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Remaining Useful Life Prediction of Rolling Bearings Based on RMS-MAVE and Dynamic Exponential Regression Model

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ABSTRACT The remaining useful life (RUL) prediction of rolling bearings has recently gained increasing interest. Many models have been established to catch the degradation performance of bearings. However, there are two shortcomings existing in those models: (1) the health indicator (HI) that used for the first predicting time (FPT) selection is insensitive to incipient faults; (2) the parameter estimation must be based on the historical data, which are not available for some applications due to expensive experiment cost. To overcome the first shortcoming, this paper firstly adopts the mean absolute value of extremums (MAVE) of signals to feature signal energy. Then, the root mean square of the MAVE values (RMS-MAVE) is developed as a new HI to embody signal changes. After that, based on RMS-MAVE values, an adaptive FPT selection approach is proposed by the 3σ approach. For the second shortcoming, through coupling acquired measurement data with the exponential model, a dynamic exponential regression (DER) model based on RMS-MAVE values is proposed to predict the RUL of bearings. The comparison study indicates that RMS-MAVE is superior to the existed ones in FPT selection for distinguishing different health state of bearings, and the DER model performs better than the existed ones in RUL prediction.

INDEX TERMS Remaining useful life, rolling bearings, first predicting time, root mean square, the mean absolute value of extremums, dynamic exponential regression model.

I. INTRODUCTION

Rolling bearings are widely used in rotating machinery, and their failure is one of the foremost causes of the failures in both industry and domestic appliances [1]. Prognostics and health management (PHM) of rotating machinery, especially for bearings, has attracted extensive attention due to its effectiveness in avoiding the abrupt shutdown. Since the key of PHM is to accurately predict the remaining useful life (RUL) of machinery in advance, different approaches have been proposed for the RUL prediction of rolling bearings in recent decades.

Generally, the existed RUL prediction approaches can be categorized into model-based approaches and data-driven approaches generally. Model-based approaches build physical or mathematical models to describe the degradation processes of machinery on the basis of the failure mechanisms. Paris and Erdogan [2] proposed a Paris-Erdogan (PE) model to describe the crack growth, and it has been widely extended into many versions [3]–[6] for the RUL prediction of machinery. Tian and Liao [7] and Liao *et al.* [8] developed a proportional hazards model-based approach to estimate the RUL of bearings. Gebraeel *et al.* [9] established an exponential model to compute the residual-life distribution for devices, where the parameters were updated by Bayesian approach. Li *et al.* [10] enhanced the exponential model by applying SIS algorithm to the posterior residual-life distribution estimation of bearings. Wang and Tsui [11] improved the exponential model to a more general case by relieving the underlying assumption of drift coefficient. Model-based approaches can provide accurate estimation for the RUL if the failure mechanisms are well understood and

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the model parameters are accurately estimated. However, their applications will be restricted when the mechanical systems are too complex to understand the physics of damage.

Data-driven approaches build the degradation model from the historical data using machine learning [12] or statistical approaches [13]. Gebraeel *et al.* [14] applied an ANN-based model to predict the RUL of bearings. Liu *et al.* [15] proposed an RNN-based model for the RUL prediction of Lithium-lon battery. In addition, a number of studies have been published on SVM/RVM-based approaches [16]–[18] and neuro-fuzzy systems based approaches [19], [20]. Compared to model-based approaches, data-driven approaches can deal with prognostic issues of complex systems without considering the failure mechanisms, therefore, they are attracting more and more attentions in the machinery prognostic field. However, both of the above two approaches require that the unknown parameters of models must be estimated from the historical data, which is often not available for some applications due to expensive experiment cost. Therefore, this paper intends to develop a new framework for the RUL prediction of bearings without the historical data by coupling acquired measurement data with the degradation model.

There are two challenges associated with the development of the RUL prediction of bearings: (1) determine the first predicting time (FPT); (2) build an appropriate degradation model to describe the bearing degradation process accurately.

In general, the bearing degradation process contains two distinct stages. In Stage I, a bearing stays in normal operation condition without any faults, while in Stage II, bearing faults occur and get severer as time goes on. The time beginning to predict the RUL is defined as the first predicting time (FPT), and it should be the time that the first bearing fault occurs. It is important to determine the FPT appropriately since the FPT can significantly affect the accuracy of RUL prediction [10], [13]. The key for FPT selection is to develop a health indicator (HI) that can reflect the health state of bearings effectively. HI is a feature or a set of features of the measured data of bearings that can express the health state of bearings. Several approaches to HI extraction have been published, and among them, the most widely used HI is the root mean square (RMS) value of the vibration signals. RMS is defined as the square root of the arithmetic mean of the squares of a set of signals, and its value usually remains steady when the bearing stays in Stage I and keeps increasing during Stage II [21]. However, RMS is insensitive to incipient faults [10]. The reason is that the energy of fault signals is weak in the early stage of the lifecycle, and it will be covered by a large number of noises. Confronted with that, this study firstly uses the wavelet denoising method to remove the Gaussian noise. Then noticed that the local extremums of signals in degradation stage are mainly caused by faults, and they are much higher than the local extremums of signals in normal operation stage, therefore, the mean absolute value of the extremums (MAVE) of signals is adopted to feature the energy of incipient faults. Finally, the root mean square of the MAVE values of signals (RMS-MAVE) is adopted as a new HI to better embody the distinction between the signals in normal operation stage and the signals in degradation stage. Once the vibration signals are obtained, the FPT can be determined quickly based on the behavior of RMS-MAVE values. Different methods have been proposed to determine the FPT, such as the engineering norm ISO 10816 based approach [16] and the system's longest time constant based approach [22]. The 3σ approach has been widely used in FPT selection [10], [23], [24], one advantage is that the alarm, which is used to determine the FPT, can be set adaptively according to the HI behavior of bearings. Therefore, the 3σ approach is adopted here to select the FPT based on the new developed HI, i.e., RMS-MAVE.

Though RMS-MAVE is able to reflect the progression of faults, due to the existence of noise, the value of RMS-MAVE will show large local fluctuations, which will affect the improvement of prediction accuracy. Inspired by the smooth method shown in [25], a cumulative sum technique (CST) method is adopted in this paper to smooth RMS-MAVE, so that the underlying monotonic trend that correlates to the degradation performance of bearings can be revealed. Furthermore, to model the degradation process of bearings and predict its RUL without historical data, noticed that the exponential model has been shown effective in modeling the degradation processes when the cumulative damage has a particular effect on the rate of degradation [9]–[11], [26], a dynamic exponential regression (DER) model is proposed based on the most recent smoothed RMS-MAVE values, where the parameters of the model are updated in real-time to ensure the RUL prediction accuracy.

This paper proposes an RUL prediction method for rolling bearings based on RMS-MAVE and DER model. The major contributions of this work are summarized as follows:

(1) A new HI named RMS-MAVE is developed to improve the sensitivity of RMS to incipient faults, where the MAVE of signals is extracted to better embody the distinction between the signals in normal operation stage and the signals in degradation stage.
(2) A novel DER model is proposed for the RUL prediction of bearings in the absence of historical data, and the model parameters are updated in real-time, which ensures the RUL prediction accuracy.

The remainder of the paper is organized as follows. In Section II, the FPT selection based on RMS-MAVE is first introduced, and the RUL prediction method based on the DER model is carried out. In Section III, a simulated dataset of vibration signals is used to demonstrate the effectiveness of the RMS-MAVE in FPT selection and the superiority of DER model in RUL prediction. In Section IV, the effectiveness of the proposed methods is further demonstrated by two real datasets of bearing vibration signals. Finally, some conclusions are given in Section V.

II. THE PROPOSED METHOD FOR ROLLING BEARINGS RUL PREDICTION

The health prognostic program of rolling bearings is generally composed of four technical processes [27], i.e., data acquisition, HI construction, health stage division, and RUL prediction, while two challenges among those processes are determining the FPT and predicting the RUL of bearings. The key to FPT selection is to construct a HI that can well reflect the health state of bearings. Recently, the RMS of vibration signals has been widely used as the HI due to its ability in characterizing different health stages well [27]–[29]. However, since the energy of fault signals is weak in the early stage of lifecycle, and it will be covered by a large number of noises, the common used RMS that extracted from signals directly will be insensitive to incipient faults. Therefore, in this section, to overcome this shortcoming, the Gaussian noise is firstly removed from the signals using the wavelet denoising method. Then, considered the fact that the local extremums of signals in degradation stage are mainly caused by faults, and they will be much higher than the local extremums of signals in normal operation stage, the mean absolute value of extremums (MAVE) of signals is extracted to well feature the energy of incipient faults. After that, by calculating the RMS of MAVE values of signals, a new HI called RMS-MAVE is developed to better embody the distinction between the signals in normal operation stage and the signals in degradation stage. Finally, the 3σ method is adopted to determine the FPT based on RMS-MAVE values. Once the FPT is determined, the RUL prediction process is carried out. To catch the degradation performance of RMS-MAVE in degradation stage in real-time, the RMS-MAVE is firstly smoothed using the cumulative sum technique (CST). Then, a dynamic exponential regression (DER) model is proposed based on the smoothed RMS-MAVE values. Finally, the predicted RMS-MAVE value is compared with a given failure threshold to determine whether a bearing is failed or not. If the bearing is determined to be failed, the RUL is calculated based on the numbers of the predicted RMS-MAVE values before the failure threshold is reached. Otherwise, the parameters in DER model are updated by the new predicted RMS-MAVE values, and the prediction process is repeated until the failure threshold is reached. Instead of requiring large amounts of historical data, the proposed method can predict the RUL of bearings only relying on the most recent measurement data of bearings, and the parameters of the model can be updated in real time to ensure the prediction accuracy. More details of the major steps involved in the proposed method are described as follows.

A. FPT SELECTION BASED ON THE RMS-MAVE VALUES

This subsection describes the details of the RMS-MAVE construction process and the adaptive FPT selection method based on 3σ approach.

1) RMS-MAVE CONSTRUCTION

As mentioned in the introduction section, the lifecycle of rolling bearings has two stages, i.e., normal operation stage

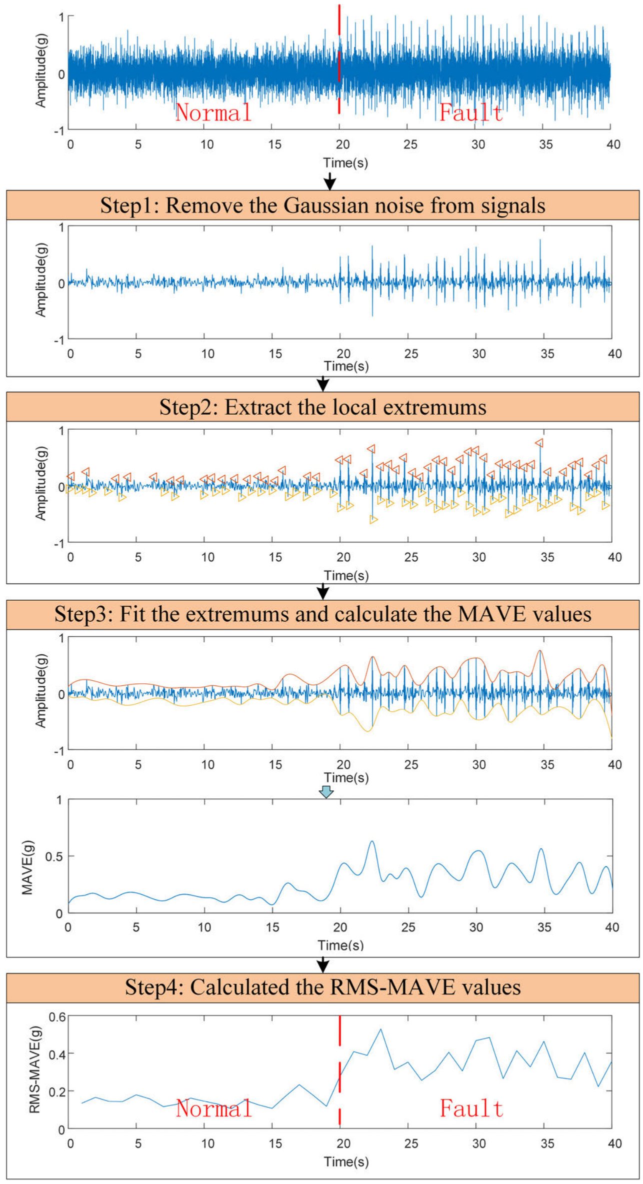

FIGURE 1. The construction process of RMS-MAVE.

and degradation stage, and it is important to select an appropriate FPT value. Confronted with the shortcoming of RMS in monitoring the incipient faults of bearings, a new HI called RMS-MAVE is proposed in this work. The construction process of RMS-MAVE can be shown in Fig. 1, and it is described in details as follows:

Step 1: Remove the Gaussian noise from signals.

In signal processing, wavelet denoising is considered as an efficient approach to handle the Gaussian noise for non-stationary vibration signals, and different works have suggested using db4 wavelet as the basic wavelet with 3^{rd} or 4^{th} level of decomposition [30], [31]. Therefore, in order to reduce the influence of the noise on vibration signals, the wavelet denoising using db4 function with 4^{th} level of decomposition is first applied to the signals, and the soft threshold approach is employed.

Step 2: Extract the local extremums (including maximum and minimum values).

The local extremums of signals in the degradation stage are caused by faults, and they are much stronger than the local extremums of signals in normal operation stage. Therefore, the local extremums contain more information about faults, thus they can better embody the distinction between the signals in normal stage and the signals in degradation stage. The length of window to extract the local extremums is set to the rotation period of bearings.

Step 3: Fit the extremums and calculate the MAVE values.

Based on the extremums extracted in Step 2, the cubic spline interpolation method is used to fit the extreme curves, i.e. the maximum curve and minimum curve. Then a new feature called MAVE is obtained by calculating the mean absolute value of the extremums (MAVE) of signals, and it can be expressed as follows:

$$x_{MAVE}(t_i) = \frac{|x_{up}(t_i)| + |x_{down}(t_i)|}{2}, \quad i = 1, 2, \cdots, M \tag{1}$$

where $x_{up}(t_i)$ and $x_{down}(t_i)$ are values of maximum curve and minimum curve at time t_i respectively, $x_{MAVE}(t_i)$ is the MAVE value at time t_i, and M is the total number of the measurement data.

Step 4: Calculate the RMS-MAVE values.

Based on the MAVE values obtained in Step 3, the RMS-MAVE can be calculated by the next expression:

$$x^{(n)}_{RMS-MAVE} = \sqrt{\frac{1}{m_n}\sum_{i=1}^{m_n}(x_{MAVE}(t_i))^2}, \quad n = 1, 2, \cdots, N \tag{2}$$

where $x^{(n)}_{RMS-MAVE}$ is the nth RMS-MAVE value of signals, N is the total number of RMS-MAVE values, m_n $(< M)$ is the length of the nth window of MAVE values, and m_n usually takes the integer multiple of the number of samples extracted in a single cycle.

2) FPT SELECTION

The RMS value usually remains steady in the normal operation stage [26], and once a fault occurs, the RMS will begin to increase until the end of life. Therefore, an alarm boundary should be determined by the performance of RMS-MAVE value in normal operation stage. Since the main source of the fluctuation in normal operation signals is Gaussian noise, the 3σ approach is adopted to set the alarm boundary for FPT selection.

The 3σ approach has been widely used in the FPT selection of bearings [10], [23], [24], and one advantage of it is that the alarm boundary can be set adaptively according to the HI behavior of bearings. The basic theory of 3σ approach is Chebyshev's inequality, which can be expressed in the following manner:

$$P(|x-u| \geq K\sigma) \leq \frac{1}{K^2} \tag{3}$$

where P is the probability of the event, x is a random variable with mean u and standard deviation σ, and K is a positive number.

It can be derived from (3) that, when K is set to 3, the probability of any data point falling outside 3σ distance away from the mean is less than 1/9. However, for the real bearing vibration signals, there are still some outliers in the normal operation stage because of the existence of noise, and it will affect the accuracy of FPT selection. Confronted with this, a strategy is adopted to determine the FPT, i.e., the time t_i is the FPT only if the following condition is satisfied:

$$|x(t_j) - u| \geq 3\sigma, \quad j = i, i+1, \cdots, i+v-1 \tag{4}$$

where v is usually taken as 5 as [24] suggested. Accordingly, the FPT can be determined if there are five consecutive data points falling outside the 3σ limits.

B. RUL PREDICTION BASED ON THE DYNAMIC EXPONENTIAL REGRESSION MODEL

This subsection describes the details of the smooth process using the CST method, and the RUL prediction process using the DER model.

1) SMOOTHING THE HEALTH INDICATOR USING CUMULATIVE SUM TECHNIQUE (CST)

Any rolling bearing is bound to degrade as time grows. A monotonic HI that properly correlates to the degradation performance of the bearing can lead to a simple and accurate prognostic model [25]. However, due to the tremendous amount of noise existed in the gathered vibration signals, the RMS-MAVE values exhibit large local fluctuations that will severely affect prediction accuracy. Therefore, the main idea of this step is to smooth the RMS-MAVE values so that they can clearly reflect the failure progression of bearings.

Noticed that the faults of bearings like wear are a cumulative process without self-recovery, this paper adopts the cumulative sum technique (CST) to smooth the health indicator. Consequently, the smoothed value of the nth RMS-MAVE value is calculated by the following equation:

$$HI_n = \frac{\sum_{j=1}^{n} x^{(j)}_{RMS-MAVE}}{n \cdot \bar{x}_{RMS-MAVE}}, \quad n = 1, 2, \cdots, N \tag{5}$$

where HI_n denotes the nth smoothed RMS-MAVE value, $x^{(j)}_{RMS-MAVE}$ is the jth RMS-MAVE value of vibration signals, and $\bar{x}_{RMS-MAVE}$ is the RMS-MAVE of vibration signals in the normal operation, which is taken as the mean value of the RMS-MAVE values when the bearing is in normal operation stage.

Furthermore, to assess the effectiveness of the CST method, two simple measures called monotonicity and correlation [32] are adopted to compare the monotonic trends of the RMS-MAVE and the smoothed RMS-MAVE. They are defined as follows:

(1) Monotonicity:

$$Mon=\frac{1}{k-1}\left|\sum_{i=1}^{k-1}\delta\left(y\left(t_{i+1}\right)-y\left(t_{i}\right)\right)-\sum_{i=2}^{k}\delta\left(y\left(t_{i}\right)-y\left(t_{i-1}\right)\right)\right| \tag{6}$$

where k is the total number of observing times, $y(t_i)$ is the observing value at the time t_i, and $\delta(\cdot)$ is the simple unit step function. It can be seen from (6) that the monotonicity.

(2) Correlation:

$$Corr=\frac{\left|k\left(\sum_{i=1}^{k}y\left(t_{i}\right)t_{i}\right)-\left(\sum_{i=1}^{k}y\left(t_{i}\right)\right)\left(\sum_{i=1}^{k}t_{i}\right)\right|}{\sqrt{\left[k\sum_{i=1}^{k}y\left(t_{i}\right)^{2}-\left(\sum_{i=1}^{k}y\left(t_{i}\right)\right)^{2}\right]\left[k\sum_{i=1}^{k}t_{i}^{2}-\left(\sum_{i=1}^{k}t_{i}\right)^{2}\right]}} \tag{7}$$

It can be seen from (7) that correlation measures the linearity between the observing value and the time, and the value of correlation is taken from 0 to 1, while the higher value of correlation corresponds to the stronger correlation.

2) RUL PREDICTION OF BEARINGS

Once the FPT is determined, the RUL of bearings can be predicted based on the HI values in the degradation stage. In this paper, the exponential regression model is applied to depict the degradation performance of bearing, since it has been widely used in the degradation processes where the cumulative damage has a particular effect on the rate of degradation [33], such as corrosion, bearing degradation, etc. The exponential regression model is constructed based on a window of the smoothed RMS-MAVE values with size l, and it is given as follows:

$$y(t)=a\exp(bt) \tag{8}$$

where the unknown parameters amplitude a and slope b are estimated using the ordinary least squares (OLS) method, that is to solve the minimization problem in (9):

$$\underset{a,b}{\arg\min}\left\{\sum_{i=1}^{l}\left(y\left(t_{i}\right)-a\exp\left(bt_{i}\right)\right)^{2}\middle|a,b>0\right\} \tag{9}$$

and the window size l is suggested to be varied from 40 to 60 [21]. Therefore, in this paper, the RUL prediction results are set to the average of all estimated values of RUL obtained by varying the window size l from 40 to 60.

In summary, the future values of RMS-MAVE can be predicted using the exponential regression model obtained from the most recent l smoothed RMS-MAVE values, and the RUL prediction process can be updated once a new value of RMS-MAVE is acquired. In detail, suppose the most recent l smoothed RMS-MAVE values are $\{HI_1, HI_2, \cdots, HI_l\}$, Then, the RUL prediction process is shown as follows:

Step 1: Calculate the amplitudes and slopes respectively based on the l smoothed RMS-MAVE values via (9).

Step 2: Predict the next value HI_{l+1} in the next time point, and transform it into the RMS-MAVE value via (5).

Step 3: Compare the predicted RMS-MAVE value with the failure threshold. If the failure threshold is reached, the RUL of a bearing is calculated as follows:

$$RUL_q=q\cdot\Delta T \tag{10}$$

where q is the number of new predicted RMS-MAVE values before the failure threshold is reached, and ΔT is the time between two consecutive samples of RMS-MAVE values. Otherwise, the new obtained value HI_{l+1} is appended to the dataset consisted of the most recent l smoothed RMS-MAVE values, while the oldest smoothed RMS-MAVE value is discarded, i.e., the dataset is updated to $\{HI_2, HI_3, \cdots, HI_{l+1}\}$, and return to Step 1.

Through the above steps, the RUL of bearings can be estimated using the most recent l smoothed RMS-MAVE values, and once a new RMS-MAVE value is acquired, the window of the smoothed RMS-MAVE values is updated, and the process is repeated until the failure threshold is reached.

III. SIMULATION

In this section, a simulation of the degradation process of rolling bearings is utilized to evaluate the effectiveness of the RMS-MAVE in FPT selection, and the accuracy of the dynamic exponential regression model in RUL prediction. Furthermore, to make a comparison, three other approaches recently proposed by Li *et al.* [10], Wang and Tsui [11] and Ahmad *et al.* [21] are also used to select the FPT and predict the RUL of the simulation signals. The first two approaches are used to indicate the effectiveness of the dynamic regression approach since they are both carried out based on the exponential model. And the last method is used to show the suitability of the exponential model, as it used the dynamic quadratic regression model to depict the degradation process of bearings.

A. SIMULATION OF THE BEARING DEGRADATION PROCESS

The vibration signals in this section are simulated by the method shown in [10] and [34], and the parameters of the bearings in the simulation are listed in TABLE 1, which are referred from [10].

According to the parameters in TABLE 1, the fault characteristic frequency can be calculated by (11), and we have its value is 169 Hz:

$$F_{outer}=\frac{Z\cdot N}{120}\left(1-\frac{(D_1-D_2)\cos\alpha}{D_1+D_2}\right) \tag{11}$$

To indicate the suitability of the simulation method, a sample of simulation signals in the normal operation stage and a sample of simulation signals in the degradation stage are shown in Fig. 2 (a) and (b) respectively. It can be seen from Fig. 2 (b) that the mean length of the time interval between

TABLE 1. Parameters of the bearing in the simulation.

Symbol	Parameter	Value
D_1	Out race diameter	29.1mm
D_2	Inner race diameter	22.1mm
Z	Rollers number	13
α	Contact angle	0
-	Fault type	Wear
-	Fault location	Outer race
N	Rotating speed	1800rpm
-	Sampling frequency	25.6kHz

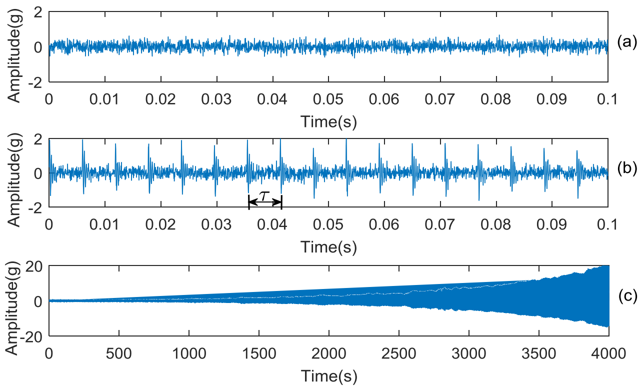

FIGURE 2. The simulation of the bearing: (a) signals in the normal operation stage, (b) signals in the failure stage and (c) signals of the whole lifetime.

two obvious impacts is $\tau = 0.0059$ s, which is corresponding to the fault characteristic frequency calculated by (11). Finally, a set of bearing signals with increasing fault severity are simulated to describe the degradation process of bearings. The simulation results are shown in Fig. 2 (c), where the real FPT is 500s and the lifetime is 4000s, and the bearing useful-life ends at the time when the amplitude of vibration signals exceeds 20g.

B. RUL PREDICTION BASED ON THE SIMULATION

1) FPT SELECTION BASED ON THE RMS-MAVE VALUES

Before the RUL prediction of bearings, the new developed RMS-MAVE is used to determine the FPT of the simulation vibration signals firstly. The process is described in Section II, and the result is shown in Fig. 3(a). It can be seen that the RMS-MAVE values after $t = 510$s are significantly higher than the RMS-MAVE values before $t = 510$s, and the FPT is set to 510s since it is the first time that has 5 consecutive data points falling outside the 3σ limits. To make a comparison, three other FPT selection approaches respectively proposed by Li et al. [10], Ahmad *et al.* [21] and Wang and Tsui [11] are also used to determine the FPT of the simulation signals. The FPT selection results are shown in Fig. 3(b), Fig. 3(c) and Fig. 3(d) respectively, and the FPT values are given in TABLE 2.

It can be seen from Fig. 3 that the FPT determined by the proposed approach and Wang's approach are much closer to the real change point than the approaches proposed by Li *et al.* [10] and Ahmad et al. [21]. Therefore, the developed RMS-MAVE is indicated to be more sensitive to the incipient fault of bearings.

2) RUL PREDICTION BASED ON DER MODEL

After the FPT has been determined, the proposed dynamic exponential regression model is used to predict the bearing RUL. The values of RMS-MAVE after $t_f = 510$s are firstly smoothed using the CST method described in Subsection II-B, and the smoothed RMS-MAVE values are input into the DER model for RUL prediction. The monotonicity and correlation introduced in Subsection II-B are used to compare the monotonic trends of the RMS-MAVE before and after applying the CST method, and the results are shown in TABLE 3. It can be seen that the monotonic trend of the RMS-MAVE has been significantly improved after applying the CST method.

Furthermore, to identify the effectiveness of the proposed DER model in RUL prediction of bearings, the RUL prediction results of the proposed model are compared with those of

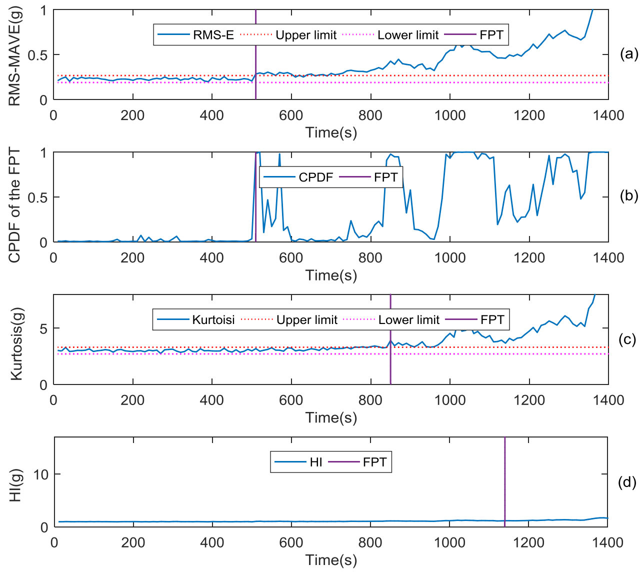

FIGURE 3. FPT selection results in the simulation signals: (a) The proposed approach, (b) Wang's approach, (c) Li's approach and (d) Ahmad's approach.

TABLE 2. Selected FPT of simulation signals.

Real change point	Li's approach	Ahmad's approach	Wang's approach	Proposed approach
500s	850s	1140s	510s	510s

TABLE 3. Comparisons of monotonic trends of the RMS-MAVE of the simulated signal before and after applying the CST method.

Measure	Monotonicity		Correlation	
	Before	After	Before	After
Simulated signal	0.2493	0.8682	0.9115	0.9369

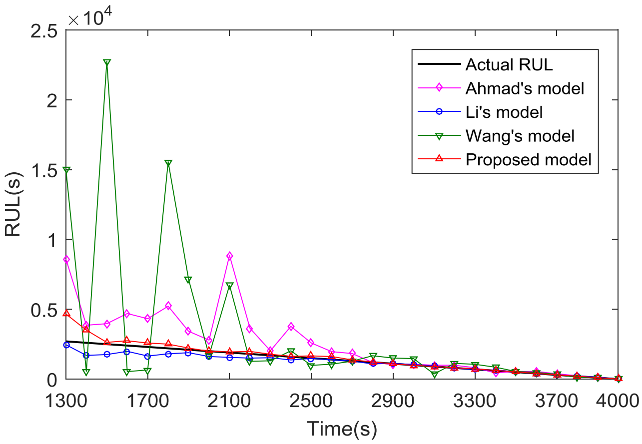

FIGURE 4. RUL prediction results based on the simulated signals.

TABLE 4. Score of CRA in the simulation.

Metric	Li's model	Ahmad's model	Wang's model	Proposed model
CRA	0.9318	0.7079	0.7172	0.9610

the models proposed by Li *et al.* [10], Ahmad *et al.* [21] and Wang *et al.* [11], and the results are shown in Fig. 4. In Fig. 4, it can be seen that the RUL prediction results of all the four models have large errors at the beginning of the prediction process since there is no enough information to accurately estimate the model parameters. However, as time goes on, all of them converge to the actual RUL. In addition, it can be observed that the RUL prediction result of the proposed model has the fastest convergence and the highest accuracy.

To quantitatively compare the performance of those four models, a commonly used metric called Cumulative Relative Accuracy (CRA) proposed in [35] is used. CRA is a normalized weighted sum of the relative accuracies, which is useful in reflecting how well an algorithm does over time. The range of CRA is [0, 1], where the higher score of CRA corresponds to the better prediction performance. As [10] suggested, the CRA is calculated at the time indexes from the half-lifetime to the end of lifetime, and the scores are shown in TABLE 4. It can be seen that the CRA score of the proposed approach is the highest among the four models. Therefore, the proposed model is indicated to get the highest prediction accuracy.

IV. EXPERIMENTAL DEMONSTRATIONS

In this section, two real datasets of vibration signals acquired from degradation tests of rolling bearings are used to further verify the effectiveness of the proposed FPT selection approach and the RUL prediction model.

A. DATASET 1

1) INTRODUCTION TO THE TESTS AND VIBRATION DATA

The first bearing degradation dataset is provided by the PRONSTIA platform [36]. This system is designed to provide real experimental data to characterize the degradation performance of rolling bearings along their whole operation lifetime. To conduct bearings' degradation in only a few hours, three operational conditions (i.e., 1800rpm and 4000N, 1650rpm and 4200N, 1500rpm and 5000N) are applied to the bearings to accelerate the degradation processes, where the force is generated by a cylinder pressure. During the test, both horizontal and vertical vibration accelerations of bearing housings were recorded, and the sampling frequency is 25.6 kHz, i.e., 2560 data points are recorded for each bearing in every 10 seconds. The experiments were stopped once the amplitude of the vibration signal overpassed 20g.

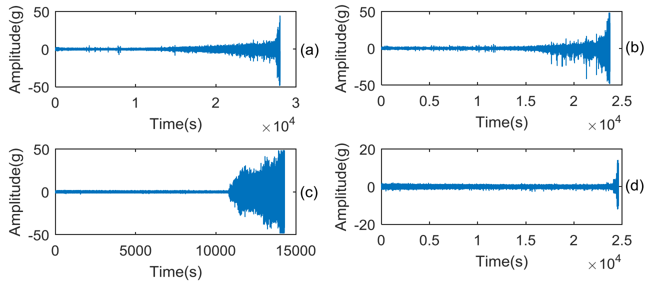

FIGURE 5. Vibration signals of four bearings: (a) bearing 1, (b) bearing 2, (c) bearing 3 and (d) bearing 4.

Since each bearing is in a healthy state without any initially initiated defects at the beginning of the test, each degraded bearing may contain almost all types of defects. As a result, the vibration signals of bearings under the same operational condition may be different. For example, the degradation performance of four bearings under the first operational conditions (i.e., 1800rpm and 4000N) are shown in Fig. 5. It can be seen that the vibration signals of the four bearings are varied between each other, therefore, different defects have occurred on those bearings.

In this paper, the vibration signals of bearing 1, bearing 2, bearing 3 and bearing 4 shown in Fig. 5 are used to carry out the proposed PFT selection approach and the RUL prediction model.

2) RUL PREDICTION OF THE FOUR BEARINGS

As described in Section II, the RMS-MAVE values are first extracted from the vibration signals, and then based on the 3σ approach, the FPT can be determined. The FPT selection results are shown in Fig. 6. To make a comparison, the FPTs determined by Li's approach and Ahmad's approach are also shown in Fig. 6, as those approaches have been validated using the same dataset in this study. All FPT values are given in TABLE 5. It can be seen from Fig. 6 that the proposed approach can better distinguish the two stages of bearings than others.

Once the FPT is determined, the RUL prediction is performed based on the proposed dynamic exponential regression model. As described in Subsection II-B, the extracted RMS-MAVE values are firstly smoothed by the CST method. Then, the most recent $l = 40 \sim 60$ smoothed RMS-MAVE

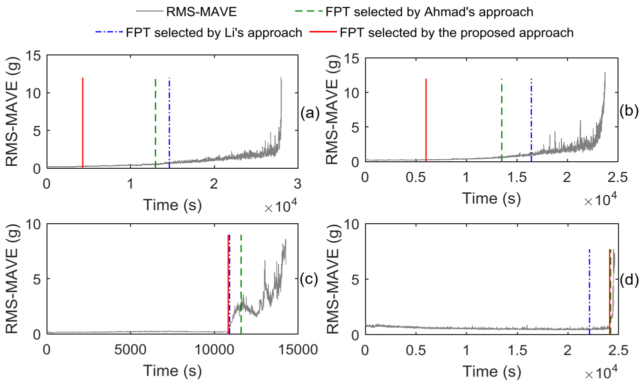

FIGURE 6. The FPT selection results: (a) bearing 1, (b) bearing 2, (c) bearing 3 and (d) bearing 4.

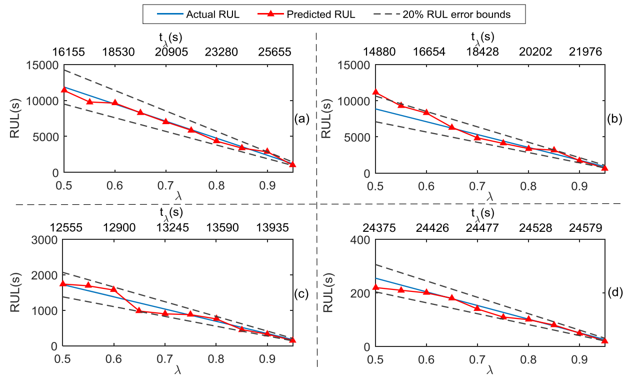

FIGURE 7. $\alpha - \lambda$ metric results: (a) bearing 1, (b) bearing 2, (c) bearing 3 and (d) bearing 4.

TABLE 5. The FPT selection results of four bearings.

Technique	Bearing 1	Bearing 2	Bearing 3	Bearing 4
Li's approach	14630s	16440s	10910s	22130s
Ahmad's approach	12970s	13510s	11600s	24210s
Proposed approach	4280s	6010s	10830s	24120s

TABLE 6. Comparison of monotonic trends of the RMS-MAVES of four bearing signals before and after applying the CST method.

Measure	Monotonicity		Correlation	
	Before	After	Before	After
Bearing1	0.0122	1	0.7831	0.9733
Bearing2	0.0147	0.9921	0.7231	0.9417
Bearing3	0.0377	0.9826	0.8083	0.9901
Bearing4	0.0196	1	0.8145	0.9191

values are used to estimate and update the parameters of the model. The comparison results on monotonicity and correlation of the RMS-MAVE values before and after applying the CST method are shown in TABLE 6, from which it can be seen that the monotonic trends of the RMS-MAVE values of the four bearings have been significantly improved after applying the CST method.

To evaluate the performance of the proposed DER model in RUL prediction, the $\alpha - \lambda$ metric [35] is adopted, where the parameter α is used to determine the acceptable RUL error bounds, and the parameter λ is used to determine a specific time point t_λ between the FPT t_f and the lifetime t_l of bearings such that $t_\lambda = t_f + \lambda\left(t_l - t_f\right)$. The value of α is set to 20% as [37] suggested, and the value of λ is taken from 0.5 to 0.95. The results are shown in Fig. 7, and it can be seen that most of the predicted RUL values lie within the acceptable RUL error bounds for the four bearings. Furthermore, as the bearing approaches its lifetime, the prediction performance becomes better, since more and more information about the bearing degradation performance is used.

In addition, to compare the prediction performance of the proposed RUL prediction method with the methods developed by Li *et al.* [10] and Ahmad *et al.* [21], the CRA scores

TABLE 7. Score of CRA for the four tested bearings.

Case	Li's model	Ahmad's model	Proposed model
Bearing 1	0.8696	0.9362	0.9441
Bearing 2	0.7623	0.9003	0.9010
Bearing 3	0.8712	0.9608	0.9031
Bearing 4	0.9324	0.7790	0.9361
Average value	0.8589	0.8941	0.9211

of the above three methods are calculated, and the results are summarized in TABLE 7. It can be seen that the proposed method has the highest average CRA score, which implies that the dynamic exponential regression model performs best in the RUL prediction of the bearings.

B. DATASET 2

1) INTRODUCTION TO THE TESTS AND VIBRATION DATA

The second bearing degradation dataset is designed by Gebraeel *et al.* [38], [39] with the aim to build a statistical model to describe the degradation performance of bearings. The HI in this test is defined as the sum of seven harmonics of the bearing fault characteristic frequency, and a total of 25 bearings are used to obtain the degradation signals, and the failure threshold is set to 0.03. More details about the experiment can be found in [38] and [39]. In this paper, 5 bearing degradation signals are used to carry out the dynamic exponential regression model, and the results are compared to the model proposed by Wang and Tsui [11] since the same dataset is used. The 5 degradation signals are shown in Fig. 8, which are read from Fig. 7(b) of Wang and Tsui [11]. It can be seen that each of the 5 bearing degradation signals has two distinct stages, i.e., the normal operation stage and the degradation stage. Therefore, the bearing degradation signals in the degradation stage are used to show the effectiveness of the proposed DER model.

2) RUL PREDICTION

Since the bearing degradation signals in this test have obvious FPT, the rest of this section only focuses on the DER modeling based on the HI values in the degradation stage

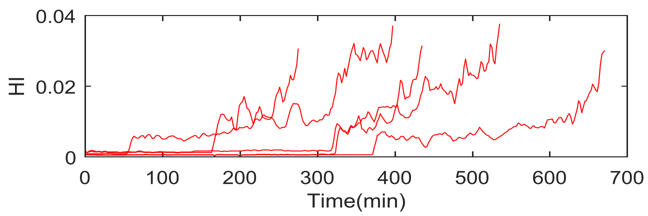

FIGURE 8. Five bearing degradation signals.

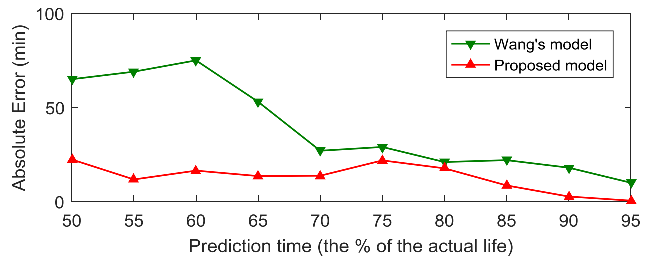

FIGURE 9. Absolute RUL prediction error results.

and the corresponding RUL prediction. First, the CST method is applied to HI values to smooth the degradation signals. Then, the most recent $l = 40 \sim 60$ smoothed HI values are used to estimate the parameters of the model. To make a comparison with the RUL prediction results carried out by Wang and Tsui [11], the absolute error (AE) of RUL prediction is used to measure the prediction performance. Consequently, the mean of the AE values for 5 bearings at different prediction time is obtained and plotted in Fig. 9. From the RUL prediction results shown in Fig. 9, it can be found that the proposed model achieves the lower RUL prediction errors, which demonstrates that the proposed dynamic exponential regression model is more accurate in bearing RUL prediction.

V. CONCLUSION

In this paper, an RUL prediction method of bearings based on RMS-MAVE and DER model is proposed. There are two major contributions contained in this work. First, an adaptively FPT selection approach based on the new developed RMS-MAVE and 3σ approach is established, through which the health state of bearings can be better distinguished. Second, a DER model is proposed for the RUL prediction of bearings without historical data, and the parameters of model are updated in real-time to ensure the RUL prediction accuracy. A simulation and two real datasets of bearing vibration signals are carried out for the comparison studies with the methods proposed by Ahmad *et al.* (2017), Li *et al.* (2015) and Wang *et al.* (2017). Results demonstrate that the RMS-MAVE is superior to the existed ones in the FPT selection, and the DER model based on RMS-MAVE obtains the highest RUL prediction accuracy among those models.

This paper provides an RUL prediction method for bearings without the historical data, and there are two main limitations existing in the proposed method. Firstly, the FPT selection approach is developed based on the assumption of two-stage degradation process, and it needs to be improved when facing the multi-stage degradation process. Secondly, the proposed RUL prediction method mainly focuses on the degradation process in which the degradation rate increases with time, and it may not be suitable for the degradation process with a constant degradation rate or that in which the degradation rate decreases with time.

For future works, as it has been demonstrated that the environmental or operational condition has significant impacts on the degradation performance of bearings [40], RUL prediction for bearings under time-varying operational conditions will be considered in our future research. In addition, since different operational conditions will lead to different failure thresholds, how to adaptively set the failure threshold based on the operational conditions should be considered. Finally, after obtaining the relationship between the degradation performance and operational conditions, the usage strategy optimization for the maximization of lifetime will also be carried out in further work.

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