Reliability Estimation Based on Moving Average and State Space Model for Rolling Element Bearing

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Abstract: Reliability analysis based on equipment's performance degradation characteristics is one of the important research area in reliability analysis. Many a times, research is carried on the basis of multi-sample analysis, but application is limited to a single equipment reliability prediction. Therefore, the method of reliability prediction based on state space model is proposed for small sample analysis. First, signals about machine working conditions are determined based on-line monitoring technology. Secondly, wavelet packet energy is applied on characteristic extraction for the monitored signals. Frequency band energy is determined to be as characteristic parameter. Then, the degradation characteristics of signal to noise ratio is improved by moving average filtering processing. In the end, state space model was established to predict degradation characteristics of probability density distribution, and the degree of reliability is determined. Rolling element bearing reliability analysis is used an example to demonstrate the rationality and effectiveness of this method.

Keywords: Reliability prediction, state space model, feature extraction, wavelet analysis, moving average

1. Introduction

Reliability analysis based on equipment's performance degradation characteristics is one of the important research areas for safe operation. The operation equipment reliability estimation can let the operator accurately grasp equipment status, which is important to the production efficiency and the safe production. With the rapid development of modern industrial technology, mechanical equipment updates fast. It also needs the quality and life to be improved. The traditional method reliability analysis relies on large sample experiment and statistical approach. It is time-consuming and it cannot run on small sample equipment, such as gas turbine, centrifugal compressor, and so on. Therefore, it is urgent to improve the small samples reliability estimation method, especially for single sample prediction.

Reliability can reflect the health degree of equipment and provides important information for equipment reliability evaluation and prediction. There are many researchers in this area. Chinnam et al.[1] put the thrust and torque on-line monitored in the process of high-speed steel drill for running status analysis. Polynomial regression models including Gaussian white noise is investigated. Neural network is applied on life prediction process. Lu et al.[2] uses quadratic exponential smoothing time series forecasting model for real-time reliability estimation. Zhang et al.[3] extract there characteristic indicators of vibration signals in the bearing life test, such as RMS value, peak-peak value, and kurtosis. Combined with bearing temperature, there are a total of four indicators. The recursive Bayesian analysis method is used to estimate the reliability. Nagi et al.[4] extract feature from the vibration signal of real-time monitoring bearing as degradation indicators. Neural network is used to predict life distribution of bearing. Fong[5] points out that degradation situation of each individual equipment is unique because of the difference of operation environment and using conditions. Condition monitoring information in running can be made reliability evaluation and prediction effectively for single equipment. When Hua[6] conducts condition monitoring data...
to estimate reliability on individual equipment, the lack of experience information and many
uncertainty in equipment operation are considered. Failure threshold and degradation model
are difficult to be directly confirmed. So he proposes a reliability prediction method of
adaptive failure threshold. This method is applied to bearing and high pressure cleaning pump
successfully. Lin et al.\[7\] demonstrates a procedure to extract useful condition indicators from
vibration signals and use the proportional hazards model (PHM) to develop optimal
maintenance policies for the gearboxes. Lin and Tseng \[8\] combine the Weibull PHM and
vibration-based machine condition monitoring techniques to estimate several machine
reliability statistics. All above mentioned methods are helpful the development of reliability
estimation. However, these methods require a specific mechanical knowledge and make many
assumptions about condition parameters degradation paths and their distribution probability
density functions.

Heng et al.\[9\] present a prognostics approach using feed forward neural network on pump
vibration data. The model incorporated population characteristics and suspended condition
trending data of historical units into prognostics. Ding Feng\[10\] extracts the degradation
characteristics from monitored bearing vibration signals, sets up two parameters Weibull
Proportional Hazards Model combined with the state information of bearing, and evaluates the
reliability of railway locomotive bearing. Chen Baojia\[11\] extracts the relevant characteristic
parameters from vibration signals of the tool cutting process combined with the tool condition,
evaluates reliability and predicts the residual life of tools using Logistic regression model. The
two methods need certain historical failure data, but historical failure data for some large
equipment are often difficult to be obtained. Zhengjia He\[12\] proposed a variety of reliability
evaluation methods based on mechanical equipment state information and made a reliability
assessment and life prediction of bearing based on signal processing and feature extraction.
The studies show that the degradation characteristic extracted from monitored equipment
signals can accurately reflect the dynamic characteristic of the equipment performance
degradation. It is reasonable and effective for reliability evaluation, and it makes up for the
deficiency of the traditional reliability evaluation.

Wavelet packet energy method can divide signal in many layers in the whole frequency
band, and the detail distribution information of original signal at different frequencies is
obtained; Moving average is a data processing method with smoothing and filtering effect. It
can filter out the stochastic fluctuant data. Thus the statistical characteristics can be estimated.
State space model (SSM) is a special form of Hidden Markov Model. It can be used to describe
the dynamic process changing in time; In recent years, it is used on fault diagnosis and
prediction of mechanical equipment by many scholars. Orchard\[13\] uses SSM for equipment
diagnosis and forecast online. Remaining life distribution of planetary gear fault instance
combined with particle filtering technology is used to validate the rationality of the model.
Gasperin \[14\] extracts the degradation characteristics of gear box and establishes the SSM of
degradation characteristics to predict the remaining service life of gear box combined with the
Monte Carlo simulation\[14\]. SSM can describe the system state using the current and past
minimum information form without needing a lot of historical data. For single equipment
reliability, it is difficult to be evaluated using traditional reliability method. So this paper
proposes a reliability prediction method based on SSM. This method does not rely on historical
failure data, and can realize the real-time prediction of single equipment reliability.
Traditionally, particle filter is used on reliability estimation based on SSM. It has good
performance on nonlinear time series prediction. But the convergence is a problem for particle
filter. Kalman filter has good performance on line prediction.

In this research, a new method for operational condition reliability estimation is developed
by combining SSM and feature extraction. Wavelet packet feature extraction is used to determine the related parameter for reliability analysis based on above statement. To improve the accuracy of reliability estimation, moving averaging is used for the extracted data. A rolling element bearing operational condition estimation is carried out to verify the effectiveness of this method. The results show that this method can estimate the operational condition estimation for small sample, which has good accuracy for reliability estimation. At the same time, it is simple and convenient for practical application. This paper is structured as follows. Section 2 introduces theory of this state space model. Section 3 presents reliability estimation based on feature extraction and data mining. Section 4 and Section 5 provides the data analysis by using this method for rolling element bearing and cutting machine, respectively. Concluding remarks are given in Section 6.

2. State Space Model

2.1 Instantaneous Reliability

State space model is used to obtain device performance characteristics index \( y_t \), it is used to measure the instantaneous reliability. Reliability is an important quality index of mechanical equipment, and the degree of reliability is one of the most important reliability evaluation indexes. The definition of reliability is that under prescribed conditions and within the time limit, the probability of equipment completes the required function without failure. However, in actual production the reliability based on probability statistics solution cannot give meaningful help. For analyzing and evaluating dynamic performance of the individual equipment, Lu\[3\] firstly suggests the method to compute the reliability of equipment using interval integral defined by the failure threshold and index observation to predict the probability distribution of equipment performance degradation index. Xu\[15\] and Hua\[6\] use the similar concept of reliability prediction and evaluation method and apply it in the instance estimation. If the instantaneous reliability of equipment at time \( t \) is the probability which the device performance characteristics index \( y_t \) is less than the failure threshold \( y_c \).

\[
R(t) = P(y_t \leq y_c) = \int_0^{y_c} f_t(y_t)dy_t
\]  

(1)

In Eq. (1), \( f_t(y_t) \) is the probability density function of the state characteristic \( y_t \). As shown in Figure 1, the red line is the failure threshold set, the probability which the state characteristic is bigger than the failure threshold. The shadow part of the Figure 1 is the failure probability, and the probability of the state characteristic is lower than the failure threshold. It is the instantaneous reliability.

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**Figure 1:** The Instantaneous Reliability.
2.2 State Space Model

The degradation process of equipment has the property of first order Markov. It means that the device status next time is only related to the device status this condition. The device status of different time is represented by $x_t$. The state characteristic extracted from monitored data is regarded as observed values, which is represented by $y_t$. Establishing equipment degradation SSM is as follows:

$$x_t = A \cdot x_{t-1} + w_t$$  \hspace{1cm} (2a)  

$$y_t = C \cdot x_t + e_t$$  \hspace{1cm} (2b)

Eq.(2a) is the state equation, $A$ is the transformation matrix acting on the device status $x_t$. The future value of $x_t$ is only related to current condition, and is independent with the past state. It also named as Markov property. Eq.(2b) is the observation equation, and the mapping relationship between the system state and observation value is established. $C$ is the transformation matrix, $w_t$ is the process noise. Assuming the mean value is zero, the covariance for multivariate normal distribution is $w_t \sim N(0, Q)$, $e_t$ is the observation noise, and $e_t \sim N(0, R)$. The state of the system can reflect the variables of system features, characteristics and status. But the state vector has physical meaning. Sometimes it is introduced for modelling need, and there is no specific physical meaning.

Obviously, when the model parameters $\theta = \{A, C, Q, R\}$ and the device status $x_{t_0}$ are known, the mean value and variance of observed values $y_t$ at the moment $t > t_0$ can be directly calculated by Eq.(2). Setting the equipment failure threshold $y_{f}$, and the equipment reliability can be forecast by Eq.(1).

2.3 Solution of SSM

SSM solving method \cite{14, 16} is the Expectation Maximization (EM) algorithm, and its core is Kalman Filter. Kalman Filter is a recursive estimate that is as long as the state estimation of last moment and the observation of current state are known, the estimate of current state can be calculated. If the system state vector $X$ is known, the optimal value of the parameter $\theta = \{A, C, Q, R, \mu_0, \sigma_0\}$ can be obtained through the Maximum Likelihood estimation (MLE). MLE method is by means of the maximizing likelihood function Eq.(3).

According to the nature of the logarithmic function, when $\theta$ is a maximum value, the function $L(\theta)$ is also a maximum value. However, in fact state vector $X$ is unknown, the condition of parameter estimation is deficient.

$$L(\theta) = \ln P(Y | X, \theta)$$  \hspace{1cm} (3)

The sequence of observations at $1 \sim n$ , $y_{1n}$ is given , EM algorithm is estimating system parameters by Step E and M iterative. It can be expressed as:

$$\theta_{\text{new}} = \arg \max \{E_{X_{\theta_{\text{old}}}} [\ln P(Y, X|\theta)]\}$$  \hspace{1cm} (4)
2.3.1 Step E Calculation

The initial parameters \( \theta_0 \) and \( y_{in} = \{y_1, y_2, \ldots, y_n\} \) are given, the optimal value of state vector \( x_t, P(x_t|y_{in}) \) is estimated by Rauch - Tung - Striebel (RTS) smoother. The steps of RTS smoother are as following: Initial state: \( x_0 \sim N(\mu_0, P_0) \), the observation sequence \( y_{in} = \{y_1, y_2, \ldots, y_n\} \) is filtered along the positive direction by Kalman filter: For \( t = 1, 2, \ldots, n - 1 \)

\[
\begin{align*}
x_{i+1} &= A x_i \\
P_{i+1} &= A P_i A^T + Q \\
K_i &= P_{i+1} C^T (C P_i C^T + R)^{-1}
\end{align*}
\]

Updating:

\[
\begin{align*}
x_{i+1} &= x_{i+1} + K_i (y_{i+1} - C x_{i+1}) \\
P_{i+1} &= P_{i+1} - K_i C P_{i+1}
\end{align*}
\]

Start from the state \( x_n \) estimated by Kalman filter before, recursive smoothing: For \( T = n, n-1, \ldots, 1 \)

\[
\begin{align*}
J_i &= P_i A P_i^{-1} \\
x_{i} &= x_{i} - J_i (x_{i+1} - C x_{i+1}) \\
P_{i} &= P_{i} - J_i (P_{i+1} - P_{i+1}) J_i^T
\end{align*}
\]

2.3.2 Step M Calculations

If the state is known, the likelihood function with Bayesian Criterion system output can be written as:

\[
P(Y|\theta) = P(Y|X, \theta)P(X|\theta)
\]

The process noise and observation noise of Model are Gaussian Distribution, and the multivariate normal distribution exists as:

\[
\begin{align*}
&x_t \sim N(A x_{t-1}, Q), y_t \sim (C x_t, R). \\
\text{According to the multivariate normal distribution density function Eq.}(3)\text{ and Eq.}(13), the likelihood function can be written as:}
\end{align*}
\]

\[
\begin{align*}
-2 \ln(L(\theta)) &= \ln|C_0| + (x_0 - \mu_0)' C_0^{-1} (x_0 - \mu_0) \\
&+ n \ln|Q| + \sum_{i=1}^{n} (x_i - A x_{i-1})' Q^{-1} (x_i - A x_{i-1}) \\
&+ n \ln|R| + \sum_{i=1}^{n} (y_i - C x_i)' R^{-1} (y_i - C x_i)
\end{align*}
\]

The current parameters \( \theta_k \) and complete observation data \( Y \) are given, the expectations in Eq. (14) are expressed as:

\[
I(\theta|\theta_k) = E\{-2 \ln L(\theta|Y, \theta_k)\}
\]

At the moment, the RTS smooth results in step E can be used to calculate the expectations of the following:

\[
E_{x|y}(x_t|x_t') = x_{i+1} x_{i+1}' + P_{i+1}
\]
Putting Eq. (16) into Eq.(14) can get the following results:

\[
\begin{align*}
R_{\text{new}} & = \Gamma_1 \Gamma_1^{-1} \\
Q_{\text{new}} & = n^{-1} (\Gamma_3 - \Gamma_2 \Gamma_1^{-1} \Gamma_2') \\
R_{\text{new}} & = n^{-1} (\Gamma_3 - \Gamma_2 \Gamma_1^{-1} \Gamma_2') \\
\mu_{\text{new}} & = x_{\text{new}} \\
\sigma_{\text{new}} & = P_{\text{new}}
\end{align*}
\]

where,

\[
\begin{align*}
\Gamma_1 & = \sum_{i} x_{1,i} x_{3,i} + P_{3,1} \\
\Gamma_2 & = \sum_{i} x_{1,i} x_{2,i} + P_{2,1} \\
\Gamma_3 & = \sum_{i} x_{1,i} x_{4,i} + P_{4,1} \\
\Gamma_4 & = \sum_{i} v_{1,i} v_{3,i} \\
\Gamma_5 & = \sum_{i} v_{1,i} v_{4,i}
\end{align*}
\]

Take the partial derivatives of Eq. (17), that is:

\[
\frac{\partial l}{\partial C} = -R^{-1} \Gamma_4 + R^{-1} C \Gamma_3 = 0
\]

It can be obtained:

\[
C_{\text{new}} = \Gamma_1 \Gamma_1^{-1}
\]

As well, it can also be obtained,

\[
\begin{align*}
A_{\text{new}} & = \Gamma_1 \Gamma_1^{-1} \\
Q_{\text{new}} & = n^{-1} (\Gamma_3 - \Gamma_2 \Gamma_1^{-1} \Gamma_2') \\
R_{\text{new}} & = n^{-1} (\Gamma_3 - \Gamma_2 \Gamma_1^{-1} \Gamma_2') \\
\mu_{\text{new}} & = x_{\text{new}} \\
\sigma_{\text{new}} & = P_{\text{new}}
\end{align*}
\]

Through the iterative loop of Step E and M, when the difference value between the former and later likelihood function value is less than the setting threshold value or the cycle index reaches the setting value, iteration stops. The final parameter \( \theta = \theta_{\text{new}} \) is determined, and the dynamic model is obtained. Based on this dynamic model, the equipment reliability prediction evaluation is guided. Thus, the predicting maintenance of the equipment is applied.

An example for the state space model is as follows. Consider the problem of remaining useful life estimation in a process for which the evolution in time of a known failure condition (for example, a crack in a material) is described by the model, where \( \omega_3(t) \) is zero mean Gaussian noise. The state equation is:
\[ x_t(t + 1) = x_t(t) + 3.10^{-3} (0.05 + 0.1 \cdot x_t(t))^3 + w_2(t), x_2(t + 1) = x_2(t) + w_2(t) \]  \hspace{1cm} (26)

The observation equation is 

\[ y(t) = x_t(t) + v(t). \]

where, 

\[ w_t(t) \sim \text{Gamma}(0.15, 0.3), v(t) \sim \frac{1}{4} N(-0.5, 0.25) + \frac{3}{4} N(0.5, 0.25). \]

Results are summarized in Figure 2, where the light-dark and black lines represent, respectively, the noisy measurements and the process output estimation obtained from an SIR particle filter, and where the dotted line shows the actual evolution of the failure condition for future time instants (information that is unknown when the RUL estimation is performed).

![Image](https://example.com/image.png)

**Figure 2:** Result Comparison for RUL Statistical Characterization

### 3 Feature Extraction and Reliability Estimation

RMS has been broadly used on machine condition estimation and reliability prediction. But it is not sensitive to some signals and further extraction should be investigated. Many researchers have worked on the signal processing technology. Vibration signal processing and feature extraction have been intensively investigated in the last two decades, such as time domain analysis, frequency domain analysis, time-frequency domain analysis. With the development of the wavelet analysis for last three decades, it has been broadly used to process vibration signals and the effect is remarkable [4]. As the extension and development of wavelet transform, Wavelet Packet Decomposition (WPD) is multi-dimensional. Therefore, it has been investigated by many researchers. The deposition process can be shown Figure 3.

![Image](https://example.com/image.png)

**Figure 3:** Three-level Wavelet Packet Decomposition

#### 3.1 Wavelet Packet Energy

Wavelet packet transform is a more refined signal processing method. It can help to determine the details of signal after the wavelet decomposition (that is the high frequency part). It overcomes the shortcoming of a low resolution of high frequency of the wavelet transform, and has an effect on the fine division of signal frequency band characteristic.

Suppose there is a scaling space of limited energy signal \( U_0^0 \). Through wavelet packet transformation \([17]\), \( U_0^0 \) is decomposed into several spaces in binary format. The iterative relation is:
In Eq. (27), $j(j \leq 0)$ is decomposition level, $\oplus$ expresses orthogonal decomposition, $U_{j+1}^k$, $U_j^k$, and $U_{k+1}^{2k}$ three closure spaces respectively corresponding wavelet function are:

$$\psi_{2n}(t) = \sqrt{2} \sum_{k \in \mathbb{Z}} h(k) \psi_n(2t - k) \quad (28)$$
$$\psi_{2n+1}(t) = \sqrt{2} \sum_{k \in \mathbb{Z}} g(k) \psi_n(2t - k) \quad (29)$$

When $n = 0$, $\psi_0(t)$ is a scaling function $\varphi(t)$ and $\psi_1(t)$ is a wavelet basis function $\psi(t)$, $h(k)$ and $g(k)$ are discrete quadrature mirror filter coefficients. The signals in the space $U_j^{n-1}$ can be obtained by wavelet packet function $\psi_{j,n}^k(t)$ reconstruction, which is shown in Eq. (30).

$$s_j^n(t) = \sum_{k \in \mathbb{Z}} D_{k,n}^j \psi_{j,n}^k(t), k \in \mathbb{Z} \quad (30)$$

In Eq. (30), $D_{k,n}^j$ is wavelet packet coefficient, and it can be obtained by the following equation:

$$D_{k,n}^j = \int_{-\infty}^{+\infty} f(t) \psi_{j,n}^k(t) dt \quad (31)$$

The wavelet packet function $\psi_{j,n}^k(t)$ is orthogonal basis function in $L^2(\mathbb{R})$, so the energy of $s_j^n(t)$ is:

$$WPE_n = \sum_k |D_{k,n}^j|^2 \quad (32)$$

The normalized wavelet packet energy is:

$$E_n = WPE_n / \sum WPE_n \quad (33)$$

### 3.2 Moving Average Filtering

Moving average is a data processing method with smoothing and filtering effect. It can filter out the stochastic fluctuant data. At the same time, it can also determine the changing process of random error, thus the statistical characteristics can be estimated. As shown in Figure 4, let the length L sliding window move through the sequence $\{ y(t), t = 1, 2, \ldots, N \}$, compute the mathematic average for all elements inside the window and put the average value as one element of the new sequence. The new sequence is the moving average of $y(t)$. Mathematical expression is as follows:

$$y_{ma}(t) = \frac{1}{L} \sum_{i=L}^{2L-1} y(t) \quad i = 0, 1, \ldots, N - 2L + 1 \quad (34)$$

The moving average method is easy to process non-stationary data in real time. It can reduce the effects of noise on the signal waveform and improve the signal-to-noise ratio. It should be pointed out that moving average has the end effect. It can only get most of the values with lack of the end that is the part $t < L$ cannot be obtained. Whether trying to add it is also according to the actual needs.
3.3 Flow Chart for Reliability Estimation

In this paper, wavelet packet feature extraction, moving average method, and SSM method are applied to the reliability evaluation of rotating machine working condition. The method process is shown as Figure 5. First, signals about machine working conditions are determined based on on-line monitoring technology for equipment. Secondly, wavelet packet energy is applied on characteristic extraction for the monitored signals. Because for signal analysis of bearing, wavelet packet technology can not only distinguish types of bearing defect, but also can determine the severity of the bearing defect. Frequency band energy is determined to be as characteristic parameter. Then, the degradation characteristics of signal to noise ratio is improved by moving average filtering processing. It can filter out the stochastic fluctuant data and determine the changing process of random error. In the end, state space model was established to predict degradation characteristics of probability density distribution, for it can obtain device performance characteristics index $y_i$ who measures the instantaneous reliability, and the degree of reliability is determined. Rolling element bearing is used to verify the effectiveness of the method in this research.

4. Reliability Prediction of Rolling Element Bearing

Any rotating machinery about is inseparable from the bearing and its importance is self-evident. The bearing life and reliability prediction have a certain practical significance. Vibration signal analysis method is the most commonly used of fault diagnosis methods and the health information of bearing is largely embodied in the vibration signal. So extracting the relevant characteristics from the bearing vibration signal and the reliability assessment are based on vibration signal analysis.

4.1 Condition Monitoring Data

The bearing accelerated life test data are from the IEEE 2012 Prognostic challenge $^{[18-19]}$. There are three different working conditions in the test. In the working condition 1, the speed is 1800 rpm, the load is 4000 N, and seven bearings full life tests were conducted. The sampling frequency of vibration signal is 25.6 kHz, and the sampling length is 2560 points. The test setting failure determination is that the acceleration signal amplitude is more than 20g, and 2375 samples of vibration signal are collected from the normal
operation to the failure of the bearing. Figure 6 provides different bearing information. In the last stage, the bearing is completely broken based on the acceleration testing.

Figure 6: The Bearings in Different Working Conditions

4.2 Wavelet Packet Frequency Band and Moving Average

It is important to monitor the wearing data $x_t$ shown in Eq.(2) for the bearing. Bearing degradation process should be a process of monotonic unabated, and with the deterioration of the bearing, the degradation characteristic value must increase continually with wearing condition in theory. But it is not convenient for monitoring. Therefore, it needs indirect monitoring data $y_t$ to demonstrate bearing condition. In the most circumstance, vibration signal is used in the practical diagnosis. The time domain waveform of bearing vibration signal is shown in Figure 7. The vibration amplitude of the failure time (2375 #) is much higher than the vibration amplitude of the normal time (2 #). With the method in Section 3, complete 4 layer wavelet packet decomposition of bearing vibration signal using Db1 wavelet basis, and calculate wavelet packet energy of 16 frequency bands. The comparison of normalized wavelet packet energy of each band of bearings in different periods is shown in Figure 8. It can be found the energy value of Band 2 $E_2$ is more and more bigger with the increasing bearing degradation, the trend is shown in Figure 9. There are ups and downs, but the overall trend is obvious. It objectively reflects the degradation performance of bearing.

Figure 7: The Time Domain Signals of the Bearing # 2 and # 2375.

Figure 8: The Normalized Wavelet Packet Energy of Bearings at Different time
4.3 State Space Model

According to the method of Section 3, moving average filtering is used for $E_2$, and the sliding window length is $L = 200$. Because of the end effect, the data point of $E_{2_{max}}$ is $L-1$ fewer than $E_2$. Considering the bearing is in good health in the early and the features change little, it doesn't need to be padded out. The trend of $E_{2_{max}}$ is shown in Figure 9 with red line. The new characteristic value sequence becomes pure through the filter, and the new sequence and the original sequence keep high consistency up and down, which fully shows the variation features of the original sequence. The moving average filtering method is effective in reducing the noise of the observed value. Take the sequence $E_{2_{max}}$ after moving average filtering as the characteristic index of the bearing reliability prediction. In the test, take 100 values of $E_{2_{max}}$ at the current time and earlier time for the SSM parameter estimation, and then forecast the $E_{2_{max}}$ later. Initial parameters setting has no effect on parameter estimation results, and the general settings are as follows:

$$
\begin{align*}
A &= \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, Q = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, C = \begin{bmatrix} 1 \\ 0 \end{bmatrix}, \mu_0 = \begin{bmatrix} 0 \\ 0 \end{bmatrix}, \sigma_0 = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, R = [1]\end{align*}
$$

(35)

As the new observations obtained, update the SSM of degradation characteristics forecast in time. We select the data at several time points at later period to make predictions, and the effect is close to the real values. Figure 10 (a), (b), and (c) represent the prediction results of bearing degradation characteristics at different time. If the bearing degradation characteristic is without smoothing, the prediction results are shown in Figure 11. The forecast mean value is higher than the actual value at 2050 time, and the big noise leads to parameter estimation convergence problems at 2150 time. The prediction at 2250 time is good, though comparing the predictive results without moving average processing is poor overall.
4.4 Reliability Estimation

Set the bearing failure threshold $E_{2,\text{max}} = 0.42$, and calculate the running reliability of the bearing by Eq.(1). After the previous forecasts, make the corresponding reliability estimation. Figure 12 (a), (b), and (c) show the corresponding instantaneous reliability prediction results at 2050, 2150 and 2250 time separately. Setting the bearing failure reliability threshold as 0.5, the corresponding non-lethal failure moment of the three times forecast are: 2834, 2248 and 2369. Thus, it can be obtained that with the new observation obtained, forecast model is updated. The prediction result is more and more closer to the real bearing failure moment 2373, which provides the effective basis for the predicting maintenance of the bearing.
5. Conclusions

In this research, a new method for rotating machine reliability estimation is put forward. Wavelet packet feature extraction, moving average, and SSM are combined together for condition estimation. Based on the rolling element bearing analysis, the effectiveness of this method is demonstrated. The result shows that the moving average filtering can effectively improve the signal noise ratio of the degradation characteristics and improve the accuracy of the prediction. It is accorded with the time dynamic characteristics of the equipment performance degradation. This method has good performance on reliability analysis. Further investigation should be carried on the application of this method on practical question analysis.

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References


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