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Research Article

Bearing Fault Prognosis Method Based on Priori Knowledge-Enhanced Particle Filter

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A priori knowledge-enhanced particle filter (PKE-PF) method is proposed to solve the problem of particle impoverishment in bearing fault prognosis with incomplete data. Based on the existing bearing life degradation data and the parameter transfer method in the transfer learning theory, particle initialization optimization, which is very important in the PF method, is carried out to effectively improve particle effectiveness and avoid the problem of premature particle exhaustion. Based on the whole-life degradation experiment of rolling bearings, the validation results show that the traditional PF method and its improved method are prone to particle exhaustion, which seriously affects the fault prediction results. The PKE-PF method proposed in this paper can effectively avoid the problem of premature particle depletion and obtain a more ideal fault prognosis results.

1. Introduction

Bearing occupies a critical position in the power transmission system of rotating machinery, and its health state directly affects equipment safety and functional implementation [1, 2]. Bearing condition monitoring and fault diagnosis technology have been implemented in many types of equipment [3–5]. With the complexity of mechanical equipment and the high-efficiency requirements put forward in engineering practice, how to reduce the operation cost and improve the economic benefit as much as possible under the premise of ensuring the safe use of equipment has become a hot topic of concern. With the continuous development of prognosis and health management (PHM) technology, bearing failure prognosis has gradually become possible [6–8].

Among many fault prognosis methods, the particle filter (PF) proposed by Orchard et al. [9], as a typical prediction method based on statistical models, can obtain fault prediction results under uncertainty evaluation and has been widely used in the field of RUL prediction. Luo Yue et al. [10] and Miao Qiang et al. [11] applied the particle filter method to predict the remaining service life of lithium batteries. Wang Meinan et al. [12] proposed a method to predict the remaining life of equipment based on degradation trajectories. Fan Bin et al. [13] proposed an RUL prediction method for degradation rate tracking-based particle filter (DRT-PF) in view of the shortcomings of traditional particle filtering methods. Yuning Qian et al. [14] proposed an enhanced particle filtering method based on the improved resampling function for the particle attenuation phenomenon.

However, particle filtering requires a large amount of prior sample knowledge to achieve an accurate estimation of the posterior distribution of unknown parameters [15]. However, the total life degradation data of bearings in engineering practice is as rare as it is, and the total life historical degradation data of bearings of the same type are even rarer. For the bearing fault prediction problem with incomplete data, the particle degradation phenomenon often occurs in the fault prediction method based on the particle filter, which leads to tracking loss and false tracking, and it is difficult to obtain ideal prediction results. In view of the above problems, the typical solution adopted by researchers is to select an appropriate particle resampling strategy [14, 16], so as to improve the diversity of particles and the

weight of useful particles. However, while the resampling method selects the useful particles, it will eliminate some particles and eventually lead to particle exhaustion. Neither the particle degradation problem nor the particle exhaustion problem has the root cause of incomplete sample prior knowledge, so the existing particle resampling improvement methods are still faced with the problems of uncertain prediction process, unstable operation process, and easy fall into local optimal prediction results. Therefore, in view of the existing problems, the priori knowledge-enhanced particle filter (PKE-PF) method has been proposed in this paper from the perspective of particle initialization.

In engineering practice, because of the irreversibility of the fault, the equipment tends to degenerate exponentially after the failure. Therefore, although the whole-life degradation data of the same type of bearings are small, the degradation data of different types of bearings are relatively large and contain rich and referable degradation information, which can provide beneficial support for the fault prediction process of the current prediction object. Therefore, the core of the PKE-PF method is to use the method of parameter transfer in transfer learning to strengthen the prior knowledge of particles and then obtain a more scientific initial distribution of particles so as to improve the diversity and effectiveness of particles from the root.

2. The Theoretical Introduction of the Proposed Method

2.1. Transfer Learning. The core idea of transfer learning is to use domain correlation to complete the target-domain task [4]. Based on the relationship between the source domain and the target domain, transfer learning can be divided into inductive transfer learning, deductive transfer learning, and unsupervised transfer learning. Specific classification criteria and further subdivisions are shown in Figure 1.

Compared with traditional machine learning, transfer learning is no longer limited to the condition that the source domain and the target domain must obey independent and identical distributions and the knowledge in the domain subject to different marginal probability distributions can be transferred to strengthen the prior knowledge in the target domain. There are several concepts involved. First, the domain and second, the task.

Domain: it is defined as $D = \{\mathrm{x}, P(X)\}$, where x represents the feature space, $X = \{x_1, \cdots x_n\} \in \mathrm{x}$, and $P(X)$ is the marginal probability distribution.

Task: it is defined as $T = \{\mathrm{y}, f(X)\}$, where y represents label space, $f(X)$ represents the target prediction function, and $f(X)$ can be understood as the mapping relationship between sample data and sample labels.

The mathematical definition of transfer learning is as follows.

The sample data of the source domain are represented as D_s, and the sample label is Y_s; the sample data of the target domain are represented as D_t, and the sample label is defined as Y_t, where $D_s \neq D_t$ or $T_s \neq T_t$. $D_s \neq D_t$ means $x_s \neq x_t$ or $P_s(X) \neq P_t(X)$; $T_s \neq T_t$ means $y_s \neq y_t$ or $f_s(X) \neq f_t(X)$. Transfer learning is used to improve the prediction model $f_t(X)$ of the target domain by using sample data D_s and sample labels Y_s from the source domain.

As far as bearing fault prognosis is concerned, it is more consistent with the purple line in Figure 1, namely, scenario 2. In other words, the fault prediction object has observed data, but it is not complete. Multitask learning can be carried out based on other existing bearing lifetime degradation data, and then, the prediction function parameters in the source domain can be shared to achieve the effect of transfer learning.

2.2. Particle Filter (PF). As a parameter estimation method based on Bayesian theory, the PF method recursively estimates the current state of the system or the parameters of the system degradation model through a series of sample observations $y_{1:k} = \{y_1, y_2, \cdots y_k\}$. In general, the PF method needs to establish the state transition equation and measurement equation of the dynamic system.

$$\begin{aligned} x_k &= f(x_{k-1}, a_k, \omega_k), \\ y_k &= h(x_k, \eta_k). \end{aligned} \tag{1}$$

Here, x_k and y_k represent the state value and observed value of the system at time k, respectively. ω_k and η_k represent the state noise and measurement noise at time k, respectively.

The particle filter method mainly includes the following two steps:

Step 1: predicting the status of the target object. The prediction model based on historical samples and generated samples is used to predict the state of the research object. The formula for calculating the prior probability of the existing sample state is

$$p(x_k \mid y_{1:k-1}) = \int p(x_k \mid x_{1:k-1}) p(x_{k-1} \mid y_{1:k-1}) dx_{k-1}. \tag{2}$$

Step 2: updating the prediction model. The prior probability is updated based on the observed value at the current moment, and the posterior probability of the system state is obtained to guide the particle resampling. The posterior probability calculation formula is

$$p(x_k \mid y_{1:k}) = p(y_k \mid x_k) \frac{p(x_k \mid y_{1:k-1})}{p(y_k \mid y_{1:k-1})}, \tag{3}$$

in which, $p(y_k \mid y_{1:k-1}) = \int p(y_k \mid x_k) p(x_k \mid y_{1:k-1}) dx_k$.

As the integral calculation is involved in the previous formula, it is generally difficult to obtain the analytical solution of the posterior probability directly. Therefore, the PF method uses a series of particles to approximate the posterior distribution with the help of the Monte Carlo resampling idea, which is called sequential importance sampling (SIS) [17]. The PF method can directly predict the health status of the research object or estimate the parameters of the prediction model, but the former will

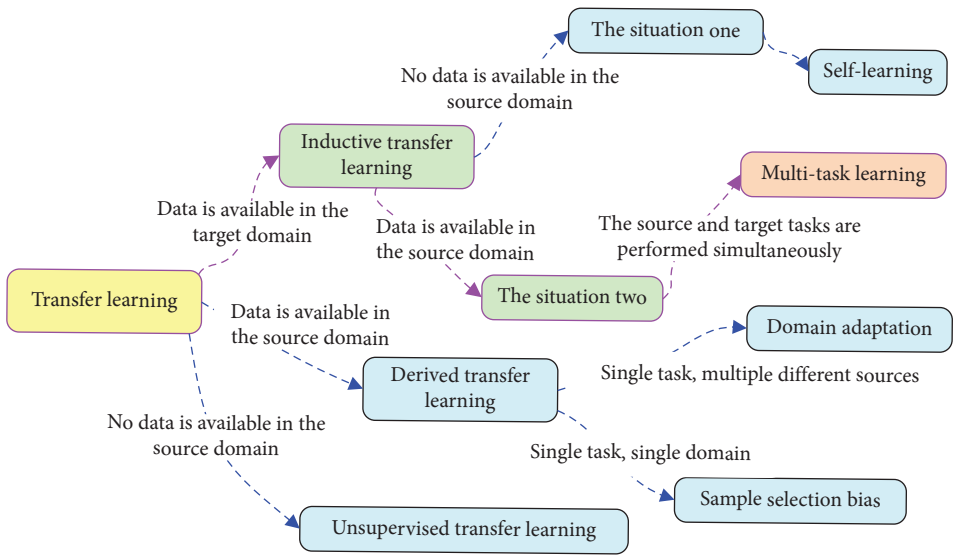

FIGURE 1: Overview of transfer learning classification.

introduce multidimensional hyperparameters, which greatly increase the uncertainty of the model. The second approach, adopted by researchers, is more straightforward.

2.3. Prior Knowledge-Enhanced Particle Filter (PKE-PF). It can be seen from the introduction of the PF method that an appropriate state transition equation and measurement equation need to be constructed before fault prediction based on the PF method and particles need to be initialized. In the face of the problem of bearing fault prediction in the absence of full-life data, these experiments cannot be carried out or are difficult to carry out accurately, especially with inappropriate particle initialization, which will lead to tracking loss or mistracking. Therefore, based on the parameter transfer theory in transfer learning and with the help of the existing bearing lifetime degradation data, this paper realizes the enhancement of the prior knowledge of the initial distribution of particles and then improves the diversity and effectiveness of particles, avoids the problem of premature particle exhaustion, and obtains higher precision fault prediction results.

The basic steps of fault prediction based on the PKE-PF method are as follows:

Step 1: We extract the appropriate health indicator (HI). Based on the existing bearing lifetime historical data and the current bearing observation values, feature index extraction and preprocessing oriented to prediction were carried out, the trend tracking was performed, and the stable HI was constructed. When bearing failure occurs, its representation is usually an impact signal. According to a literature survey [18–22], for bearing fault prediction in engineering practice, researchers often extract RMS based on vibration signals as HI. In this paper, RMS is used as the HI to characterize the bearing degradation trend, and its representation is as follows:

$$X_{rms} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2}. \tag{4}$$

Here, x_i represents the original time series and N represents the sample length.

Step 2: We establish a scientific degradation model. Based on historical prior knowledge or the regression fitting of historical statistical data, a suitable predictive degradation model is constructed. The double exponential model with strong plasticity is selected as the prediction model in the method of this paper, and its expression is as follows:

$$x = a \times \exp(b \times t) + c \times \exp(d \times t). \tag{5}$$

Step 3: We establish the state transition equation and measurement equation.

$$\begin{cases} a_k = a_{k-1} + \omega_a, \omega_a \sim N(0, \sigma_a) \\ b_k = b_{k-1} + \omega_b, \omega_b \sim N(0, \sigma_b) \\ c_k = c_{k-1} + \omega_c, \omega_c \sim N(0, \sigma_c) \\ d_k = d_{k-1} + \omega_d, \omega_d \sim N(0, \sigma_d) \end{cases} \tag{6}$$
$$h_k = f(\theta_k, k) + \eta, \eta \sim N(0, \sigma_0).$$

Here, $\theta_k = [a_k, b_k, c_k, d_k]$ represents the parameter vector of the degradation model at time k and h_k represents the observed value obtained at time k. ω_a, ω_b, ω_c, ω_d, and η, respectively, represent random variables subject to Gaussian distribution; σ_a, σ_b, σ_c, σ_d, and σ_0, respectively, represent the Gaussian distribution variance of the above three variables.

Step 4: We perform parameter estimation of the degradation model based on the PKE-PF method.

We suppose that the system has a total of K observation samples, and at each time k, $k = 1, 2, ..., K$, and the prior probability can be updated based on the observed sample.

Initialization: Based on the HI extracted from the existing bearing full-life data, the least-squares regression fitting method was introduced to obtain the fitting parameter sets of multiple groups of full-life degradation data and weighted to obtain the final combination of parameters to be migrated, so as to realize the effective guidance for the initial particle distribution of the estimated parameter $\theta_k = [a_k, b_k, c_k, d_k]$.

Prediction: At time k, based on the importance distribution, N particles $\theta_k^i = [a_k^i, b_k^i, c_k^i, d_k^i], i = \{1, 2, \cdots N\}$, are sampled to represent the prior distribution of the system state.

Update: We calculate the weight of each particle.

$$w_k^i \propto w_{k-1}^i p\left(y_k \middle| x_k^i\right),$$
$$\overline{w}_k^i = \frac{w_k^i}{\sum_{i=1}^N w_k^i}. \tag{7}$$

The minimum mean square estimate of system state x at time k can be obtained as follows:

$$\overline{x}_k \approx \sum_{i=1}^N \overline{w}_k^i x_x^i. \tag{8}$$

Resampling: A particle is resampled based on its weight to obtain a new particle set $\{x_{1:k}^{i^*}, i = 1, 2, \cdots N\}$.

Step 5: We extrapolate RUL prediction based on the prediction model.

Based on the prediction model of parameter update, the RUL extrapolation prediction of the research object is carried out to obtain the time when multiple particles reach the set threshold and the number of particles.

Step 6: Uncertainty assessment of forecast results is done.

The probability statistics of the results obtained in Step 5 were conducted to obtain the probability density distribution function under different failure times, and then, the probability distribution corresponding to each RUL prediction time was obtained to provide the decision maker with the prediction results under different confidence levels. In summary, the overall flowchart of the proposed methodology is shown in Figure 2. Firstly, an appropriate health indicator, that is RMS, is extracted based on the current monitoring bearing vibration data and historical data. Secondly, based on the health index obtained from a large number of historical data, the appropriate prediction model is constructed and the prior knowledge of the initial parameter distribution of the model is obtained. Thirdly, based on the transfer learning method, the current bearing information and historical knowledge are deeply integrated to effectively guide the dynamic updating process of particles. Finally, the particle distribution at the threshold is calculated to obtain the values under different confidence intervals.

3. Experimental Verification

The experimental bearing is a 6313-2RS ball bearing, and the number of rolling bodies is 8. The rated dynamic load of the bearing is 93.8 kN, the equivalent dynamic load is 29.8 kN, the experimental speed is 1300 rpm, and the bearing dimension is 65 × 140 × 33 mm. In the experiment, sensors 1 and 2 were arranged in the axial direction of the bearing housing and sensors 3 and 4 were arranged in the vertical direction. The sampling frequency was set at 5.12 kHz, the sampling length was set at 4096, and the sampling interval was set at 60 s. A total of four channels were collected for vibration acceleration signals.

3.1. Determining the Starting Point of Failure Prognosis. The data acquisition time started on the morning of July 9th, when the experiment had been running for 231.5 hours, and lasted until the experiment was shut down at noon on July 14th. The RMS value of acceleration vibration data of the first channel from July 9 to July 14 was obtained, and its time-domain variation waveform is shown in Figure 3.

It can be seen from Figure 3 that the RMS amplitude suddenly increased sharply between sample No. 5260 and sample No. 6431, indicating that the bearing health status was abnormal at this stage. The results are shown in Figure 4. It can be seen that the node with bearing failure should be near sample No. 6250 and the corresponding time is 07:08 on July 14. Stop inspection found that the inner ring of the experimental bearing had a large radian angle of circumferential fatigue peeling, the details of which are shown in Figure 5.

Based on the relevant size parameters and operating condition information of the experimental bearing, the fault characteristic frequencies of the experimental bearing components are obtained as shown in Table 1.

The bearing life degradation experiment was started at 9 : 36 on July 14 and ended at 10 : 17 on July 20. The amplitude spectrum and power spectrum corresponding to the first sample of the first channel are obtained, and the results are shown in Figure 6. Indeed, the fault characteristic frequency of the inner ring of the bearing is obviously known. In addition, the turn frequency is found to be 22.5 Hz, and the approximate fault characteristic frequency of the outer ring is found to be 67.5 Hz and its double frequency. This indicates that the outer ring of the experimental bearing also has a fault, which is because the bearing is not uniform and prone to failure in the actual operation of the bearing. After obtaining the bearing fault occurrence node information, the fault prediction work is carried out based on the bearing fault data obtained from July 14 to July 20.

3.2. Data Cleaning. The RMS values corresponding to the acceleration vibration data of channels 1 to 4 in the open bearing dataset were calculated, and the obtained results are shown in Figure 7.

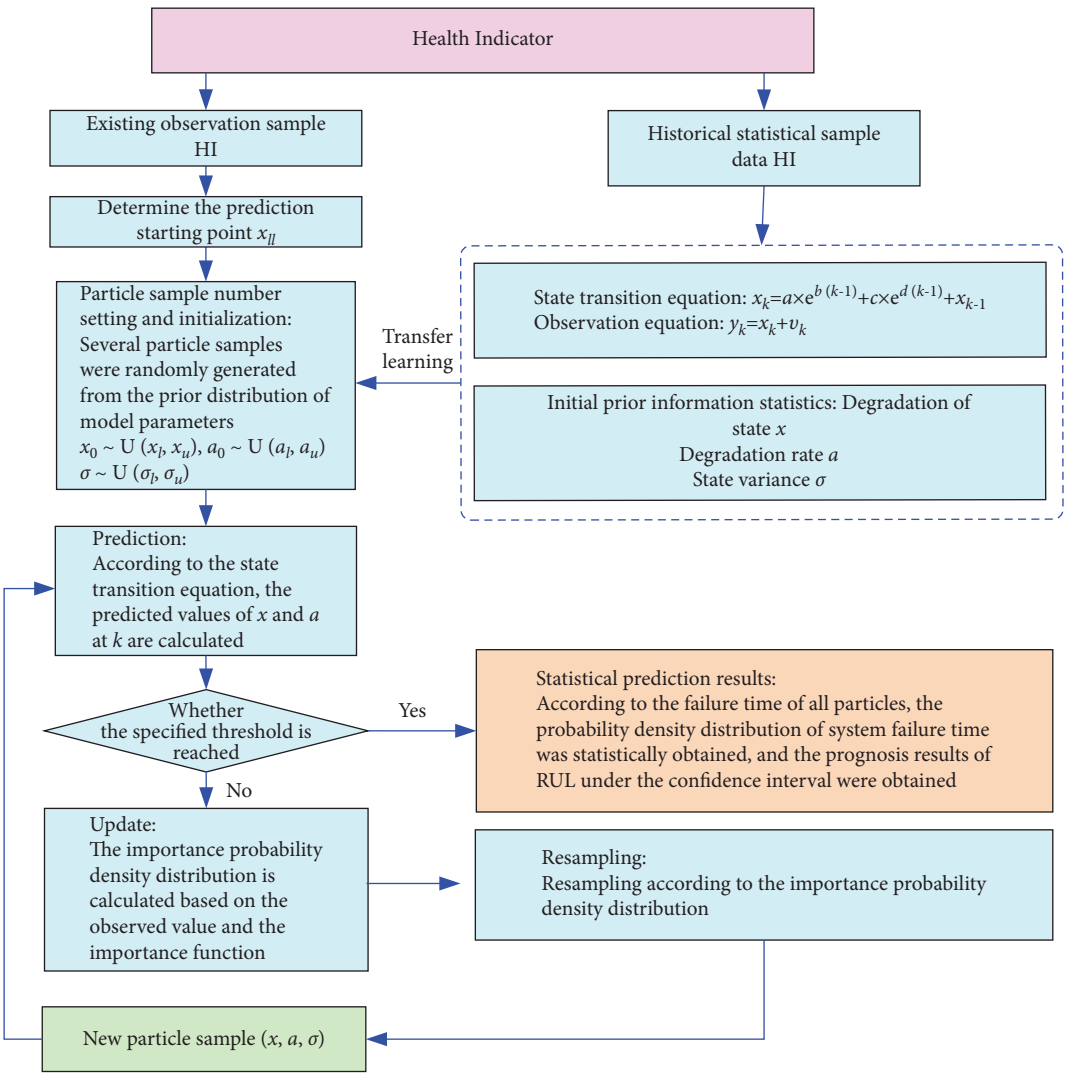

Figure 2: Fault prognosis process of the PKE-PF.

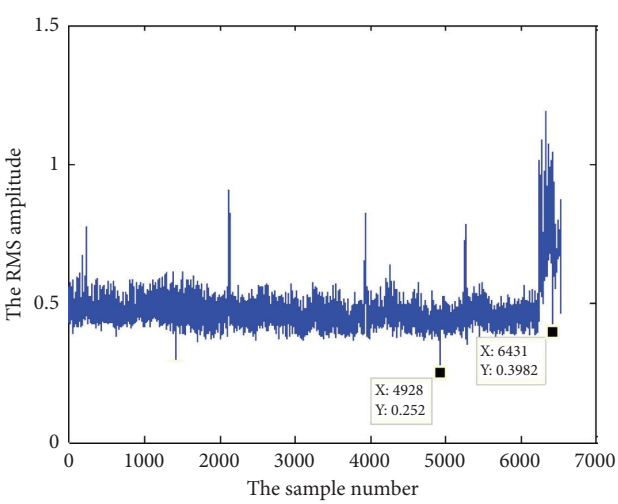

Figure 3: The trend of RMS of channel 1.

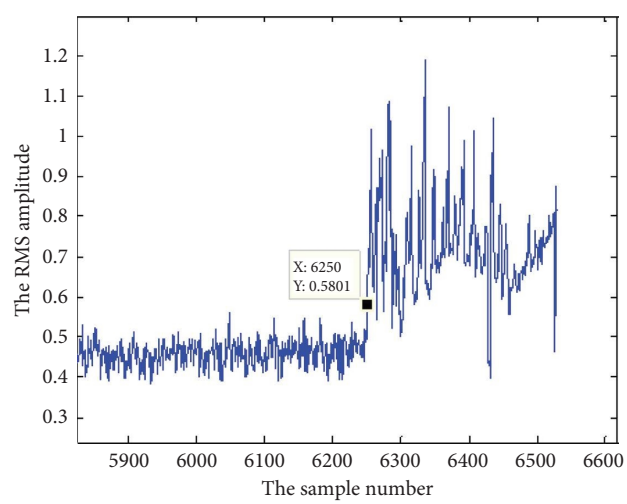

Figure 4: Locally enlarged view.

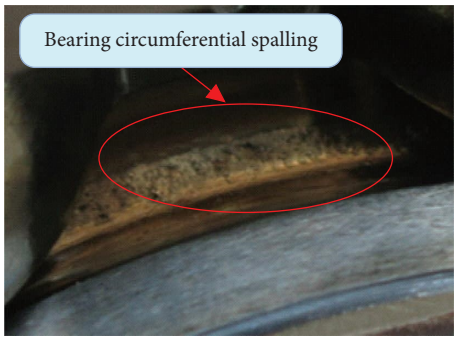

Figure 5: Example of spalling of the experimental bearing and inner ring.

Table 1: Bearing parameters.

Name	Frequency (Hz)
Fr (frequency conversion)	22.5
FTF (cage fault characteristic frequency)	9
BSF (rolling body fault characteristic frequency)	41.4
BPFO (outer ring fault characteristic frequency)	68
BPFI (inner ring fault characteristic frequency)	108

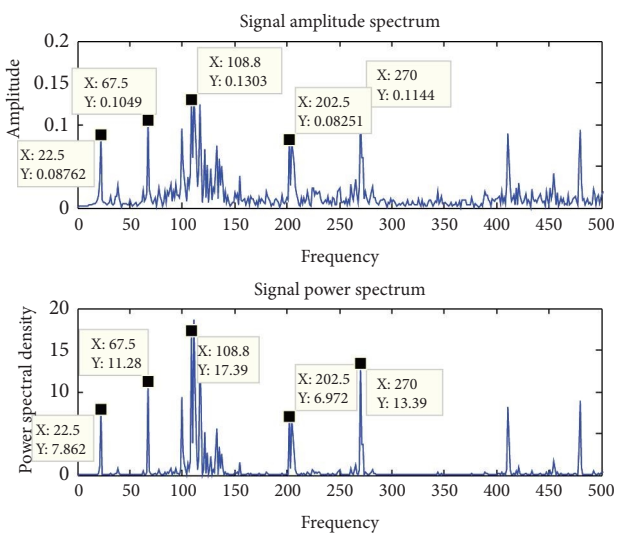

Figure 6: The No. 1 data of channel 1 correspond to amplitude spectrum and power spectrum.

According to the changing trend of the RMS value calculated from the above four channels, compared with the changing trend of the RMS value obtained from July 9 to July 14 (as shown in Figure 3), the change of the RMS value obtained from the data collected from July 14 to July 20 was quite drastic. In view of this situation, further relevant analysis was carried out. Taking the data collected in channel 1 as an example, based on the time information of the original data, the quantity of data collected from July 14 to July 20 is obtained as shown in Table 2.

Based on the time node information obtained in Table 2, combined with the RMS value obtained from the vibration data of the first channel, the amplitude change of the RMS time-domain trend map was briefly analyzed. Taking channel No. 1 as an example, by visualizing the time information of all samples (as shown in Figure 8), the fault nodes of the time information are mined to obtain the missing samples of the large data sample set.

As can be seen from Figure 8, since the original data are mixed with the start and stop data of the experimental bench, it is necessary to carry out data cleaning before fault prediction. Taking the data of channel No. 1 as an example, the samples in the start-stop phase were successively removed and the remaining samples were formed into a new HI sequence. The obtained results are shown in Figure 9, based on which bearing fault prediction is carried out.

3.3. Prior Knowledge Reinforcement Based on Parameter Transfer Learning. In the field of remaining service life prediction of rolling bearings, one of the more classical public datasets includes the experimental dataset of accelerated degradation of bearings in the PHM2012 data challenge [23]. Therefore, prior knowledge reinforcement can be realized based on this dataset and the parameter transfer theory in transfer learning. The first, second, third, fourth, and seventh groups of data under condition one were selected from the open dataset to carry out relevant knowledge transfer learning. The RMS values of the above five groups of lifetime degradation data are obtained, and the results are shown in Figure 10.

Based on the RMS values of the above five groups of lifetime degradation data, the least-squares regression fitting method was used to obtain the fitting parameters under 95% confidence intervals corresponding to the RMS values of the above groups by taking the double exponential model expressed in (5) as the benchmark model, and the results are shown in Table 3. The above data are given the same weight; that is, the average value of the five groups of fitting parameters is obtained again, and the result is shown in Table 4. The combination of these parameters is used to guide the particle initialization in the particle filtering method so as to realize the transfer of the whole-life degradation information of existing rolling bearings and finally realize the enhancement of prior knowledge.

3.4. Comparative Analysis of Remaining Useful Life Prediction. 1000 observation samples, 1500 observation samples, 1800 observation samples, and 2500 observation samples of the first channel are randomly selected for fault prognosis, respectively. When the RMS amplitude exceeds 2, the default bearing failure is set (corresponding to sample No. 4624). In order to compare and verify the effectiveness of the method proposed in this paper, it is compared and analyzed with the DRT-PF method proposed by Fan Bin [24], and the obtained results are shown in Figures 11–14.

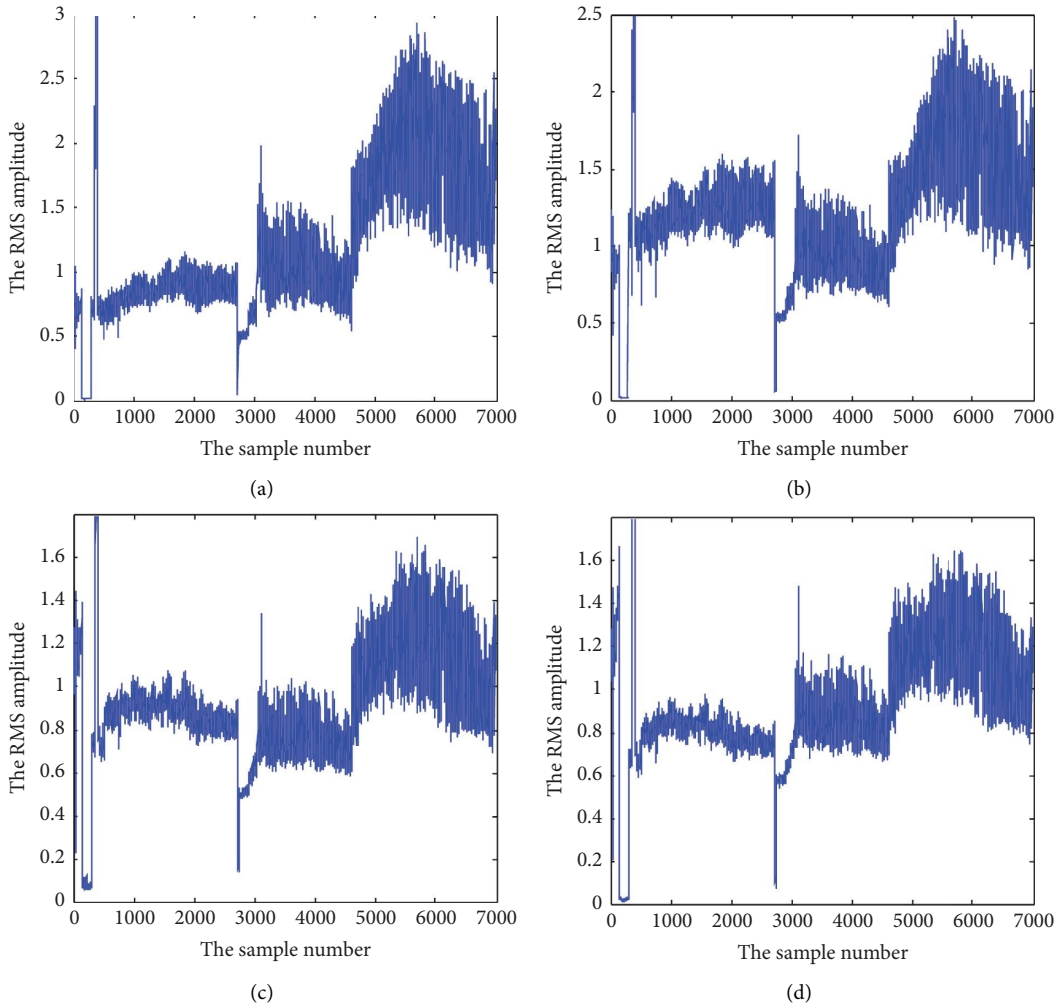

Figure 7: The RMS value time-domain waveform was obtained by calculating the data from four sampling channels. (a) RMS value of channel 1. (b) RMS value of channel 2. (c) RMS value of channel 3. (d) RMS value of channel 4.

Table 2: Data collection in channel 1.

Time	The no. of samples	Total number of samples
Date 14	305	305
Date 15	540	845
Date 16	1388	2233
Date 17	1324	3557
Date 18	1411	4968
Date 19	1401	6369
Date 20	606	6975

According to the prediction results of remaining service life under different observation sample lengths mentioned above, although the DRT-PF method has strong model adaptation ability, compared with the PKE-PF method proposed in this paper, the particle depletion problem is particularly prominent. Thanks to parameter transfer learning, the PKE-PF method can effectively solve the particle depletion problem and obtain higher precision prediction results. The prediction results of the above PKE-PF method are summarized, and the prediction accuracy of each observed sample length can be obtained based on the actual failure sample serial number corresponding to the set

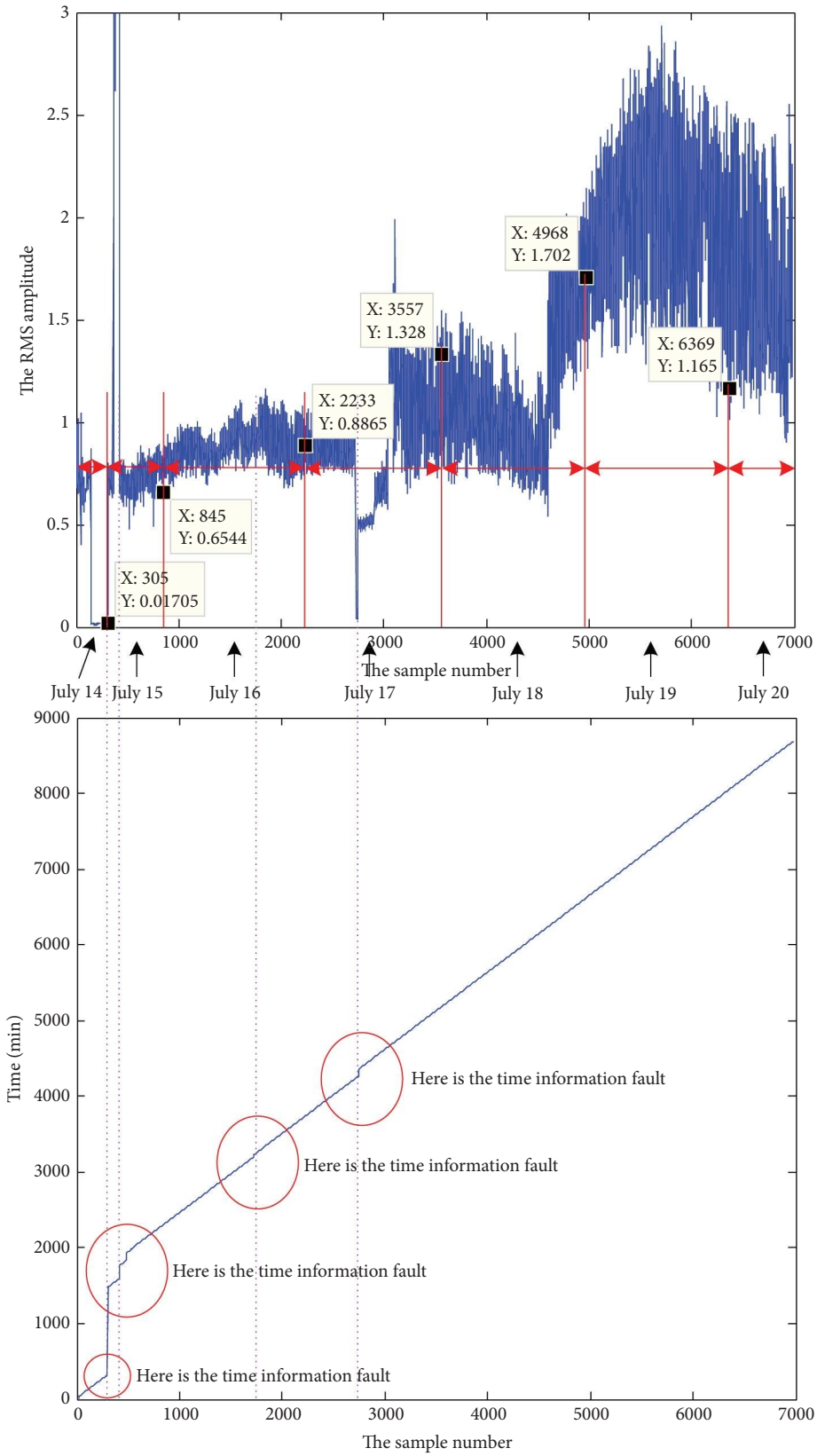

Figure 8: Time division of channel 1 data and information of missing nodes in samples.

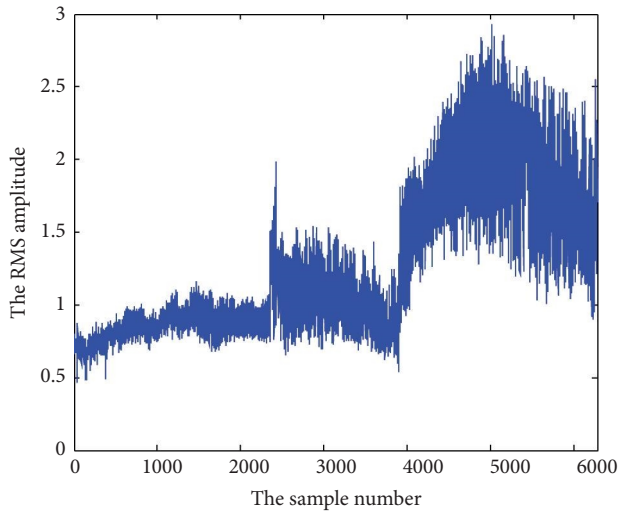

Figure 9: RMS value after channel 1 data cleaning.

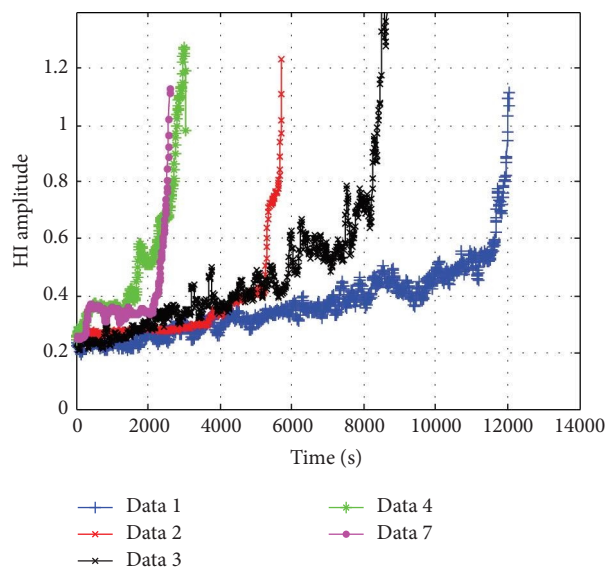

Figure 10: RMS values of five groups of bearing whole-life data were obtained based on the PHM2012 public dataset.

Table 3: The fitting values under the 95% confidence interval of parameters of the double exponential model.

Dataset	Parameter	Floor level	Upper level
Data 1	a	2.20×10^{-10}	2.25×10^{-04}
	b	7.05×10^{-04}	7.38×10^{-03}
	c	3.95×10^{-05}	9.16×10^{-04}
	d	2.70×10^{-05}	3.12×10^{-04}
Data 2	a	2.45×10^{-10}	2.56×10^{-04}
	b	5.55×10^{-04}	7.10×10^{-03}
	c	8.39×10^{-05}	1.46×10^{-04}
	d	2.64×10^{-05}	2.95×10^{-04}
Data 3	a	2.25×10^{-10}	2.36×10^{-04}
	b	1.24×10^{-04}	1.33×10^{-03}
	c	4.87×10^{-05}	1.62×10^{-04}
	d	3.56×10^{-05}	3.99×10^{-04}

Table 3: Continued.

Dataset	Parameter	Floor level	Upper level
Data 4	a	2.83×10^{-10}	3.07×10^{-04}
	b	1.49×10^{-04}	2.48×10^{-03}
	c	4.51×10^{-05}	1.39×10^{-04}
	d	1.99×10^{-05}	2.61×10^{-04}
Data 7	a	3.05×10^{-10}	3.20×10^{-04}
	b	3.45×10^{-04}	7.54×10^{-03}
	c	3.88×10^{-05}	4.65×10^{-04}
	d	6.23×10^{-05}	7.15×10^{-04}

Table 4: The mean fitting values under 95% confidence interval of parameters of the double exponential model.

Parameter	Floor level	Upper level
A	2.56×10^{-10}	2.69×10^{-04}
B	3.76×10^{-04}	5.17×10^{-03}
C	5.12×10^{-05}	3.66×10^{-04}
D	3.42×10^{-05}	3.96×10^{-04}

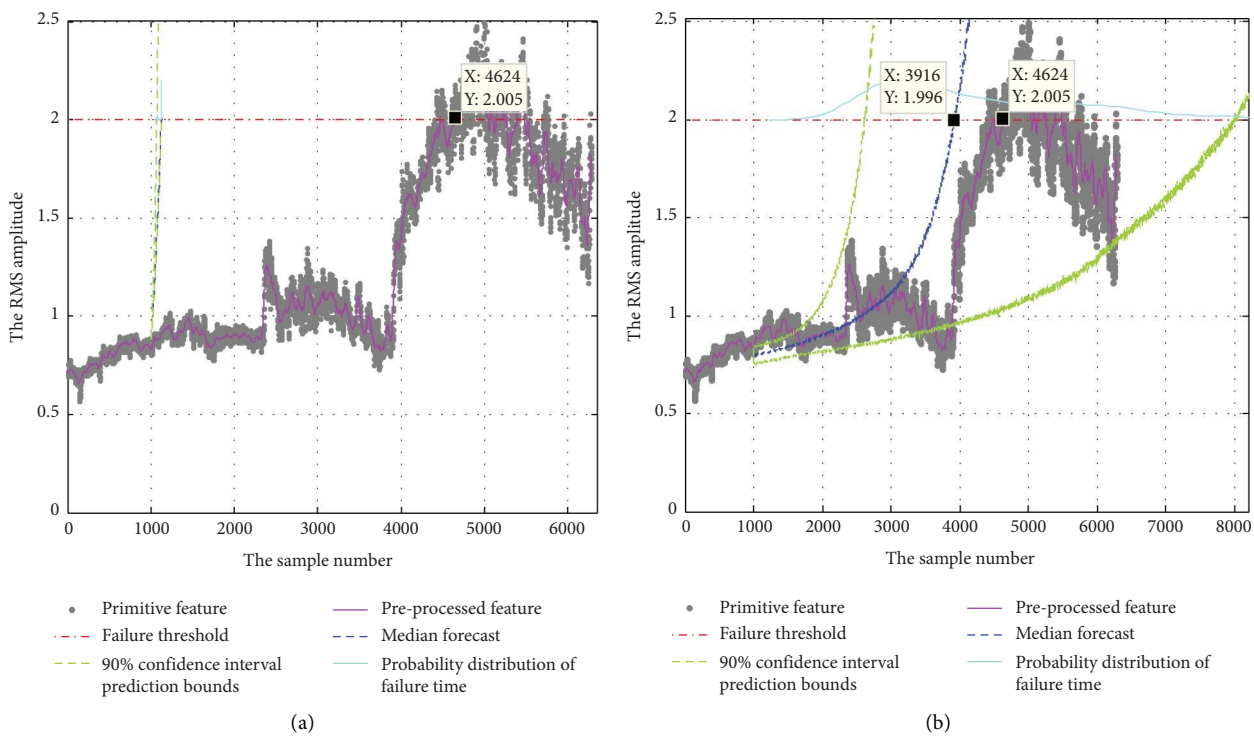

Figure 11: Fault prediction results with 1000 observation samples in channel 1. (a) DRT-PF method. (b) PKE-PF method.

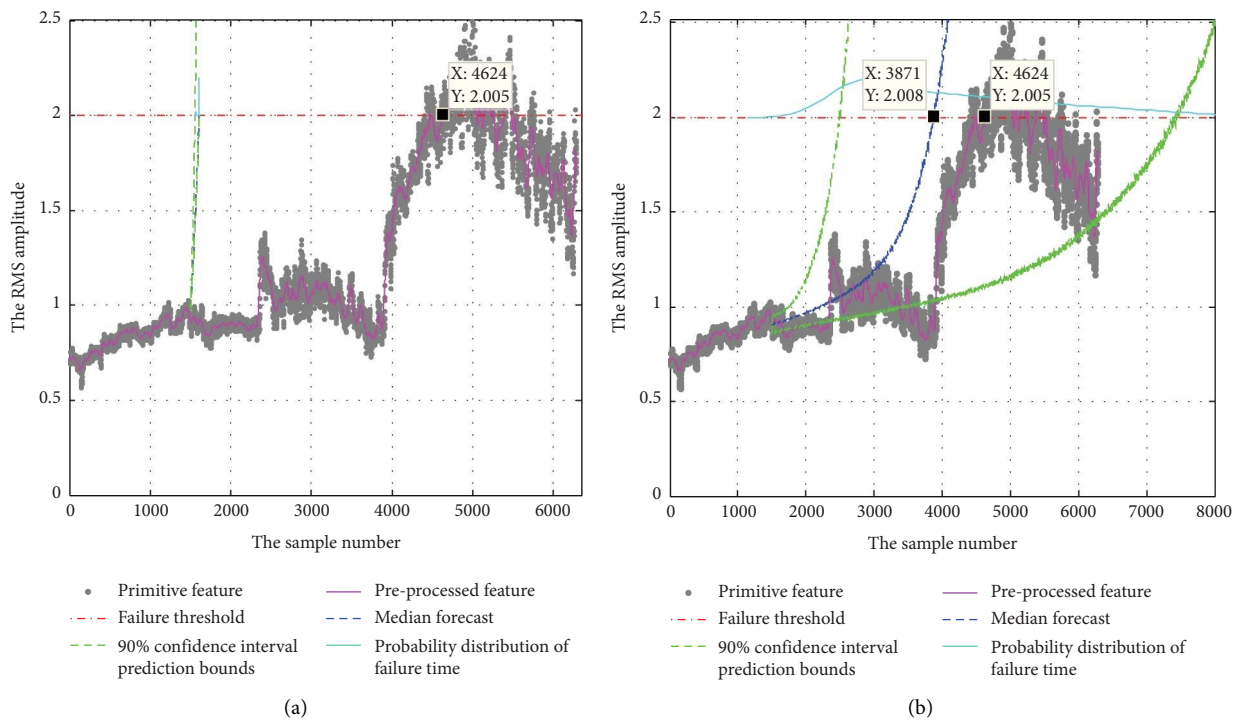

Figure 12: Fault prediction results with 1500 observation samples in channel 1. (a) DRT-PF method. (b) PKE-PF method.

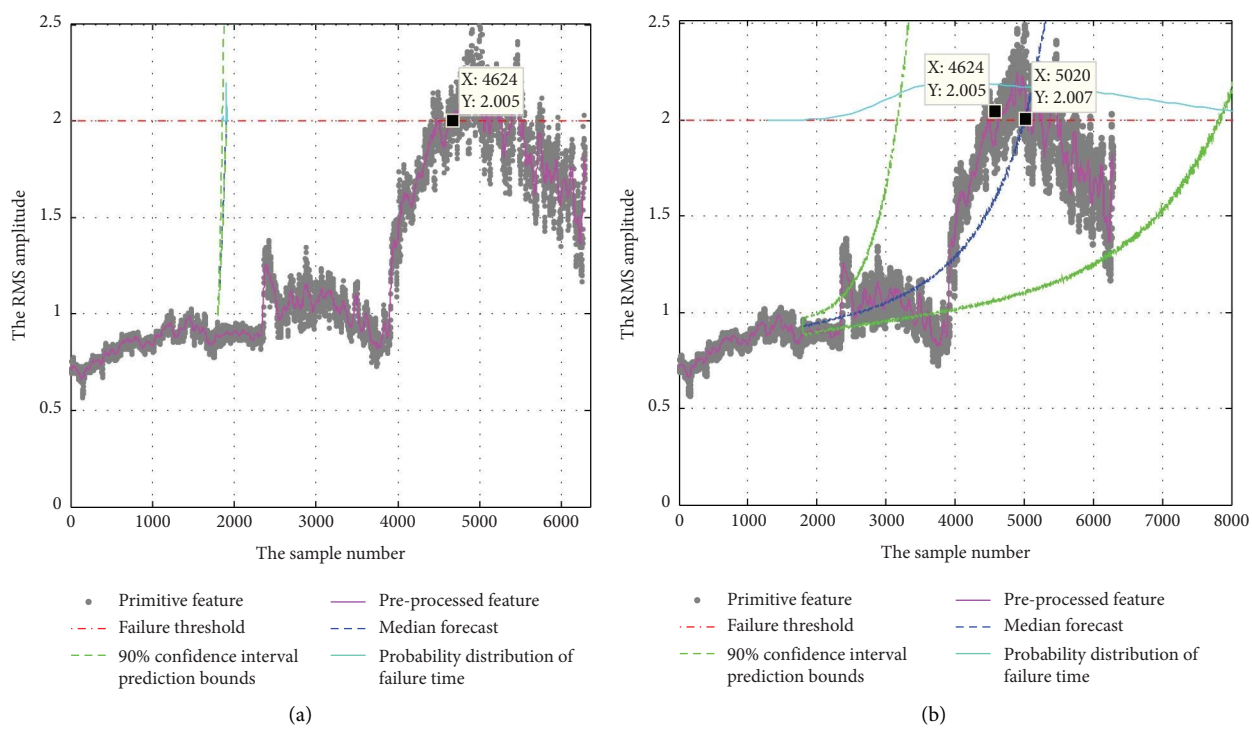

Figure 13: Fault prediction results with 1800 observation samples in channel 1. (a) DRT-PF method. (b) PKE-PF method.

threshold. The results are shown in Table 5. It can be seen that with the increase in the length of observation samples, the prediction accuracy also shows an increasing trend and the prediction accuracy under a 90% confidence interval is relatively ideal, which has a good reference significance for engineering practice.

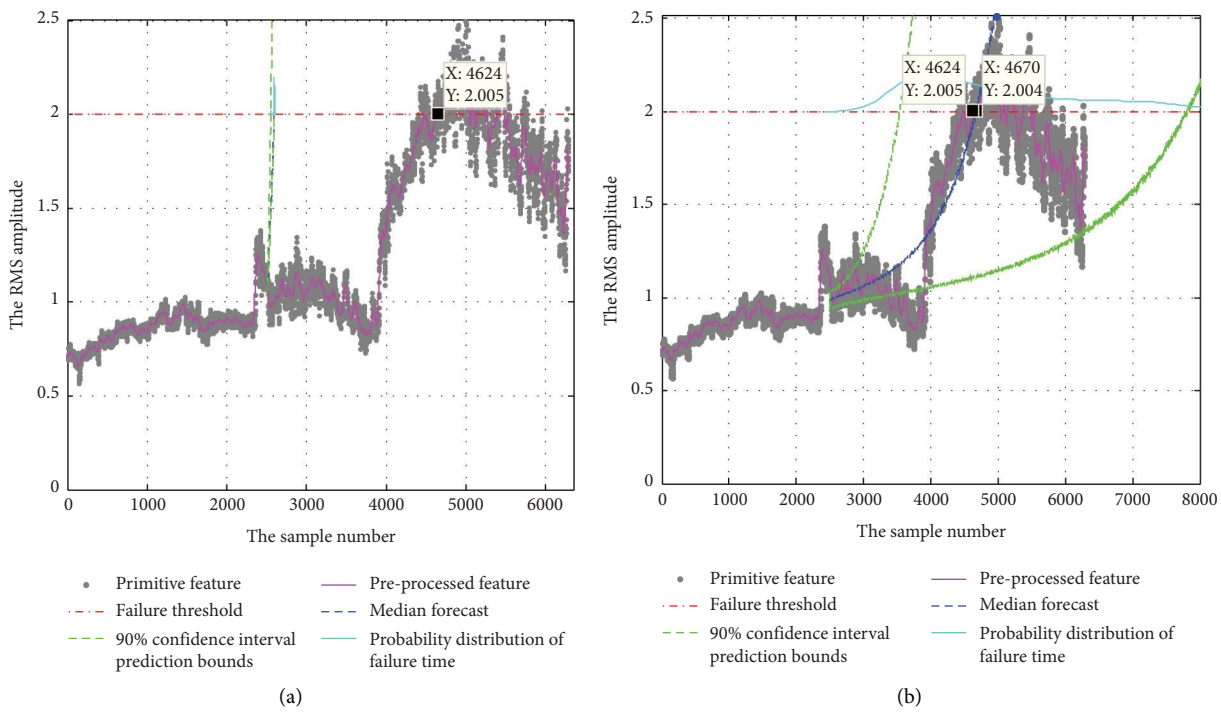

Figure 14: Failure prediction results with 2500 observation samples in channel 1. (a) DRT-PF method. (b) PKE-PF method.

Table 5: Fault prognosis results of the PKE-PF method under 90% confidence interval of different observed sample lengths.

Observed sample length	Number of predicted failure samples	Prediction accuracy (%)
1000	3916	84.69
1500	3871	83.72
1800	5020	91.44
2500	4670	99.01

4. Conclusion

In engineering practice, fault prediction technology can effectively excavate potential faults under the premise of ensuring safety. With the support of appropriate monitoring technology, labor costs can be saved to the greatest extent and economic benefits can be effectively improved. As an advanced fault prediction method, particle filtering has been widely used in engineering practice, but it also faces the problem of particle exhaustion caused by a lack of expert knowledge. This paper proposes an improved particle filtering method based on prior knowledge enhancement, namely, the PKE-PF method. For the fault prognosis problem of lack of full-life data-forecasted object, the PKE-PF method can be established based on full-life data of the same type of object to strengthen the initialization phase for more useful particles and can avoid the problem of particle depletion. At the same time, based on the actual engineering data, we carry out the fault prognosis comparative analysis and get the fault prognosis results of different observations under the 90% confidence interval. Compared with the latest PF methods available, the PKE-PF method can effectively avoid the particle depletion problem and obtain a more ideal fault prediction. It can provide a bearing fault prognosis method with simple operation and strong feasibility for engineering practice.

Data Availability

The bearing test data used to support the findings of this study are currently under embargo while the research findings are commercialized. Requests for data, 12 months after publication of this article, will be considered by the corresponding author. The bearing experimental data used in this paper are the relevant data collected and obtained during the test phase of a new bearing of a factory, which are not yet in the stage of full disclosure. In order to verify the effectiveness of the method proposed in this paper, the intermediate data obtained after the above experimental data processing have been uploaded.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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Supplementary Materials

The figure attachment uploaded by the system is the editable form of the figures in the paper. The figure introduction has been included in this paper. (*Supplementary Materials*)

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