Degradation Pattern Identification and Remaining Useful Life Prediction for Mechanical Equipment Using SKF-EN

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This work was supported in part by the Aeronautical Science Foundation of China under Grant 20142896022.

ABSTRACT Due to the influence of working environment and stress, the failure degradation process of mechanical equipment is characterized by non-stationarity and uncertainty. The degradation pattern of a large number of mechanical equipment obeys the process from steady degradation to accelerated degradation. The rotating machinery wear results in gradual degradation in the early stage while rough contact surface and spall of equipment leads to accelerated degradation stage. However, the change-point of the degradation patterns are uncertain which leads to the ambiguity of the degradation pattern transition and uncertainty of the remaining life prediction model. Aiming at the problems of ambiguity of the pattern transition and uncertainty of the prediction model, the SKF-EN method is proposed in this paper. In this method the real-time data samples are processed through Switching Kalman filters, and the current degradation pattern is identified based on the posterior probability between the two filters of steady degradation and accelerated degradation. When the filters confidence indicates the entering of accelerated degradation pattern, the Elastic Net is used to model the degradation trajectory and predict its life in real time. The method was verified with an airborne fuel pump and rolling element bearings, and it realized the real-time identification of the degradation pattern and effective prediction of the remaining useful life.

INDEX TERMS Degradation pattern recognition, switching Kalman filter, elastic net, remaining useful life prediction.

I. INTRODUCTION A large number of mechanical equipment is of high reliability and long life, such as fuel pumps [1], [2], steering gears [3], bearings [4], [5], etc. They are widely deployed in the fields of aerospace, network communication, transportation, environmental protection and other domains. They play important roles in the operation of mechanical system to ensure normal operation. A little glitch could turn into serious consequences which leads to great loss of life and property. So, it is of great significance to conduct health management and life prediction on them [6]–[8].

The degradation of mechanical equipment is often accompanied by the transformation of the degradation pattern. The identification of the degradation pattern is conducive to establishing a corresponding degradation model for a specific degradation pattern which improves the prediction accuracy. At present, for the remaining life modeling of multiple degraded patterns, most scholars adopt methods of multi-model fusion [9]. Li et al. [10] proposed local weighted linear regression to model multiple degraded models of airborne bearings, and used ensemble learning to perform online pattern recognition and life prediction. Liu et al. [11] proposed the multi kernel RVM method to train life models, and used the fruit fly algorithm to optimize the parameters of a function consisting of multi kernel functions. Xiao and Zhang [12] proposed a combined forecasting model with IMGM and LSSVM and was proved to be more accurate than single forecasting model. Methods mentioned above applied invariable models and the weighs of each model were trained from offline data and were locked during operation. When the parameters of equipment differ, the models and weighs of each model may be inaccurate.

In addition, some scholars used online data to adjust the model parameters to optimize the remaining life modeling. Sun et al. [13] proposed an exponential stochastic degradation model to model equipment degradation, and used Bayesian methods to update random parameters based on
real-time degradation data. Cai et al. [14] proposed the transfer learning method to use the process monitoring data samples to train the remaining life prediction model. They used the adversarial domain adaptation training to utilize a small number of target domain samples under new process conditions to adjust some model parameters on the source domain prediction model. Methods mentioned above took full account of individual differences between mechanical equipment and models were updated in real time, however, specific degradation patterns were not recognized in these methods and the health status were not specific.

In addition, Bae et al. [15] proposed a change-point regression formula to fit the life degradation model, and the change-point should be obtained through offline training. Lim and Mba proposed the use of Switching Kalman filtering to fit the degraded trajectory of the multi degradation models fusion, and did the multi-step prediction. However, these methods made little use of accelerated degradation data and had poor prediction effects on non-stationary degradation processes.

The regularization forms of linear regression include Lasso regression, Ridge regression and Elastic Net regression and so on. They are used to solve the problem of overfitting and the irreversibility of matrix during calculation of linear regression. Up to now, Ridge regression and Elastic Net regression have been used for key variable selection and process monitoring. The ridge regression was applied to select safety unrelated-quality related variables to build the quality related monitoring model in the PIOC method [17]. The variables of abnormal states were isolate using elastic net [18] since sparse models could be derived from it, so that the auto encoder could be established with key variables. The MSEN [19] was proposed to recognize the quality related fault with monitoring model determined by the k nearest neighbor rule and the elastic net was applied to calculate the relationship between process variables and quality variables.

Aiming at the uncertainty of the change-point [20] for life prediction, the SKF-EN method is proposed for real-time life prediction in this paper for degradation process which degradation model changes.

The life prediction start point is determined by Switching Kalman filter, and the Elastic Net is used for life prediction. The paper is organized as follows: Section 2 describes the fundamental theory of the algorithm with the Kalman filter, the switching Kalman filter and the Elastic net and the algorithm flow chart is provided. Section 3 introduces the performance degradation test of airborne fuel pumps and rolling element bearings and the data analysis is conducted using the SKF-EN. The result verifies that the algorithm proposed can recognize the starting point of the accelerated degradation pattern and realize the residual life prediction of mechanical equipment.

II. SWITCHING KALMAN FILTER-ELASTIC NET
A. KALMAN FILTER
The Kalman filter is a recursive linear minimum variance filter. Under the circumstances of system noise and measurement noise, dynamic estimation of state can be achieved according to the minimum variance criterion [21]. The Kalman filtering process is described by the state space model as follows:

\[ X_k = \Phi_{k,k-1}X_{k-1} + \Gamma_{k-1}W_{k-1} \] (1)

Measurement equation

\[ Z_k = H_kX_k + V_k \] (2)

where \( X \) is the state to be estimated in the system which cannot be directly obtained by observation; \( Z \) is the sequence of quantities collected by sensors which indirectly reflected the value of \( X \); \( \Phi \) is the one step state transition matrix for the system; \( H \) is the measurement matrix; \( \Gamma \) is the system noise driven matrix; \( W \) is the system noise sequence and \( V \) is the measurement noise sequence.

The information updating process of Kalman filter consists of two parts: the time updating process as in (3-4) and the measurement updating process as in (5-7):

\[ \tilde{X}_{k|k-1} = \Phi_{k,k-1}\tilde{X}_{k-1} \] (3)

\[ P_{k|k-1} = \Phi_{k,k-1}P_{k-1|k-1}\Phi_{k,k-1}^T + \Gamma_{k-1}Q\Gamma_{k-1}^T \] (4)

Measurement update:

\[ \hat{X}_k = \tilde{X}_{k|k-1} + K_k(Z_k - H_k\tilde{X}_{k|k-1}) \] (5)

\[ K_k = P_{k|k-1}H_k^T(H_kP_{k|k-1}H_k^T + R_k)^{-1} \] (6)

\[ P_k = (I - K_kH_k)P_{k|k-1} \] (7)

In the formulas above, \( Q \) is the system noise variance matrix, and \( R \) is the measurement noise variance matrix.

The Kalman filter can make an informed prediction of the next state of the system even with noise interference. It estimates the system state with a linear equation of state and make accurate estimation when system equations and measuring equations are nonlinear time-varying. To overcome the limitation, the Switching Kalman filter is used for real - time state estimation of nonlinear system in this research.

B. SWITCHING KALMAN FILTER
The Switching Kalman filter is composed of several standard Kalman filters, and the models are established for each degradation process to reflect its degradation trend. Multiple filters are used to filter the real-time data of a single sample, and the generalized pseudo-bayesian algorithm (GPB) [22] is used to sum the estimated values of each filter at the previous moment with a certain weight to obtain the filter input at the present moment, so as to realize the dynamic estimation of the system state. The specific algorithm is as follows:

The model transformation condition probability \( S_k^{ij} \) which represent the probability of states changing from \( S_{k-1}^{ij} \) to \( S_k^{ij} \) is obtained through the model probability \( S_k^i \) and model...
transformation probability $T_{ij}$ as follows:

$$S_{k}^{ij} = \frac{T_{ij}S_{k-1}^{i}}{\sum_{i=1}^{n} T_{ij}S_{k-1}^{i}}$$  \hspace{1cm} (8)

According to the state of each filter at the previous moment and the conditional transition probability of each filter, the input state $\hat{X}_{k-1}$ and variance $P_{k-1}$ are updated through collapse approach [23] as in (9-10):

$$\hat{X}_{k-1} = \sum_{i=1}^{n} S_{k}^{ij} \hat{X}_{k-1}$$ \hspace{1cm} (9)

$$\tilde{P}_{k-1} = \sum_{i=1}^{n} S_{k-1}^{ij}[P_{k-1} + (\hat{X}_{k-1}^{i} - \hat{X}_{k-1})(\hat{X}_{k-1}^{i} - \hat{X}_{k-1})^{T}]$$ \hspace{1cm} (10)

Then the standard Kalman filters operate via (3-7) with the revised state $\hat{X}_{k-1}$ and the variance $\tilde{P}_{k-1}$. Meanwhile the state estimate $\hat{X}_{k}^{i}$ and variance $P_{k}^{i}$ from each model are derived. After time update step (3) and (4), the measurement residuals $V_{k}$ and residuals variances $C_{k}$ are obtained by the deviation of state measurement and state estimation as in (11-12):

$$V_{k}^{i} = T_{ki} - H_{ki}\hat{X}_{k-1}$$ \hspace{1cm} (11)

$$C_{k}^{i} = H_{ki}^{T}\tilde{P}_{k-1}^{-1}H_{ki} + R_{k}^{i}$$ \hspace{1cm} (12)

Take the normal distribution probability of residual variance $L_{m}^{i}$ as the probability of each filter which is calculated as the probability at $V_{k}$ of the normal distribution with 0 as the mean and $C_{k}$ as the variance:

$$L_{m}^{i} = N(V_{k}^{i}; 0, C_{k}^{i})$$ \hspace{1cm} (13)

Calculate the probability $L_{t}^{i}$ of each filter from the state transition matrix and the model probability $S_{k-1}^{i}$ at the last moment:

$$L_{t}^{i} = \sum_{i=1}^{n} T_{ij}S_{k-1}^{i}$$ \hspace{1cm} (14)

Combining the likelihood of filters derived from measurement residual $L_{k}^{i}$ and the likelihood of filters derived from state transition, the normalized probability of each model is defined as follows:

$$S_{k}^{i} = \frac{L_{m}^{i} L_{t}^{i}}{\sum_{i=1}^{n} (L_{m}^{i} L_{t}^{i})}$$ \hspace{1cm} (15)

Input status update per iteration:

$$\hat{X}_{k}^{i} = \sum_{i=1}^{n} (S_{k}^{i} \hat{X}_{k}^{i})$$ \hspace{1cm} (16)

Input variance update per iteration:

$$P_{k}^{i} = \sum_{i=1}^{n} S_{k}^{i}[P_{k}^{i}(\hat{X}_{k}^{i} - \hat{X}_{k})(\hat{X}_{k}^{i} - \hat{X}_{k})^{T}]$$ \hspace{1cm} (17)

where $i,j = 1, 2, 3 \ldots, n$ are the index of filters, and $k = 1, 2, 3 \ldots, m$ is the sequence of time. The relation of model probability between different models reflects the confidence of each degradation stage at present. The phase of degradation process can be judged by monitoring the model probability in real time. Fig. 1 shows the transfer process from the former state to the later state and the relation between parameters.

**C. ELASTIC NET REGRESSION**

The regularization forms of linear regression include Lasso regression, Ridge regression and Elastic Net regression [24]. The regularization method adds regular terms to the cost function of the original linear regression to achieve the purpose of minimizing the weight of the model while fitting data. The regular term of Ridge regression is $l_{2}$ norm of weight vector $\alpha \sum_{i=1}^{n} \theta_{i}^{2}$ and the regular term of lasso regression is the $l_{1}$ norm of weight vector $\alpha \sum_{i=1}^{n} |\theta_{i}|$. Elastic net regression combines Ridge regression and Lasso regression, so that $l_{2}$ norm and $l_{1}$ norm each have a certain contribution value in the cost function expression. The regular term of Elastic net algorithm can be expressed below:

$$r \alpha \sum_{i=1}^{n} |\theta_{i}| + \frac{1-r}{2} \alpha \sum_{i=1}^{n} \theta_{i}^{2}$$ \hspace{1cm} (18)

where $r$ is a very important parameter, which determines the dominant regular method. In this paper, the parameter $r$ was determined traversing with the step of 0.1 from 0.1 to 1. The cost function of elastic net can be expressed as the following equation:

$$J(\theta) = MSE(\theta) + r \alpha \sum_{i=1}^{n} |\theta_{i}| + \frac{1-r}{2} \alpha \sum_{i=1}^{n} \theta_{i}^{2}$$ \hspace{1cm} (19)

Since Elastic Net gives consideration to the advantages of the first two methods, it is more applicable, especially when the feature dimension is higher than the number of training samples or the feature is strongly correlated, the regression of Elastic Net is more stable [25].
D. SKF-EN ALGORITHM FLOW

The switching Kalman filters can distinguish degradation stages, but the remaining useful life prediction is not accurate when the mathematical model is not precise. The Elastic Net has advantage in small sample analysis, and the data in the same degradation stage have better linearity which reduce the degree of difficulty to predict the RUL. The specific algorithm flow is as Fig. 2. And the specific implementation steps are given below:

(1) Model establishment. The rough degradation trend is estimated according to the prior acknowledge. The number of degradation stages is fixed and the mathematical models for each degradation pattern are established.

(2) Data filtering. The real time data are input to the filters and multiple Kalman filters process simultaneously according to (1)-(7). The parameters in standard Kalman filters are updated and the outputs of each filter are the predicted state estimate $\hat{X}_k^i$, the predicted estimate covariance $P_k^i$, the measurement residual $V_k^i$ and the residual covariance $C_k^i$.

(3) Pattern identification. The normalized probability of each model $S_k^i$ is calculated using (13)-(15). As the degradation state aggravates, the steady degradation model probability decreases while the accelerated degradation model probability increases accordingly, so the probability $S_k^i$ can be regarded as the confidence of the specific degradation pattern. If it enters the accelerated degradation stage, move on to the next step. The prediction start point will be defined and the training set will be sampled between the change point and the start point. If it does not, continue the filtering procedure.

(4) Data reprocessing. According to the data characteristics, the data space is reconstruction to multi-dimensional space with the target of autocorrelation of the data. The parameter K in K-CV is selected traversing with the step of 1 from 2 to 11 and the objective function is set as the RMS of the mean square error. Then the training dataset is divided into K subjects to implement the K-Cross Validation method.

(5) Predictive model training. The parameter $r$ in elastic net is selected by traversing from 0.1 to 1 with the step of 0.1. The objective function is set as the RMS of the mean square error. The cost function is set as (19), and the data sampled between the start point and change-point are used to train the prediction model. The three-dimensional vector is input to the elastic net and the next data point is the output of it. If the cost function $J(\theta)$ is convergent, move on to the next step. If it does not, continue updating the parameter $\theta$.

(6) RUL prediction. Reconstruct the online data into multi-dimensional space and input it to the predictive model. The single point iteration method is used for multi-step prediction as the single-step prediction results are added to the training set for prediction.

III. PERFORMANCE DEGRADATION TEST AND DATA ANALYSIS

To verify the effectiveness and practicability of the proposed method SKF-EN, two case study are carried out. In the first case study, the airborne fuel pump degradation test platform is established and the online data are collected to access the performance of SKF-EN. In the second case study, the method is further validated using the XJTU-SY bearing datasets with different state transfer models according to the characteristic of the datasets.

A. CASE STUDY I; FUEL PUMP PERFORMANCE DEGRADATION TEST AND DATA ANALYSIS

The aircraft fuel system is an important part of modern aircraft which is used to store fuel on the aircraft and deliver fuel to the engine. It also has the function of providing heat dissipation for the working medium of the air conditioning system, the generator cooling system, the hydraulic system, etc. The continuous and stable operation of the fuel system is vital to ensure the safety and reliability of the aircraft. The airborne fuel pump is the core accessory of the aircraft fuel system and its reliability is directly related to the safe operation of the aircraft fuel system.

1) PERFORMANCE DEGRADATION TEST DESCRIPTION

Airborne fuel pumps have the characteristics of high reliability and high price and the trouble-free operation time is quite long for thousands of hours, so it is difficult to obtain...
full life cycle degradation data [26]. Degradation data, which can reflect product performance, are the basis of degradation modeling and remaining life prediction, so a degradation test is performed to obtain degradation data.

In the previous study, it was found that the outlet pressure signal of the airborne fuel pump was closely related to the health status of the airborne fuel pump [27], so the outlet pressure signal of the airborne fuel pump was selected as an indicator of performance degradation. Cyclic electrical stress tests under three kinds of voltages are carried out for a certain airborne fuel pump and the outlet pressure is collected in-time. Each test cycle spans 10h, and each cycle contains three processes as follows:

The test simulates the working conditions of the fuel pump in the real operating environment. The sensors are used to measure the outlet pressure signal value of the fuel pump as the degradation characteristic. The data collection is carried out every three hours in the third voltage process of each cycle. Fig. 4 shows the degradation curve of the collected outlet pressure over time:

As from the degradation curve, the degradation process of fuel pump can be roughly divided into two stages: steady degradation stage (0h-1000h) and accelerated degradation stage (1000h-1950h).

2) DEGRADATION MODE RECOGNITION

The degradation process is divided into two stages and each stage are linearized with linear state equations. Two Kalman filters are established for two modes of degradation processes of fuel pump, and their state transfer matrixes are as follow:

\[
\Phi_1 = \begin{bmatrix}
1 & -T & 0 \\
0 & 1 & 0 \\
0 & 0 & 0
\end{bmatrix}, \quad \Phi_2 = \begin{bmatrix}
1 & -T & -T^2/2 \\
0 & 1 & -T \\
0 & 0 & 1
\end{bmatrix}
\]

where \( \Phi_1 \) is the state transition matrix of the filter representing the stationary degradation process, and \( \Phi_2 \) is the state transition matrix for the accelerating degradation process. The three states in the input vector \( \hat{X} \) respectively represent the outlet pressure \( x \), the first derivative \( \dot{x} \), and the second derivative \( \ddot{x} \).

The measurement matrix, the measurement noise variance matrix and the system noise variance matrix are shown below:

Measurement matrix:
\[
H_1 = H_2 = \begin{bmatrix}
1 & 0 & 0
\end{bmatrix}
\]

Measurement noise variance matrix:
\[
Q_1 = 0.01 \begin{bmatrix}
1/3 & 1/2 & 0 \\
1/2 & 1 & 0 \\
0 & 0 & 0
\end{bmatrix}, \quad Q_2 = 0.01 \begin{bmatrix}
1/20 & 1/8 & 1/6 \\
1/8 & 1/3 & 1/2 \\
1/6 & 1/2 & 1
\end{bmatrix}
\]

System noise variance:
\[
R_1 = R_2 = 0.017
\]

The fuel pump outlet pressure data obtained from the experiment mentioned above are used as the input state of Switching Kalman filter. The filter data are obtained using switching Kalman Filter as in Fig. 5.

The probability of each model \( S_k^i \) which is obtained by (15) and it reflects which model is dominant and which degradation stage is more likely. So, in the research, \( S_k^i \) is regarded as the degradation pattern confidence. The confidence of the degradation mode obtained by the weight of each filter in the filtering process is as shown in Fig. 6.

As Fig. 5 shows that the filter does not reach a stable state in the early working period, and tends to stable convergence as the number of iterations increases. At the time point \( t = 1000h \), the accelerated degradation starts to dominate, which is the same as the conclusion in Fig 4.
3) REMAINING USEFUL LIFE PREDICTION

The outlet pressure signal of the airborne fuel pump is a set of one-dimensional data, which has certain correlation in time dimension [28]. To make full use of data sequence correlation, this research employs the method of data space reconstruction [29], and the one-dimensional data sequence is converted into the following matrix:

\[ E = \begin{vmatrix}
    x_1 & x_2 & \cdots & x_{N-m+1} \\
    x_2 & x_3 & \cdots & x_{N-m+2} \\
    \vdots & \vdots & \ddots & \vdots \\
    x_m & x_{m+1} & \cdots & x_N
\end{vmatrix} \]

Then multi-step prediction can be conducted using single point iteration method:

\[
\hat{x}_{k+1} = f(x_k, x_{k-1}, \ldots x_{k-m+1}) \\
\hat{x}_{k+2} = f(\hat{x}_{k+1}, x_k, \ldots x_{k-m}) \\
\vdots \\
\hat{x}_{k+h} = f(\hat{x}_{k+h-1}, \hat{x}_{k+h-2}, \ldots \hat{x}_{k+h-m}) \quad (h > m)
\]

As in the equations, \( f \) is the prediction model and \( m \) is the dimension of reconstructed space.

Through autocorrelation analysis of the collected exit pressure data series, this research reconstructs the data space into three-dimensional space so as to use three consecutive data to predict the last data to be measured, which improves the accuracy of the prediction results.

The elastic net model is established to predict the next state with three-time continuous state points, and the predicted state was used as the input of the next prediction step. The multistep prediction using reconstructed data space can describes nonlinear characteristics and matches the actual degradation trend.

During the experiment, the proportion of two basic filters in SKF algorithm is compared in real time to vote on the degradation mode of the fuel pump currently. In order to eliminate the influence of abnormal points on filter weight, it is stipulated in this paper that only when the weight of a filter is larger than that of another filter for at least one test cycle can the mode be regarded as the degradation mode of fuel pump.
When it is determined that the fuel pump enters into the acceleration degradation mode, the collected data will be saved in real time. For data with a limited number of samples, it is difficult to obtain sufficient training sets and validation sets when constructing the classifier, and the stability of training results is poor. Therefore, K-Cross Validation method is usually adopted to obtain training sets and validation sets. Combining the method of K-CV with Elastic Net solves the problem of insufficient sample size in the initial life prediction. In this paper, a 10-CV scheme is selected to further improve the accuracy of life prediction by using 10-CV-EN.

After a period of data are collected, the data of this period will be input into 10-CV-EN for training, and a life prediction model will be established. The data collected in the later period will be input into this model for prediction.

Since the outlet pressure of the fuel pump is 63-75KPa during normal operation, the failure threshold is set as 63KPa, and the value decrease to 63KPa after 1350 hours in the degradation test. Then different starting points are selected as prediction starting points: \( t_1 = 1100 \)h, \( t_2 = 1150 \)h, \( t_3 = 1200 \)h, \( t_4 = 1250 \)h. The prediction results are shown as Fig. (8-11):

According to Figures 7-10, under different starting points, the predicted failure time of life is 1356h, 1359h, 1347h and 1350h respectively, with a small difference from the true value of 1350h. For any prediction starting point in accelerated degradation mode, the method can get relatively accurate results. And the accuracy of life prediction is increased when the start point approaches the failure point.

### CASE STUDY II: ROLLING ELEMENT BEARING PERFORMANCE DEGRADATION TEST AND DATA ANALYSIS

As one of the key components of rotating machinery, rolling bearing’s health status directly affects the operating...
S. Wang 
et al.: Degradation Pattern Identification and Remaining Useful Life Prediction for Mechanical Equipment

FIGURE 13. (a) Pattern confidence and change-point of Bearing1_1; (b) Pattern confidence and change-point of Bearing1_2; (c) Pattern confidence and change-point of Bearing1_3.

performance of the entire mechanical equipment. Accurate prediction of the life degradation trend provides valuable state information and sufficient response time for equipment maintenance which is of great significance to ensure normal operation and reduce the maintenance cost [30].

1) DATA DESCRIPTION
The data set is collected by two acceleration sensors in horizontal and vertical directions, and the data are recorded every 1 minute with the recording time of 1.28s and sampling frequency of 25.6kHz. The test stress conditions are showed as Table 2. Fifteen bearings are divided into three groups according to operation conditions, and each group contains five bearings.

In these tested bearings, bearing 1_4 comes into instant failure without degradation process and bearing 3_2 has faults on the inner race, ball, cage and outer race which results in strong mutability. On line prediction can not be implemented on such equipment. In this paper, the life cycle data of thirteen bearings under different operation conditions are selected to verify the SKF-EN algorithm. Firstly, three bearings are taken as examples to clarify the process of change-point detection and RUL prediction. Then the results of total thirteen bearings are presented in the end. The vibration signals of the bearings reflect the health condition and fault type, and the vertical vibration signals of bearing1_1, bearing 2_1 and bearing 3_1 are applied to conduct the RUL prediction. The three tests of bearing 1_1, 2_1 and 3_1 last for 123 minutes, 491 minutes and 2538 minutes respectively.

2) DATA PROCESSING
Firstly, the original time domain signals are preprocessed. Taking bearing 1_1 as an example, the raw data are as in Fig. 11 and the data after root-mean-square filtering is shown in Fig. 12.

As Fig. 2 shows that the degradation process of bearings is divided into two distinct stages: the stationary degradation stage and the accelerated degradation stage. Then, the RMS data are input into the SKF-EN to identify the degradation pattern. As the accelerated degradation stage is of rising trend, the corresponding Kalman filters are established for degradation processes of bearings, and the state transfer matrixes are as follows:

\[
\Phi_1 = \begin{bmatrix}
1 & 0 & 0 \\
0 & 0 & 0 \\
0 & 0 & 0
\end{bmatrix}
\quad \Phi_2 = \begin{bmatrix}
1 & T & 0 \\
0 & 1 & 0 \\
0 & 0 & 0
\end{bmatrix}
\]

The RMS data of the three bearings are input into the switching Kalman filters and the change-points are obtained at the intersection of confidence lines which represent the two degradation patterns. The change-points are shown as Fig. 13.

As the figures show, the stationary state is steady as the bearings operate, and it takes up most of the lifetime of bearings. The degradation patterns change at 74.32 minutes, 452.50 minutes and 2411.21 minutes in the degradation of the three bearings, and the accelerated degradation pattern becomes the ascendent pattern. The degradation pattern confidence is sensitive to changes of degradation patterns and
TABLE 3. The result of the RUL prediction of tested bearings.

| Tested bearing | Actual RUL (min) | Estimated RUL (min) | Error (min) | Estimated RUL (min) | Error (min) | Estimated RUL (min) | Error (min) |
|----------------|------------------|---------------------|-------------|---------------------|-------------|---------------------|-------------|
| Bearing 1_1    | 108              | 103.8               | 4.2         | 101.1               | 6.9         | 102.5               | 5.5         |
| Bearing 1_2    | 59               | 64.9                | 5.9         | 62.9                | 3.9         | 57.7                | 1.3         |
| Bearing 1_3    | 120              | 140                 | 20          | 150.8               | 30.8        | 140.9               | 20.9        |
| Bearing 1_5    | 39               | 37.5                | 1.5         | 42.3                | 3.3         | 35                  | 4           |
| Bearing 2_1    | 468              | 469.0               | 1           | 468.5               | 0.5         | 473.2               | 5.2         |
| Bearing 2_2    | 84               | 89.4                | 5.4         | 105.5               | 21.5        | 90.3                | 6.3         |
| Bearing 2_3    | 356              | 362.4               | 6.4         | 391.5               | 35.5        | 347.4               | 11.4        |
| Bearing 2_4    | 31               | 30.5                | 0.5         | 31.2                | 0.2         | 28.2                | 2.8         |
| Bearing 2_5    | 185              | 188                 | 3           | 188                 | 3           | 185.6               | 0.6         |
| Bearing 3_1    | 2505             | 2484.0              | 21          | 2571.5              | 66.5        | 2475.4              | 29.6        |
| Bearing 3_3    | 343              | 341.5               | 1.5         | 351.5               | 8.5         | 341.2               | 1.9         |
| Bearing 3_4    | 1445             | 1442.6              | 2.4         | 1458.9              | 13.9        | 1425.3              | 17.3        |
| Bearing 3_5    | 10               | 11.3                | 1.3         | 14.4                | 4.4         | 8.8                 | 1.2         |

FIGURE 15. (a) Life regression fitting of bearing 2_1; (b) Life prediction of bearing 2_1.

FIGURE 16. (a) Life regression fitting of bearing 3_1; (b) Life prediction of bearing 3_1.

when it comes into the accelerated degradation stage, the confidence changed abruptly. Though there exist fluctuations during the degradation process of bearing 2_1 and 3_1, the accelerated pattern is dominant in general. The stop threshold is often set 10 times the standard value and it is set as 10g in this research[31]. The change-points of the patterns are set as the start points of RUL prediction, and the Elastic Nets starts to operate. The life regression fitting and prediction of the bearings are illustrated as Figures 14-16.

To illustrate the superiority of the proposed method, the results of proposed SKF-EN are compared with the results of other methods including model-based method SKF and the nonlinear method SKF-GPR. The error between estimated RUL and actual RUL is selected to indicate the accuracy of the methods as in Table 3. As shown in Table 3, the proposed SKF-EN is more precise than the other two methods overall. The difference of accuracy between different bearings data is small, which
proves that the SKF-EN has a strong character of generalization. Therefore, the method proposed in this paper has high robustness in bearing life prediction. The Elastic network model training has low requirement of data volume and the life prediction is accurate even with small amount of data. However, when the signals change abruptly as bearings 1_3, 3_1, the life regression could not predict it in advance accurately, because the method is a complete online prediction algorithm and the priori knowledge is underutilized.

IV. CONCLUSION

In this paper, the SKF-EN algorithm is used to identify and predict the degradation mode of high reliability and long-life mechanical products in real time. Firstly, the SKF algorithm is used to determine the change-point between degradation patterns, making the life prediction model more accurate. Then, real-time life prediction is carried out using the model established by K-CV-EN algorithm. The two case studies show that the method can be applied in various objects and is suitable to small size sample test. The method tracks the pattern transition in time and the change-point of degradation pattern can be obtained precisely which is vital in equipment health management. In general, the method has the characteristic of great robustness, excellent real-time performance and high accuracy. For future work, the prior knowledged will be taken into fully consideration to improve the performance of non-stationary series prediction.

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