5	0.0077
9	0.0100
9.5	0.0120
10	0.0140
10.5	0.0179
11	0.0205
11.5	0.0249
12	0.0300
12.5	0.0370
13	0.0410
13.5	0.0460
14	0.0463
14.5	0.0510
15	0.0580
15.5	0.0677
16	0.0650
16.5	0.0730
17	0.0820
17.5	0.0970
18	0.1228
18.5	0.1160
19	0.1200
19.5	0.1450
20	0.1630
20.5	0.1880
21	0.2000
21.5	0.2300
22	0.2400
22.5	0.2700
23	0.3000
23.5	0.3480
24	0.3759
24.5	0.4057
25	0.4405
25.5	0.4775
26	0.4900
26.5	0.5169
27	0.5587
27.5	0.6031
28	0.6501
28.5	0.6765
29	0.6987
29.5	0.7516
30	0.8074
30.5	0.8663
31	0.9295
31.5	1

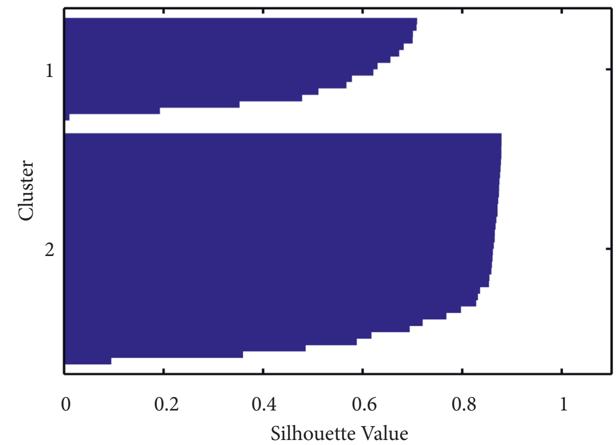

Figure 5: Silhouette value of the scroll wheel damage characteristics divided into two clusters.

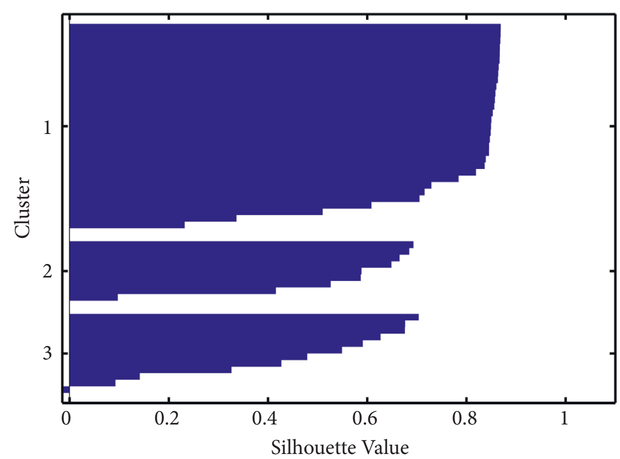

Figure 6: Silhouette value of the scroll wheel damage characteristics divided into three clusters.

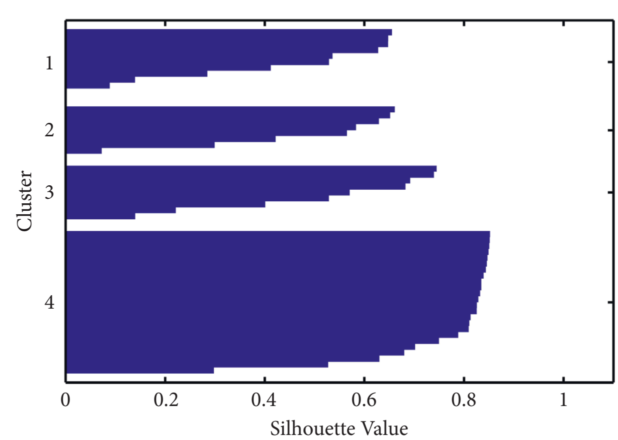

Figure 7: Silhouette value of the scroll wheel damage characteristics divided into four clusters.

pressure of the test system). The function of the simulation test object in Figure 4 is to simulate the load of the CRDM in actual operation. During the test, the CRDM operates continuously, and the vibration signals of the full life test are used to extract the damage features. The vibration signal acquisition device used in the test is a BK vibration acceleration sensor, and the sampling frequency is 16384 Hz. The rotation frequency of the wheel is 1.3 Hz, the sampling period is 20 seconds, and the number of sampling points is 327680. The test period is 31.5 days in total, and the thermal full life test is carried out from the 6th day [9]. The test data

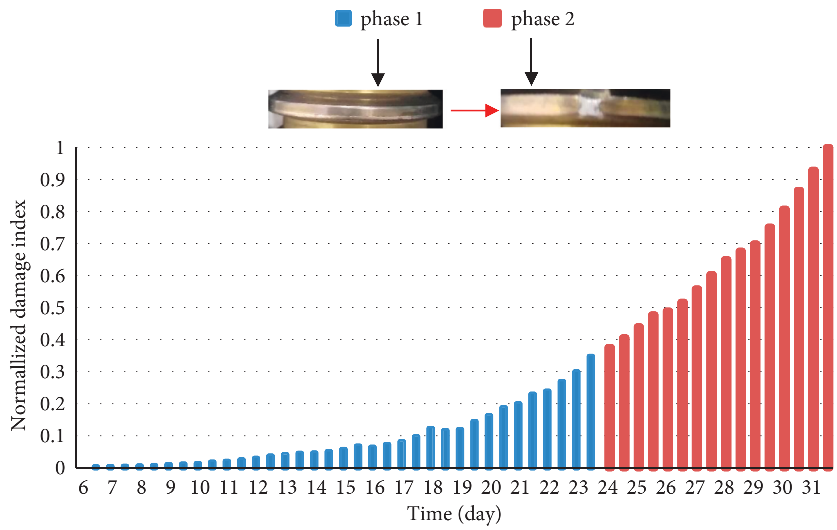

Figure 8: The segmented degradation process of the scroll wheel.

Table 2: The estimated values and AIC of different models.

Model form	a; 95% confidence interval	b; 95% confidence interval	c; 95% confidence interval	$\ln L\ (\theta)$	AIC
$A + b\exp(cx)$	−0.06101; (−0.07778, −0.04423)	0.01922; (0.01505, 0.02338)	0.1296; (0.1208, 0.1344)	−21.3897	48.779
$[a(1-b)]^{1/(1-b)}$	0.119517; (0.110238, 0.127126)	0.7352; (0.7297, 0.7407)		−21.6626	47.325

Table 3: Comparison of segmented prediction results with unsegmented prediction results.

Test data	Segmented Predictions	Unsegmented Predictions	Relative error percentage absolute value
0.4057	0.3986	0.3831	1.75%, 5.57%
0.4405	0.4282	0.4136	2.78%, 6.11%
0.4775	0.4596	0.4459	3.75%, 6.62%
0.49	0.4922	0.4799	0.45%, 2.06%
0.5169	0.5269	0.5156	1.94%, 0.26%
0.5587	0.5632	0.5530	0.82%, 1.01%
0.6031	0.6013	0.5929	0.3%, 1.68%
0.6501	0.6416	0.6348	1.31%, 2.35%
0.6765	0.6829	0.6787	0.94%, 0.33%
0.6987	0.7267	0.7245	4.01%, 3.69%
0.7516	0.7721	0.7730	2.72%, 2.84%
0.8074	0.82	0.8238	1.56%, 2.03%
0.8663	0.8696	0.8766	0.38%, 1.19%
0.9295	0.9215	0.9321	0.86%, 0.28%

from the day 6 to day 31.5 are selected to extract the damage features by using the phase space warping method [22, 23], and the mean value of the damage feature every half day is taken as the damage feature value [9], as shown in Table1, which is reproduced from the work of Zhu et al.

In this paper, the k-means algorithm [29] is used to classify the normalized damage characteristics of the scroll wheel. The k-means algorithm maximizes the similarity of data points to the cluster centroids that defines the cluster cohesion. Each centroid is the mean of the points in that cluster when using the squared Euclidean distance. The k-means algorithm is a hard clustering method that assigns data objects to a pre-determined number of clusters. In addition, the best data classification results can be determined by comparing the silhouette values under different classification numbers. The silhouette value for each point is a measure of how similar that point in its own cluster [33]. The silhouette value for the i^{th} point s_i is defined as follows:

$$s_i = \frac{(b_i - a_i)}{\max(a_i, b_i)}, \tag{17}$$

where a_i is the average distance from the *ith* point to the other points in the same cluster as i, and b_i is the minimum average distance from the i^{th} point to points in a different cluster, minimized over clusters. The silhouette value ranges from −1 to 1. A high silhouette value indicates that i is well matched to its own cluster and poorly matched to neighboring clusters. If most points have high silhouette values,

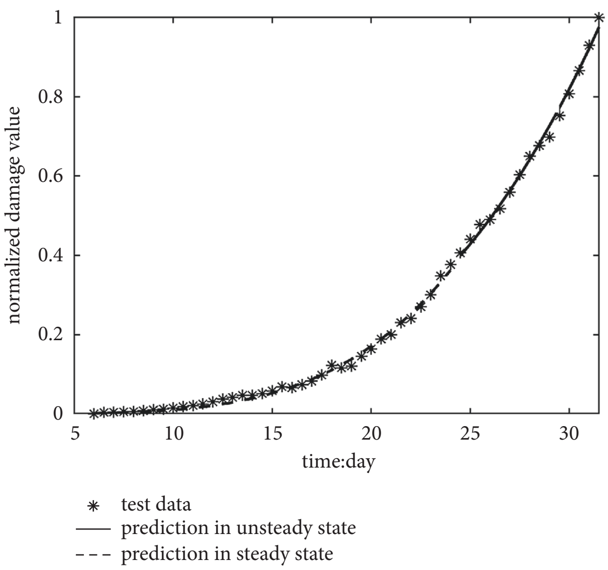

Figure 9: Predicted results of the proposed method.

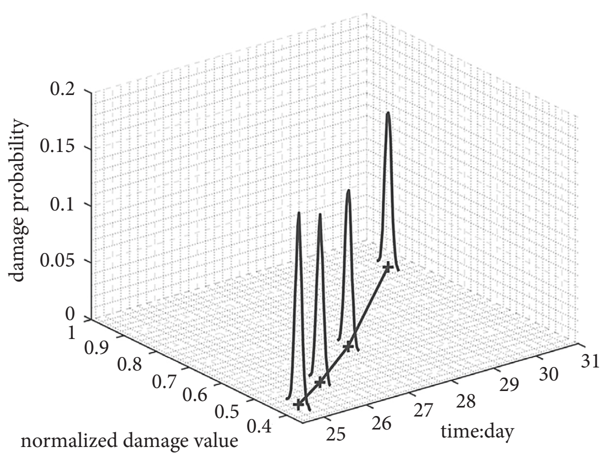

Figure 10: Distribution of the probability of damage prediction results.

then the clustering solution is appropriate. If many points have low or negative silhouette values, then the clustering solution may have either too many or too few clusters.

In order to obtain the best classification of the degradation states of the scroll wheel, this paper calculates the silhouette values when the damage characteristics are divided into two categories, three categories and four categories, respectively. The results are shown in Figures 5–7.

As shown in Figure 6, when the damage characteristics of the scroll wheel are divided into three categories, some silhouette values are negative, which indicates that the classification is inappropriate. The mean silhouette value is 0.7136 when the damage characteristics of the scroll wheel are divided into two categories, as shown in Figure 5, which is greater than 0.6103 when the damage characteristics of the scroll wheel are divided into four categories, as shown in Figure 7. The results show that it is best to divide the scroll wheel damage characteristics into two categories. The

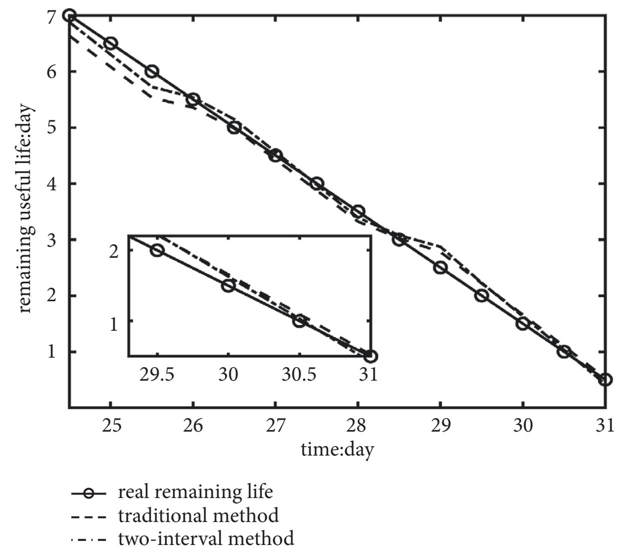

Figure 11: The comparison of the remaining useful life calculated in two ways.

performance degradation process is divided into two stages (see Figure 7) as shown in Figure 8.

In Figure 8, the blue strips represent the steady-state operation phase and the red strips represent the unsteady operation phase and the threshold to distinguish between the two phases is 0.348, which is determined by the K-means algorithm and is used as the initial point of degradation. Next step is to determine the state transfer equation of the PF algorithm. In this paper, the Akaike information criterion (AIC) [34] is used to select the suitable function of the state transfer equation. The AIC statistic is as follows:

$$\mathrm{AIC} = 2k - \ln L(\theta), \tag{18}$$

where θ is the vector of estimated parameters that can be estimated by the maximum likelihood method, $L(\theta)$ is the likelihood function, and k is the number of parameters. In addition, the model which produces minimum AIC is selected. We compared the AIC of the traditional exponential model and the proposed model shown in equation (7), and the results are shown in Table 2.

The results in Table 2 were performed without classification of the damage data. According to Table 2, the proposed model shown in equation (7) is selected as the state transfer equation of the PF algorithm and the results obtained based on it are called unsegmented prediction results. In order to get accurate results, the parameters in the model shown in equation (7) should be estimated using damage data at different phases of degradation. As shown in Figure 8, when in the steady-state operation phase, the values of parameters in equation (7) are $a_1 = 0.134929$ and $b_1 = 0.75845$; when in the unsteady-state operation phase, the values of parameters in equation (7) are $a_2 = 0.112548$ and $b_2 = 0.71934$. Then, the damage characteristics of the scroll wheel are predicted according to the calculation process in Figure 3. In addition, the comparison of segmented prediction results with unseg-

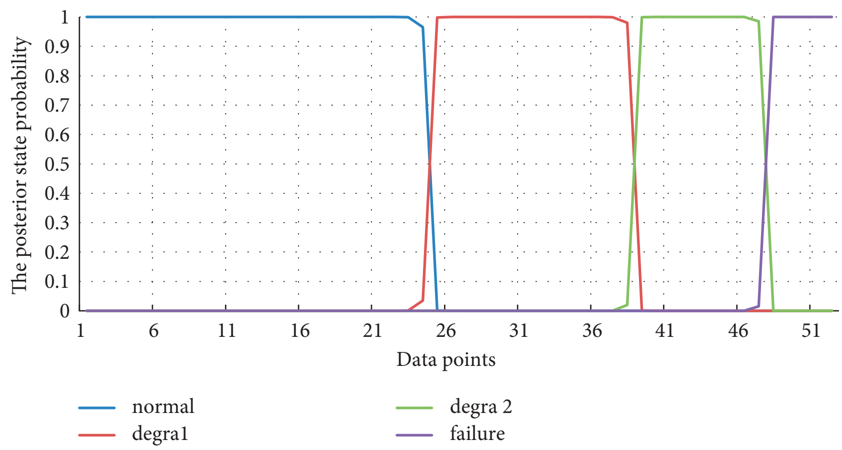

Figure 12: The posterior probabilities of hidden states.

Table 4: Transfer probability of the CRDM.

	Failure	degra2	degra1	Normal
Failure	1	0	0	0
degra2	0.1111	0.8889	0	0
degra1	0	0.0714	0.9286	0
Normal	0	0	0.0417	0.9583

mented prediction results is shown in Table 3. As shown in Table 3, the results predicted by the segmental physical model are more accurate and the maximum relative error is less than 4.5 percent. Hence, the damage values of the scroll wheel are predicted by the segmental physical model in this paper and three times the performance metric of the initial point of degradation is chosen as the failure threshold according to reference 17, and the results are shown in Figure 9.

It can be seen from Figure 9 that the accurate results can be obtained by using the proposed PF algorithm whose state transfer equation is established on the segmental damage physical model. In addition, the PF algorithm allows us to obtain not only the point estimates of the scroll wheel damage characteristics but also the probability distributions that represent the uncertainty of predicted results, as shown in Figure 10.

Next, the proportional hazard model is used to predict the remaining useful life of the scroll wheel based on equation (13)–equation (16) (see Step 3 in Section 3 for details). In this paper, the remaining useful life of the scroll wheel is predicted from the initial point of degradation where the remaining life is 7 days as shown in Figure 8 and the results when the degradation process of the scroll wheel is classified into two categories or not are also compared, and the results are shown in Figure 11. It can be seen that the prediction results of the remaining useful life are more accurate when classifying the degradation process into two stages by the k-means algorithm.

In this paper, we also compare the results based on the proposed hybrid method and the hidden Markov model (HMM) method. In the HMM method, the states of the component are classified into N levels: normal (state S_1),

Table 5: The comparison between the proposed method and HMM method (unit: day).

Real RUL	RUL based on HMM	Relative error value	RUL based on the proposed method	Relative error value
7	6.83	0.17	6.95	0.05
6.5	6.32	0.18	6.38	0.12
6	5.82	0.18	5.80	0.2
5.5	5.31	0.19	5.62	−0.12
5	4.81	0.19	5.22	−0.22
4.5	4.31	0.19	4.64	−0.14
4	3.80	0.20	4.06	−0.06
3.5	3.31	0.19	3.48	0.02
3	2.82	0.18	3.16	−0.16

level-one defect (state S_2), . . ., level-(N-2) defect (state S_{N-1}), and the failure state S_N. The RUL is obtained by calculating the remaining number of time steps to reach the final state S_N [14]. By using the HMM method, the posterior probability of the hidden states and the state transfer probabilities of the CRDM are shown in Figure 12 and Table 4, respectively, which are reproduced from the work of Zhu et al.

In Figure 12 and Table 4, the degra2 state indicates a state of rapid component degradation, and the dergra1 state indicates a state of slow component degradation [9]. Then, by using the method described in [14], we can get the RUL of the CRDM, as shown in Table 5.

As shown in Table 5, the results obtained by the proposed method are better than that by the HMM method. In addition, it should be noted that the results in this paper are obtained based on the accelerated life test of the scroll wheel, which do not represent the actual situation. However, the method in this paper has positive significance for the preventive maintenance of the CRDM. In addition, the prediction of the remaining useful life of the CRDM using the vibration signals collected during the outage period provides a basis for the maintenance determination, thus avoiding unforeseen failures of the CRDM during operation.

5. Conclusions

During the accelerated life test of the scroll wheel, we hope to find a method that can predict the CRDM's remaining useful life, thus providing a basis for the maintenance determination of the CRDM. This paper proposes a hybrid method to solve the above problem. In the case of rare available data, the prediction of the damage characteristics is achieved using the PF algorithm whose dynamic state transfer equation is built on the segmental damage model of the scroll wheel based on the multi-time scale model. Next, the relationship between the scroll wheel's damage characteristics and the reliability model is established by using the proportional hazard model to predict the remaining useful life of the scroll wheel when the failure threshold cannot be accurately defined. Though the results in this paper are obtained based on the accelerated life test of the scroll wheel, which do not represent the actual situation, the method in this paper has positive significance for the preventive maintenance of the CRDM, which provides an opportunity for condition-based maintenance of the CRDM.

This paper is a preliminary study on the prediction of the remaining useful life of the CRDM, and there are some further topics that deserve study in the future. First, in this paper, we mainly focus on the analysis of the degradation process of the CRDM based on vibration signals. However, there may be more than one degradation characteristics that can be used to analyze the degradation of the CRDM. It is interesting to find the relationships between different degradation characteristics and to construct a composite health metric for the degradation modeling of the CRDM. Second, in this study, only a single failure mode of the CRDM is considered, and the remaining useful life prediction of a single component involving multiple faults should be studied in the future. Finally, in practice, we can only get the vibration signals of the CRDM during shutdowns and the monitoring duration is aperiodic. Hence, the uncertainty introduced by the irregularity of the monitoring time should be studied in the future.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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