Research on Remaining Useful Life Prediction of Rolling Element Bearings Based on Time-Varying Kalman Filter

Lingli Cui, Xin Wang, Huaqing Wang, and Jianfeng Ma

***Abstract*— Rolling bearings are the key components of rotating machinery. Thus, the prediction of remaining useful life (RUL) is vital in condition-based maintenance (CBM). This paper proposes a new method for RUL prediction of bearings based on time-varying Kalman filter, which can automatically match different degradation stages of bearings and effectively realize the prediction of RUL. The evolution of monitoring data in normal and slow degradation stages is a linear trend, and the evolution in accelerated degradation stage is nonlinear. Therefore, Kalman filter models based on linear and quadratic functions are established. Meanwhile, a sliding window relative error is constructed to adaptively judge the bearing degradation stages. It can automatically switch filter models to process monitoring data at different stages. Then, the RUL can be predicted effectively. Two groups of bearing run-to-failure data sets are utilized to demonstrate the feasibility and validity of the proposed method.**

***Index Terms*— Remaining useful life (RUL) prediction, rolling element bearings, time-varying Kalman filter.**

I. Introduction

SUPPORTING and driving parts such as bearings, gears, and rotating shafts are crucial components of mechanical equipment. Once these components lose effectiveness, the mechanical equipment will not work properly, and even safety accidents will occur. This will bring huge losses to production and human life. Therefore, many new methods such as fuzzy theory [1], intelligent diagnosis [2]–[4], sparse representation [5]–[8], underdetermined source separation [9], wavelet analysis [10], quantitative diagnosis [11], entropy analysis [12], variational mode decomposition [13], cepstrum editing [14], morphological filtering [15], Lempel-Ziv complexity [16] have been studied and applied in fault detection and diagnosis in recent years. To a certain degree, these methods can effectively diagnose the failure of mechanical components. However, if the fault can be detected as early as possible, or even the occurrence of the fault can be predicted, it will be more valuable in practice. As mentioned in [17], the prediction of the remaining useful life (RUL) of machinery is one of the key tasks in condition-based maintenance (CBM). As rolling bearings are widely used in rotating machinery and are prone to failure, more and more attention has been paid to the prediction of the RUL of rolling bearings.

The RUL prediction methods are generally divided into two categories: physical model-based methods and data-driven methods. Physical model-based methods research the failure mechanisms and establish the performance degradation physical model. The enhanced phase space warping was integrated with a modified Paris crack growth model to track the bearing defect and predict the RUL in [18]. Paris-Erdogan model was enhanced into a state-space model in [19]. A new stress-based life model was introduced to predict the RUL of rolling bearing [20]. However, the application of the physical model-based method is limited by the difficulty in grasping the failure mechanisms of complex machinery and estimating the parameters of the model in real time.

At present, data-driven methods are the most studied RUL prediction technology. According to the condition monitoring data of rolling bearings acquired by sensors, this kind of method tracks the dynamic behavior of rolling bearings in real time, updates the model parameters, and predicts the degradation process. The data-driven methods can be generally divided into machine learning methods and statistical model-based methods. The machine learning methods use the available bearing condition monitoring data to learn the degradation process, and then it can be applied to the RUL prediction of the target bearing. A new indicator to assess the bearing health stage was derived from self-organizing map method, and back propagation (BP) neural network was used to study the degradation process of the health indicator in [21]. The neuro-fuzzy model was used to predict the health condition of bearings [22]. Support vector regression was applied to reveal the relationship between sensor values and health indicators, and then the RUL can be predicted [23]. A novel degradation assessment index was acquired from the acoustic emission signal. Then, an optimal Gaussian process regression method

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was employed to predict the RUL of slow speed bearings [24]. However, the machine learning methods need a certain amount of training data and the cost of calculation is relatively high.

The statistical model-based methods establish a statistical model to track the degradation process and predict the RUL based on empirical knowledge. This kind of method does not require a clear understanding of the degradation mechanisms, and the cost of calculation is relatively small, so it can be easily applied to practice. Therefore, this kind of method is currently the most widely used in RUL prediction. A logistic regression model was used to indicate the failure degradation process, and then the relevance vector machine could be trained in [25]. Stochastic filter method was used to establish a posterior conditional probability density function for the RUL at each monitoring point [26]. An adaptive skew-Wiener model was proposed to model the degradation drift of industrial devices [27]. Other methods such as Gamma process model [28] and Markov model [29] had also been widely applied.

In data-driven methods for RUL prediction, an important issue is to decide the time to start prediction (TSP). The general strategy is to track the health indicators of rolling bearing and divide them into several degradation stages. Thus, the establishment and selection of health indicators are very important. Appropriate indicators can accurately judge the different degradation stages of bearings, simplify the established model, and improve the efficiency and accuracy of RUL prediction. Mahalanobis distance was used to fuse multiple statistical indicators into a new feature to reflect the degradation of the bearing. The bearing lifecycle was divided into two stages: health and degradation based on 3σ principle [30]. With the aid of Box-Cox transform for Mahalanobis distance and 3σ principle, the TSP was obtained in [31]. Weighted minimum quantization error was constructed to track the degradation processes [32]. Recurrence plot entropy was extracted as input to build an autoregression model [33]. In addition to the above-mentioned indicators, the root-mean-square (rms) indicator is the most widely used in practice. Its calculation is simple and it can better reflect the different degradation stages of bearings. The regression-based adaptive prediction models were utilized to learn the evolving trend of bearing's rms index, and the gradient of the linear regression model was used to determine the TSP point [34]. The degradation processes were divided into three stages: good condition, gradual wear, and accelerated wear based on rms values. Switching Kalman filter (SKF) method was used to judge the bearing stage at each time to track the bearing degradation process [35], [36]. These studies can achieve the prediction of the RUL of rolling bearings to a certain extent, but there are still some problems to be solved. First, the determination of TSP point is easily disturbed by outliers according to the 3σ principle. Second, the rate of degradation is a dimensional physical quantity. Determining the TSP point by judging whether it exceeds a positive value may be different depending on individual bearing. Finally, as the SKF approach uses multiple models to filter and estimate the probability of each model at every calculation point, the calculation cost is relatively high.

In addition, it came to our attention that the Kalman filter algorithm gets more and more applications in the field of RUL prediction in recent years. An exponential degradation model was proposed and its parameters were evaluated by the extended Kalman filter (EKF) algorithm in [37]. The EKF method was also used in [38] to predict the RUL of rolling bearing. The above-mentioned SKF method was used in [39] to classify various linear degradation stages and predict the future condition. A constrained Kalman filter was proposed to mitigate the random noise in the condition monitoring data in [40].

In summary, in order to judge the TSP point accurately and predict the RUL of rolling bearings effectively, this paper proposes a time-varying Kalman filter method. The main works are as follows. First, a simplified mathematical model is established, whose parameters are estimated by the Kalman filter method. Second, different filter models are established for different health states of bearings. The sliding window relative error is established to monitor the change in the condition monitoring data, and the model is switched in time when the bearing degradation state changes. When the bearing enters the accelerated degradation stage, the prediction of the future condition monitoring data and the estimation of the RUL are initiated. Finally, the proposed method is validated by the run-to-failure experimental data of rolling bearings, which shows its effectiveness.

The rest of this paper is organized as follows. Section II introduces the principle of the proposed time-varying Kalman filter method. In Sections III and IV, the results of processing experimental data are discussed and analyzed. Conclusions are drawn in Section V.

II. Time-Varying Kalman Filter Method

The condition monitoring data of machinery is often disturbed by heavy noises. Therefore, it is vital to estimate the real state accurately from the contaminated signals for the prediction of the RUL. Fortunately, the Kalman filter algorithm is a very efficient method, which can directly filter the time-domain signals and estimate the real state of the system. Therefore, it has attracted more attention in the field of RUL prediction. As a linear minimum variance estimation-based method, it can estimate the true state of the system from the data polluted by the measurement noises and process noises. According to the state space theory, the state of the system is represented by a vector in the Kalman filter. The operation of the system can be seen as a state transfer process.

The state vector of a random discrete-time process is defined as $X_k \in R^n$, then the linear system discrete random difference equation is

$$X_k = AX_{k-1} + W_k \tag{1}$$

where X_k is the $n \times 1$ dimensional system state vector at time k, n is the number of state variables, X_{k-1} is the system state vector at time $k-1$, A is the $n \times n$ dimensional one-step state transition matrix from $k-1$ to k, and W_k is the $n \times 1$ dimensional process excitation noise at time k.

The measurement of X_k satisfies the linear relationship. Define the measurement vector $Z_k \in R^n$, then the measurement equation is

$$Z_k = HX_k + V_k \tag{2}$$

where Z_k is the measurement state at time k, H is the $1 \times n$ dimensional measurement matrix, and V_k is the measurement noise at time k.

Assuming W_k and V_k are mutually independent and normally distributed white noise, the process excitation noise covariance matrix is Q, the measurement noise covariance matrix is R, i.e., $W_k \sim N(0, Q)$, $V_k \sim N(0, R)$.

Thus, it can be seen that the purpose of the Kalman filter algorithm is to use the measured state value Z_k to estimate the real system state X_k which is hid in the noises. The specific steps come as follows.

1) One step prediction of state

$$\hat{X}_k = AX_{k-1}. \tag{3}$$

2) One step prediction of covariance

$$\hat{P}_k = AP_{k-1}A^{\mathrm{T}} + Q. \tag{4}$$

3) Kalman gain

$$K_k = \hat{P}_k H^{\mathrm{T}}(H\hat{P}_k H^{\mathrm{T}} + R)^{-1}. \tag{5}$$

4) State update

$$X_k = \hat{X}_k + K_k(Z_k - H\hat{X}_k). \tag{6}$$

5) Covariance update

$$P_k = (I - K_k H)\hat{P}_k. \tag{7}$$

where $\hat{X}_k$ is the prior state estimate at time k, which is an unreliable estimate made by the algorithm based on the result of the previous iteration. $\hat{P}_k$ is the prior estimate of covariance at time k. As long as the initial covariance P_0 is determined, the value of this covariance matrix at the follow-up moment can be deduced, and as long as the initial covariance $P_0 \neq 0$, its value has little effect on the filtering results and can converge quickly. K_k represents the Kalman gain. It can be known from the formula that the Kalman gain can also be recursively calculated before filtering. The determination of the Kalman gain is one of the key steps in establishing a filter model, which can significantly influence the result of the filtering. X_k and X_{k-1} are the posterior state estimates at time k and $k-1$, respectively, i.e., the optimal estimate for this moment. This value is the result of Kalman filtering. P_k and P_{k-1} are the posteriori estimate of covariance at time k and $k-1$, respectively.

It should be noted that in the above-mentioned Kalman filter algorithm, once the transfer matrix A and measurement matrix H are determined, the filter model is time-invariant. However, the degradation process of rolling bearings is time-variant and generally has different degradation stages. Based on the comprehensive analysis in [17] and [35], several representatives bearing degradation processes are shown in Fig. 1. This figure confirms that the degradation processes of the bearings can be divided into at least two stages. As the Kalman filtering algorithm requires a high-matching degree between

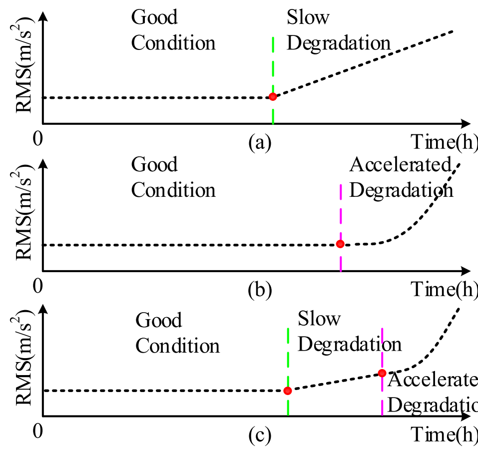

Fig. 1. Various degradation processes of different rolling bearings. (a) Good to slow degradation. (b) Good to accelerated degradation. (c) Good to slow to accelerated degradation.

the established model and the real state evolution process, if only a single filter model is used to filter the condition monitoring data, it does not conform to its actual degradation law, so it is difficult to effectively process and predict the condition monitoring data. According to the general evolution law of bearing degradation process, a novel time-varying Kalman filter method is proposed in this paper, in which two types of filter models are used, namely the Kalman filter based on the linear function model and Kalman filter based on the quadratic function model. The proposed method can track the state of the bearing and adaptively switch the filter model, in order to adapt to the actual degradation process.

The specific processes of the proposed method are shown in Fig. 2. The rms values of the bearing time-domain acceleration data measured by the sensors are used as the health indicator to measure the state of the bearing. Without losing the generality, a new bearing is considered to be initially in health state, so a Kalman filter based on a linear function model is first used to filter the rms values. Meanwhile, two data segments of the original data and the filtered data with the same length are intercepted, and the averages of the two data segments are calculated in order to obtain the relative error. This relative error indicator is defined as the sliding window relative error, which is used to determine the model switching time. The allowable error boundary is preset. If the obtained error value does not exceed the threshold, the evolution trend of the current condition monitoring data is considered to be in accordance with the initially established filter model. Thus the calculation can be transferred to the next monitoring point. Once the relative error value exceeds the threshold, it is considered that the evolution trend of the condition monitoring data at this point is no longer a linear degradation process. Specifically, it is no longer consistent with the initially established Kalman filter based on linear function model. This moment is also named TSP point as mentioned in the introduction. Generally, the process of accelerated degradation of bearings has a highly nonlinear characteristic, so this paper will use a Kalman filter based on a quadratic function model to filter the newly monitored rms values subsequently. Meanwhile, the future condition monitoring data will be predicted

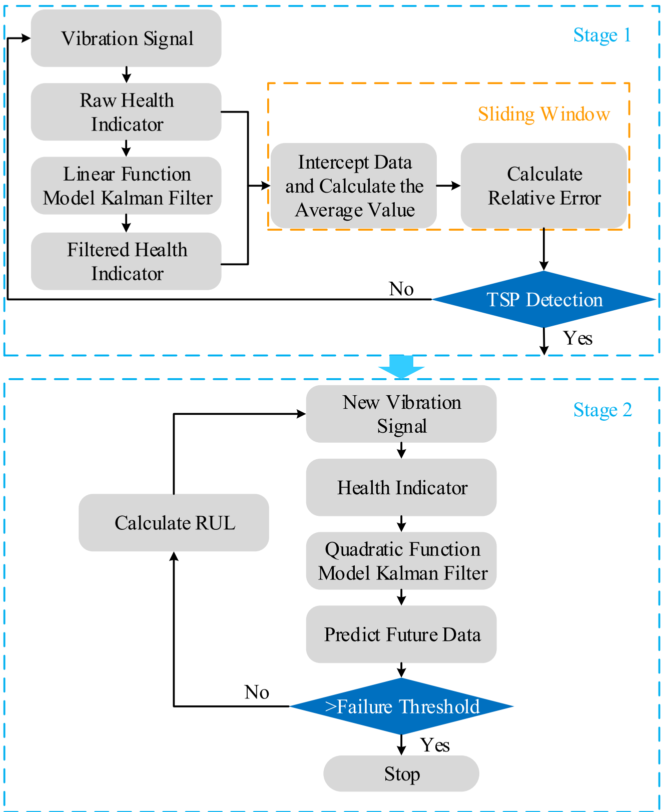

Fig. 2. Flowchart of the time-varying Kalman filter method.

with the updated model parameters at each step of filtering, and the time when the predicted data exceeds the prespecified failure threshold is also judged. Thus, the RUL of bearings can be estimated and the decision-making of CBM can be guided. The two types of established filter models, the sliding window relative error and RUL prediction method, are described in detail below.

1) *Kalman filter based on a linear function model:* The evolution curve of the bearing condition monitoring data is similar to the linear function form in the normal working stage and slow wear degradation stage. Thus, the Kalman filter can be established based on the linear function model.

a) State vector

$$X_k^1 = [x_k] \tag{8}$$

where x_k is the raw rms value at time k.

b) State transition matrix

$$A^1 = [1]. \tag{9}$$

c) Measurement matrix

$$H^1 = [1]. \tag{10}$$

d) Process noise covariance matrix

$$Q^1 = q[\Delta t] \tag{11}$$

where Δt is the sampling interval of the rms data and q is the process error that contains the uncertainty of the system. Its value can be obtained by tuning the filter model with available run-to-failure data. Besides, the measurement error R can be expressed by the variance of a series of rms values in the normal operation stage.

2) *Kalman filter based on quadratic function model:* Normally, it can be known from experience that the shape of the quadratic function curve can better fit the evolution process of the condition monitoring data during the accelerated degradation stage of the bearing.

a) State vector

$$X_k^2 = \begin{bmatrix} x_k \\ \dot{x}_k \\ \ddot{x}_k \end{bmatrix}. \tag{12}$$

b) State transition matrix

$$A^2 = \begin{bmatrix} 1 & \Delta t & \frac{\Delta t^2}{2} \\ 0 & 1 & \Delta t \\ 0 & 0 & 1 \end{bmatrix}. \tag{13}$$

c) Measurement matrix

$$H^2 = \begin{bmatrix} 1 & 0 & 0 \end{bmatrix}. \tag{14}$$

d) Process noise covariance matrix

$$Q^2 = q \begin{bmatrix} \frac{\Delta t^5}{20} & \frac{\Delta t^4}{8} & \frac{\Delta t^3}{6} \\ \frac{\Delta t^4}{8} & \frac{\Delta t^3}{3} & \frac{\Delta t^2}{2} \\ \frac{\Delta t^3}{6} & \frac{\Delta t^2}{2} & \Delta t \end{bmatrix}. \tag{15}$$

3) *Sliding window relative errors:* As described in the previous section, the Kalman filter algorithm is a strictly model-based algorithm that requires a high degree of model accuracy. Once the established model does not match the actual, the filtering results will have large errors. For the bearing degradation process, when it enters the accelerated degradation stage, the evolution curve of the condition monitoring data is no more linear, so the initially established Kalman filter based on the linear function model will cause large errors. Thus, the sliding window relative error is established. Once the error deviates from the acceptable threshold, the currently used filter model would not match the actual state, which means the bearing can be judged to enter the accelerated degradation stage. The established relative error indicator is described in detail below.

The raw rms values are expressed as $\mathrm{RMS_{mea}}(k)$ and the results of the filtered values are expressed as $\mathrm{RMS_{fil}}(k)$. At the present moment, n data points are intercepted forward from two groups of data, and their mean values are calculated. The relative error of these two mean values is defined as the sliding window relative error, which is calculated in the following equation, and its structure schematic is shown in Fig. 3:

$$\mathrm{RE}(k) = \frac{\left|\frac{1}{n}\sum_{i=1}^{n}\mathrm{RMS_{mea}}(i) - \frac{1}{n}\sum_{i=1}^{n}\mathrm{RMS_{fil}}(i)\right|}{\frac{1}{n}\sum_{i=1}^{n}\mathrm{RMS_{fil}}(i)} \times 100\%. \tag{16}$$

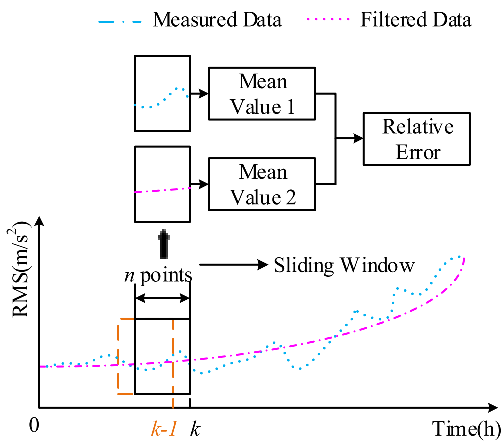

Fig. 3. Structure schematic of the sliding window relative error.

4) *RUL prediction:* Assuming that the current time k is already in the accelerated degradation stage. The future state of the bearing can be estimated by using (3) and (4). When $\mathrm{RMS}_{\mathrm{fore}}(t) \geq$ threshold, the bearing is judged to be invalid and this moment is remembered as t_{fail}. The failure threshold is generally selected based on the rms value of the bearing at the health stage. Thus, the RUL can be calculated as follows:

$$\mathrm{RUL}(k) = t_{\mathrm{fail}} - k. \tag{17}$$

In addition, the uncertainty interval of RUL prediction is also an important evaluation index. In this case, the uncertainty interval can be calculated by the covariance matrix P. This parameter gives the uncertainty between the predicted rms values and the actual measurement. With a confidence interval of 95%, the lower and upper bounds of the predicted rms values can be calculated as follows:

$$\mathrm{RMS}_{\mathrm{lb}}(t) = \mathrm{RMS}_{\mathrm{fore}}(t) - 1.96P(1,1) \tag{18}$$

$$\mathrm{RMS}_{\mathrm{ub}}(t) = \mathrm{RMS}_{\mathrm{fore}}(t) + 1.96P(1,1). \tag{19}$$

Then, the lower and upper bounds of the RUL can be obtained by the time when $\mathrm{RMS}_{\mathrm{lb}}$ and $\mathrm{RMS}_{\mathrm{ub}}$ hit the failure threshold.

III. Experimental Study I: Verification and Discussion

A. Bearing Run-to-Failure Experiment

The run-to-failure experimental data of rolling bearing analyzed in this paper was generated by the NSF I/UCR Center for Intelligent Maintenance Systems with support from Rexnord Corporation, Milwaukee, WI, USA. [41]. The bearing test rig and sensor placement diagrams are shown in Figs. 4 and 5, respectively. The rotation shaft of the test rig was supported by four Rexhord ZA-2115 double-row rolling bearings. A radial load of 6000 lbs (about 26,690N) was applied to the bearings and shaft to accelerate the degradation process. The sensors were placed on the housings of each bearing. The data was collected simultaneously every 10 min. The data sampling rate was set at 20 kHz and the sampling length of each data file was 20 480 points. The experiment was done three times.

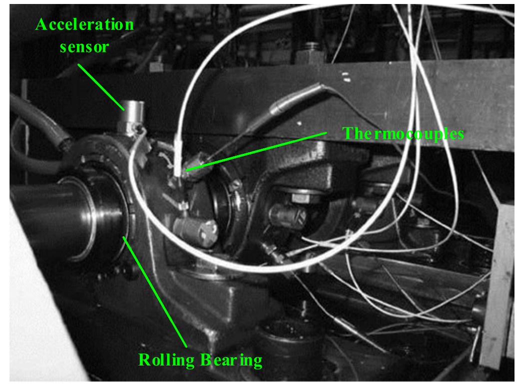

Fig. 4. Bearing test rig.

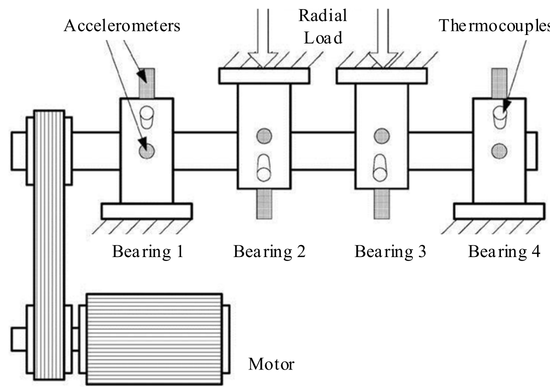

Fig. 5. Schematic of sensor placement.

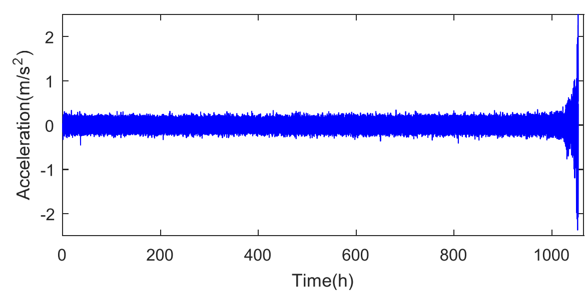

Fig. 6. Vibration signals during the whole operating life.

This paper uses the second and third sets of data to verify the proposed method. After the second experiment, 980 files were obtained for each bearing, and 6323 files were obtained for each bearing after the third experiment. Fig. 6 shows the typical time-domain vibration signals of this set of experiments. The evolution trend of data shows that the degradation process of bearing can be clearly divided into two stages: healthy stage and degradation stage. Therefore, the proposed method is expected to be applied to the RUL prediction of bearing.

B. Analysis of Filtering Results

First, the Kalman filter based on the linear function model is used to process the state monitoring data of bearing 2 in the second experiment and the results are shown by the green circle line in Fig. 7. The rectangular box shown in

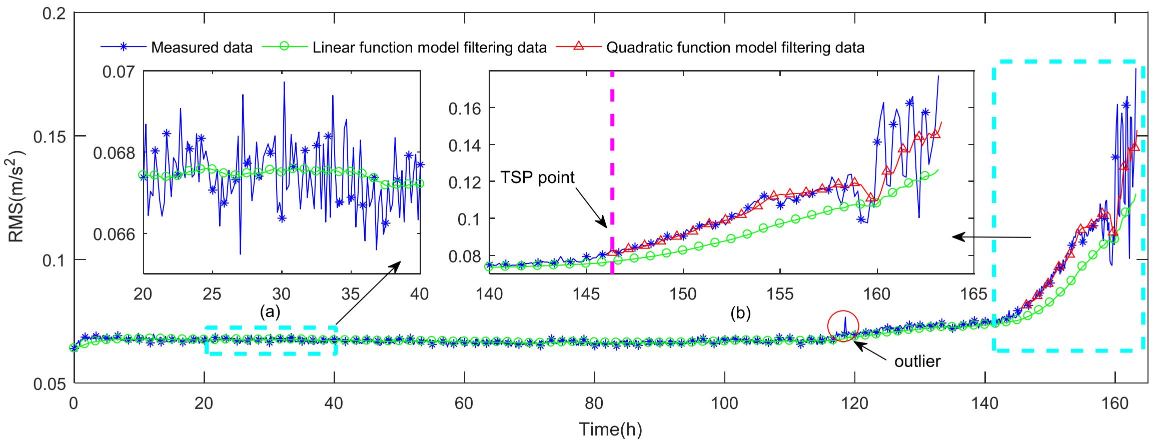

Fig. 7. Time-varying Kalman filtering results of rms values.

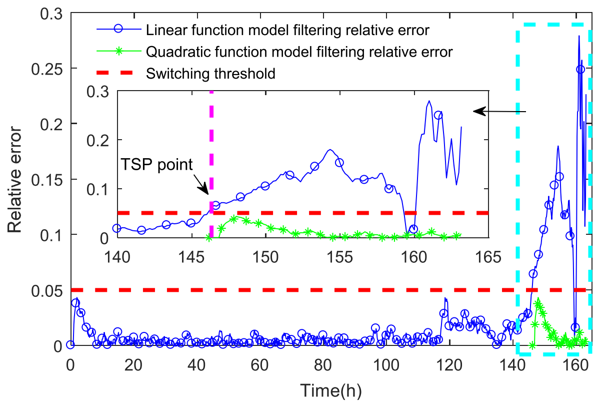

Fig. 8. Sliding window relative error.

the left of Fig. 7(a) is a partially enlarged view near 30 h. It can be seen from the overall evolution trend of the data that the bearing is in the normal working stage near 30 h and the condition monitoring data remains basically unchanged. Therefore, the established Kalman filter based on a linear function model corresponds to the actual situation at this time. It can also be seen from the figure that the Kalman filter eliminates the noise of the original condition monitoring data and the filtering results become smooth.

The rectangular box on the right shown in Fig. 7(b) is a partially enlarged view after 140 h. It can be seen from the figure that the bearing has formed obvious accelerated degradation trend after 146 h but the results of the Kalman filter based on linear function model (green circle line) have an obvious deviation from the original data. This indicates that if the Kalman filter model based on the linear function is still used to filter when the bearing is in accelerated degradation stage, it will not conform to the actual degradation process and will lead to inaccurate filtering results.

In order to accurately obtain the TSP point, the sliding window relative error proposed in Section II is calculated and drawn as shown in Fig. 8. The subgraph in the figure shows the data after 140 h by the way of amplification. The 5% indicated by the red dashed line is the prespecified switching threshold. This threshold is obtained by analyzing the data of four bearings and is universal. When the relative error index is lower than the switching threshold, the Kalman filter based on linear function model matches the true situation and the bearing is judged to be in normal working stage or slow degradation stage. In addition, it is worth noting that the red circle in Fig. 7 indicates the abnormal value of the original state monitoring data. Fortunately, the Kalman algorithm effectively filters the outlier and avoids the miscarriage of TSP point. Once the relative error index factor is monitored to exceed the switching threshold, the linear function model used initially is considered to be no longer consistent with the current monitoring data. The bearing degradation process enters the accelerated degradation stage. The Kalman filter model should be switched to the model based on a quadratic function for filtering and RUL prediction.

When the bearing is detected to enter the accelerated degradation stage, the Kalman filter based on quadratic function model is used to filter the newly monitored data and the results of the filtering are shown as the red triangle line shown in Fig. 7. It can be seen from the figure that the large fluctuations existing in the original data are smoothed and the filtered data becomes smooth and tends to increase monotonously. Moreover, at this stage, the filtering results based on a quadratic function model can better fit the original condition monitoring data. The sliding window relative error at this stage is shown as the green star line shown in Fig. 8. It can be seen that the error value at each time does not exceed the switching threshold. However, the indicators obtained by the previous linear function model mostly exceed the switching threshold, which indicates that switching the filter model in time can obtain better filtering results. In summary, it can be seen that the proposed time-varying Kalman filter method has a good effect on bearing degradation stage identification and data filtering.

C. Remaining Useful Life Prediction

According to (3) and (4), the future rms values predicted at two different moments (t_1 and t_2) in the accelerated degradation stage are shown in Fig. 9. It can be seen from the figure that the predicted curves fit well with the true rms evolution trend of the bearing. In addition, the uncertainty

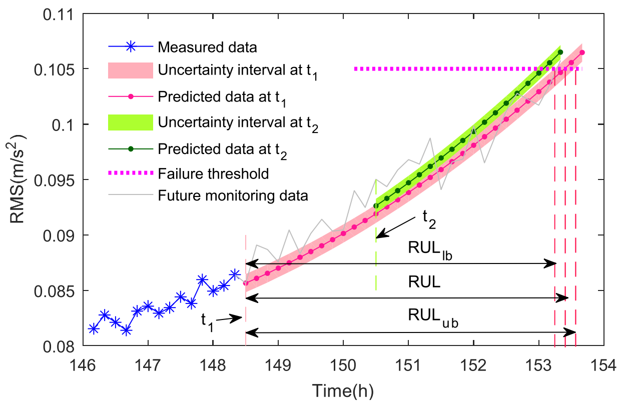

Fig. 9. Predicted results of bearing condition monitoring indicators. The predicted points are at $t_1 = 148.5$ h and $t_2 = 150.5$ h.

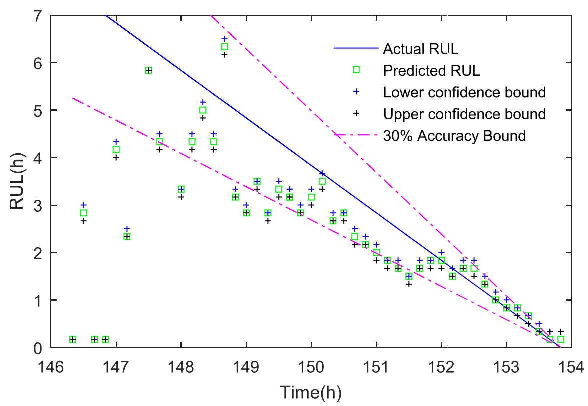

Fig. 10. Predicted RUL of bearing 2 in the second experiment.

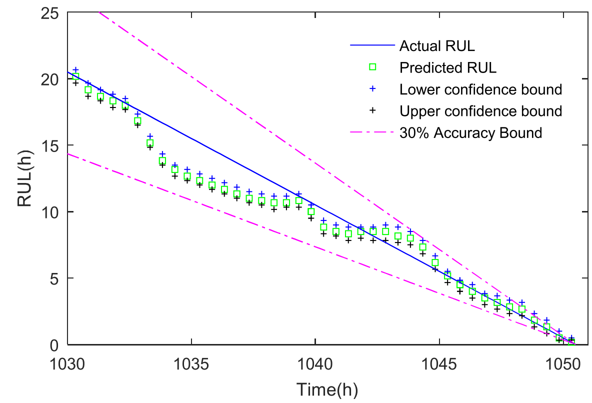

Fig. 11. Predicted RUL of bearing 2 in the third experiment.

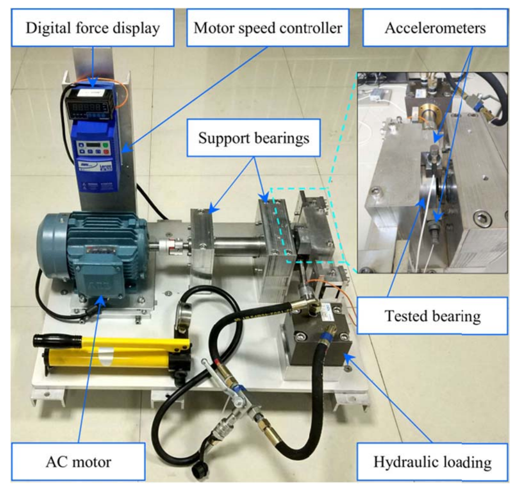

Fig. 12. Bearing test rig.

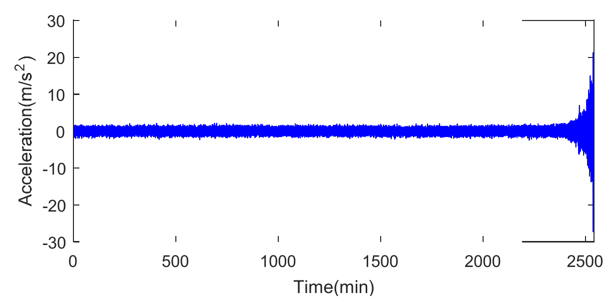

Fig. 13. Vibration signals during the whole operating life.

boundaries of state prediction are also exhibited in the figure. The upper and lower boundaries of RUL can be calculated according to the time when the uncertainty boundaries hit the failure threshold, as shown in the figure. The obtained uncertainty boundaries are very narrow in this case, which shows the high reliability for RUL prediction. Then, the RUL predicted continuously of bearing 2 in the second experiment is shown in Fig. 10. The RUL values predicted initially deviate significantly from the actual values. This is because the parameters of the switched filter model have not yet converged. With the gradual development of the degradation process, the predicted RUL values are close to the true value and only a few predicted life values exceed 30% of the allowable error limit, so the prediction effect is well. In order to further verify the proposed method, the life prediction of bearing 2 in the third experiment is also carried out. To save space, only more concerned RUL prediction results are shown in Fig. 11. It can be seen from the figure that the results of life prediction are very close to the real values, which shows the superiority of the proposed method.

IV. Experimental Study II: Verification and Discussion

A group of shared bearing run-to-failure data in [42] is used to further verify the effectiveness of the proposed method. The test rig of this experiment is shown in Fig. 12. Two accelerometers are mounted on the horizontal axis and vertical axis, respectively. The experiment is carried out under three different operating conditions and five bearings are tested under each working condition. The sampling frequency is set as 25.6 kHz, and the data files are recorded every 1 min. A group of typical time-domain vibration signals of this experiment is shown in Fig. 13. This paper uses the data of bearing 1 in the operation condition 2 and operation condition 3 to analyze.

The time-domain filtering results of bearing 1 in condition 3 are shown in Fig. 14. It can be seen that the proposed method effectively filters the noise in the original condition

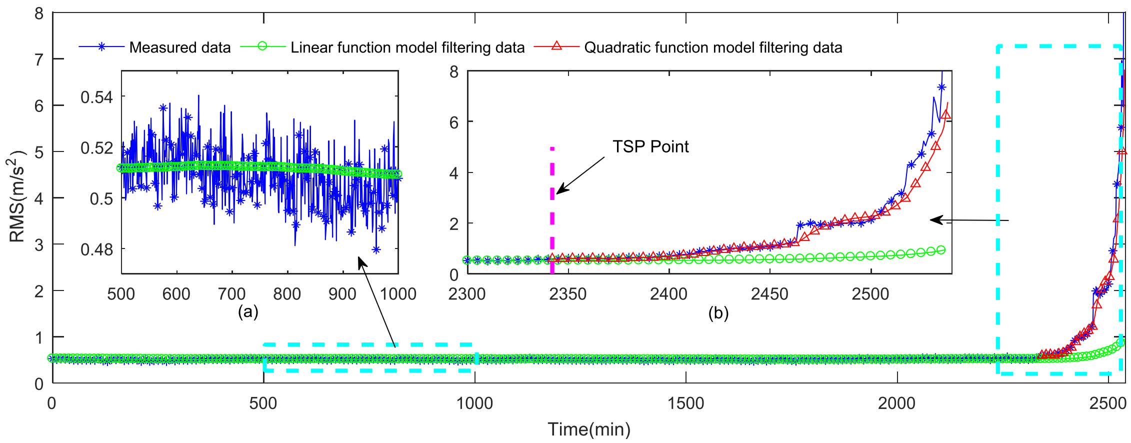

Fig. 14. Time-varying Kalman filtering results of rms values.

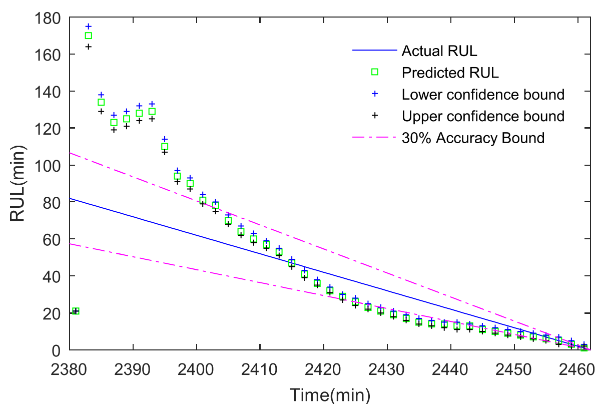

Fig. 15. Predicted RUL of bearing 1 in the operation condition 3.

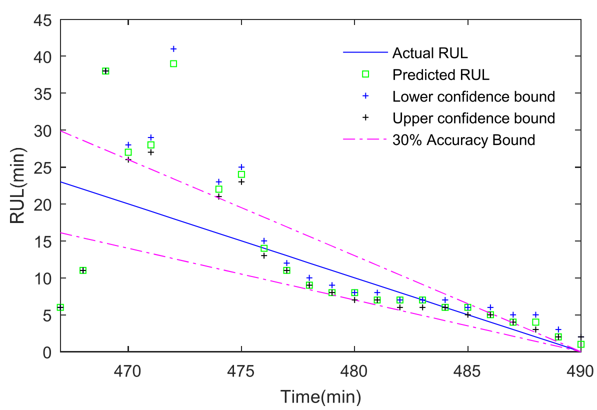

Fig. 16. Predicted RUL of bearing 1 in the operation condition 2.

monitoring data and accurately detects the TSP points. The RUL prediction results of this bearing are shown in Fig. 15. Most RUL prediction results fall within the allowable accuracy bound. In addition, Fig. 16 shows the RUL prediction results of bearing 1 in the operation condition 2. In a word, from the analysis of a large number of actual data, it can be seen that the proposed method has achieved good results in RUL prediction of rolling bearings.

V. Conclusion

A new time-varying Kalman filter method is proposed in this paper to predict the RUL of the rolling bearings. The degradation process of the bearing is divided into the normal working stage (or slow degradation stage) and accelerated degradation stage by analyzing the evolution curve of the rms index of the rolling bearing life cycle condition monitoring data. Among them, the condition monitoring data of normal working stage and slow degradation stage changes linearly, so the Kalman filter based on a linear function model is established to filter the monitoring data. The condition monitoring data of the accelerated degradation stage increases rapidly and exhibits nonlinear variation, so the Kalman filter based on a quadratic function model is used for filtering. As the Kalman filter algorithm has a high demand for the accuracy of the model, the sliding window relative error is constructed to judge the bearing degradation state and switch the two filter models. By analyzing multiple groups of data, a model switching threshold of 5% is proposed. When the relative error index exceeds the prespecified switching threshold, the bearing is judged to enter the accelerated degradation stage, so the filter can be switched adaptively from the filter model based on the linear function to that based on quadratic function. At the same time, the prediction of future condition monitoring data is started, and the time when the predicted data exceeds the prespecified failure threshold is judged, so as to estimate the RUL of the bearing.

The run-to-failure experimental data of rolling bearings verifies the effectiveness of the proposed method.

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