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A Hybrid Prognostics Technique for Rolling Element Bearings using Adaptive Predictive Models

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***Abstract*— Rolling element bearings cause the most amount of failures in induction motors. Predicting an impending failure and estimating the remaining useful life (RUL) of a bearing is essential for scheduling maintenance and avoiding abrupt shutdowns of critical systems. This paper presents a hybrid technique for bearing prognostics that utilizes regression based adaptive predictive models to learn the evolving trend in a bearing's health indicator. These models are then used to project forward in time and estimate the RUL of a bearing. The proposed algorithm addresses some key issues in existing methods for bearing health prognosis that affect their prognostic performance, specifically determining the time to start prediction (TSP), handling random fluctuations in a bearing's health indicator, and setting a dynamic failure threshold. The proposed algorithm is validated on publicly available bearing prognostics data from the Center for Intelligent Maintenance Systems (IMS). Experimental results show that the proposed approach is effective in determining an accurate TSP and failure threshold, as well as handling random fluctuations. Moreover, this approach achieves excellent prognostic performance and estimates the RUL of bearings within the specified error bounds, even at points very close to the TSP, where traditional methods yield relatively poor RUL estimates.**

***Index Terms*—Bearings, Induction Motors, Predictive Models, Prognosis, Remaining Useful Life.**

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I. Introduction

INDUCTION motors are widely used in both industry and domestic appliances, and more than 50% of their failures have been attributed to faulty bearings [1]. The failure of an induction motor can cause an abrupt plant shutdown, which can be very costly. Therefore, different methods have been proposed for the condition monitoring of these systems [2-5]. However, in order to carry out preventive maintenance of these systems, the health prognosis of bearings is of significant concern [6-11]. The health prognosis of bearings involves predicting their remaining useful life (RUL), which is helpful in arranging prior maintenance and improving overall system reliability. Most of the techniques developed for the RUL estimation of bearings are either data-driven or model-based.

Data-driven approaches are strictly dependent on the historical condition monitoring data acquired from bearings using seismic vibration sensors. The degradation behavior of a system is learned from measured data using machine learning techniques. Gebraeel *et al.* use an artificial neural network to predict the RUL of bearings [12]. In [7, 13, 14], neuro-fuzzy based approaches were used for RUL prediction, whereas in [9-11], different flavors of the Kalman filter were used to estimate the RUL of bearings. Data-driven techniques are highly useful in the health prognosis of complex systems, especially when accurate mathematical models are prohibitively costly to develop.

Model based methods set up a mathematical or a physical model that describes the degradation of a system. In [15], the fault is assumed to grow according to the Paris model, whereas the parameters of the model are determined using measured data. The RUL is estimated by projecting the parameters of the model and state of the system using particle filters. Liao *et al.* used a method based on logistic regression models to predict the RUL of rolling element bearings [16]. Li *et al.* [8] used an exponential model and particle filters to estimate the RUL of bearings. However, despite their utility, these approaches have certain limitations. Model based approaches cannot be generalized to all systems, i.e., each system requires a specific model, and developing such models can be very costly. Data-driven methods work well for complex systems and for analyzing intermittent faults by detecting changes in the measured data. However, they require historical data for both the normal and the failure modes of a system. New systems lack such historical data that could be used to train models and infer their degradation paths.

In data-driven methods for bearing prognostics, there are several unresolved issues, such as deciding the time to start prediction (TSP), handling random anomalies in the measured data or features extracted from it, and determining the failure threshold. TSP is mostly determined subjectively [17-21]. Figure 1 illustrates the behavior of different features, i.e., root mean square (RMS), mean value, skewness and kurtosis, extracted from the vibration acceleration data of a bearing in a run-to-failure test. RMS is the most appropriate choice for a health indicator to infer the bearing's health, as it shows trends that can be used to characterize different states of a bearing's health as follows: the normal stage, when the RMS value remains steady; the incipient fault stage, when the RMS value starts increasing linearly; and the severe degradation stage, when the RMS value starts increasing non-linearly.

Prognostic methods for bearings start predicting their RUL as soon as the initial signs of degradation are detected, and the time at which this happens is the TSP [22]. It is important to correctly determine the TSP, as it affects the accuracy of the RUL estimates. An incorrect TSP risks leaving out valuable information about incipient faults or incorporating pre-incipient fault data in RUL estimation. TSP has been determined using different methods, including engineering norm ISO 10816, the $\mu+3\sigma$ approach [8, 10, 11], and techniques based on the statistical properties and longest time constant of a machine [23, 24]. These approaches use the statistical properties of a large number of machines and fire an alarm after determining the TSP. The behavior of systems varies based upon different factors, and these approaches fail to adapt to variations in the system behavior in order to calibrate the alarm accordingly.

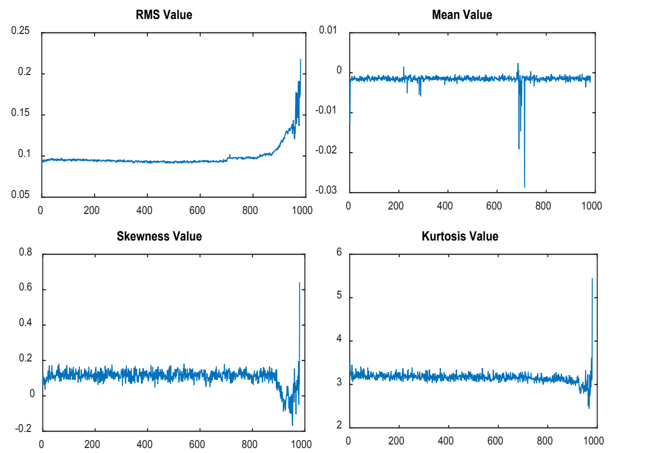

Fig. 1. The variation in RMS, mean value, skewness value and kurtosis value of a bearing's vibration acceleration in a run-to-failure test.

Handling random anomalies or spurious fluctuations in the health indicator is also critical to RUL prediction performance. If these fluctuations go unidentified, they can result in poor RUL estimates [8]. Figure 2 illustrates such spurious fluctuations in the RMS values of a bearing in a run-to-failure test, which have been appropriately rectified.

Determining the appropriate failure threshold is challenging and very significant, as it determines when the RUL prediction algorithm should stop and output the estimated RUL value. Several methods have been presented in the literature for setting a failure threshold, which include an inference based method [11], methods that use a fixed value of the vibration acceleration as the failure threshold [8, 10], methods that find static failure thresholds by averaging the failure thresholds of a number of bearings [9, 25], and clustering-based methods that determine the failure threshold using a cluster of the health indicator values that correspond to the most severely degraded state of a bearing [7].

This paper proposes a hybrid technique for bearing health prognosis that selects an appropriate regression model based on an evolving trend in the experimental data. The evolving trend in the data is determined by measuring the growth rate of the health indicator. The root mean square (RMS) value is used as the health indicator for the bearing, as it is positively correlated with deterioration in a bearing's health [7].

The main contributions of this work are as follows:

1. A new method is presented to determine the TSP, which uses the growth rate of the health indicator to determine the onset of degradation in a bearing's health condition. An accurate TSP improves the predictive performance of a prognostic algorithm, especially when the degradation is in its initial stages and the bearing has not entered the severe degradation phase.
2. A Linear Rectification Technique (LRT) is proposed to handle spurious fluctuations in the health indicator. This ensures that the health indicator is always a monotonically non-decreasing function, which improves the accuracy of the regressive model and the accuracy of the predicted RULs.
3. A new method is proposed to dynamically determine the failure threshold of a bearing using the gradient of the health indicator's trajectory, which improves the predictive performance of the proposed method.

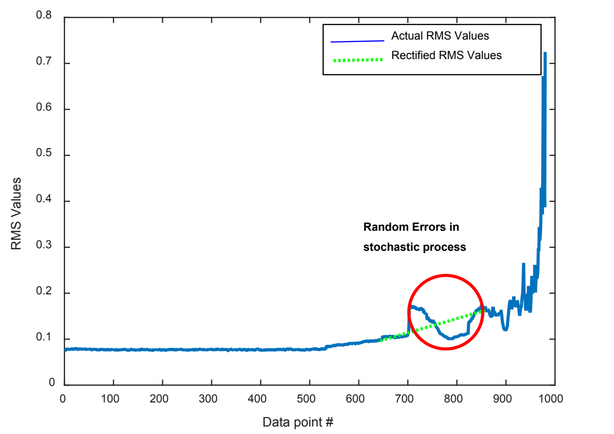

Fig. 2. Random anomalies or spurious fluctuations in the health indicator, which are rectified to improve RUL prediction performance.

The rest of the paper is organized as follows: Section II explains the proposed adaptive predictive model based approach for RUL estimation. Section III presents the experimental setup and data, and Section IV presents results of the proposed method and provides discussion. Section V concludes this paper.

II. The Proposed Adaptive predictive model based approach

The proposed approach, which selects the best regression model to approximate the degradation behavior of a bearing based on the evolving trend in its health indicator, is illustrated in Fig. 3. The approach has two distinct phases, TSP detection and RUL estimation. The TSP indicates the onset of bearing degradation, and until it is detected, the proposed algorithm does not estimate the RUL of the bearing. TSP detection starts with a window of RMS values, which is first smoothed using the proposed linear rectification technique. A linear regression model is then fitted over the smoothed window of RMS values. The gradient of the linear regression model is used to determine whether the bearing has started to degrade or not. If the bearing is declared healthy, then the window of RMS values is updated by incorporating the new measurements, and this process is repeated until the TSP is detected. Once the TSP is detected, the proposed method assumes the commencement of an irreversible process of bearing degradation and enters the RUL estimation phase. During RUL estimation, a window of RMS values is first smoothed using the proposed linear rectification technique, and then a linear regression model is fitted over this smoothed window. The gradient of the linear regression model is used to determine whether the bearing has failed or not. If the bearing is determined to have failed, the RUL estimation process terminates. The RUL of the bearing is estimated by calculating the accumulated time before the gradient of the health indicator reaches its failure threshold. However, if the failure threshold has not been reached yet, then the future values of the health indicator are estimated using a polynomial regression model. These estimated values of the health indicator are then incorporated into the fixed-size window, and a linear regression model is used to determine if the failure threshold is reached. This process is repeated until the failure threshold is reached, which then terminates the RUL estimation process. Instead of requiring large amounts of historical data, the proposed method works only on a small window of data, i.e., the most recent values of the health indicator. The major steps involved in the proposed approach are described in more detail as follows.

A. TSP Detection

The proposed method begins with a window of n RMS values and fits a linear regression model over this window. As given in Eq. (1), the parameters w and b of the linear regression model are determined using the ordinary least squares approach, which minimizes the sum of squared residuals of the regression model. The closed form expressions for w and b are given in Eq. (2) and Eq. (3), respectively. These expressions are obtained when the minimization problem in Eq. (4) is solved for w and b.

$$y = wx + b\,, \tag{1}$$

where

$$w = \frac{\sum x_i y_i - \frac{\sum x_i \sum y_i}{n}}{\sum x_i^2 - \frac{\left(\sum x_i\right)^2}{n}} \tag{2}$$

and

$$b = \frac{\sum y_i - w\sum x_i}{n} \tag{3}$$

$$\arg_{w,b}\,\min\left\{Q(\mathrm{w},\mathrm{b})\right\} = \arg_{w,b}\,\min\left\{\sum_{i=1}^{n}(y_i - wx_i - b)^2\right\}. \tag{4}$$

The coefficient w represents the gradient of the dependent variable (the health indicator) with respect to the independent variable (time). At any time t, $w_t \le 0$ means that the bearing is in a healthy state, while $w_t > 0$ means that the bearing has started to degrade. The degradation may be linear or exponential. The instant when the gradient or the regression coefficient of the linear regression model is either equal to or greater than a certain positive value (for a window of size 50, this value is ≥ 0.0001) is the time to start prediction (TSP). The relation between the gradient of the health indicator and a bearing's degradation can be inferred from the experimental data.

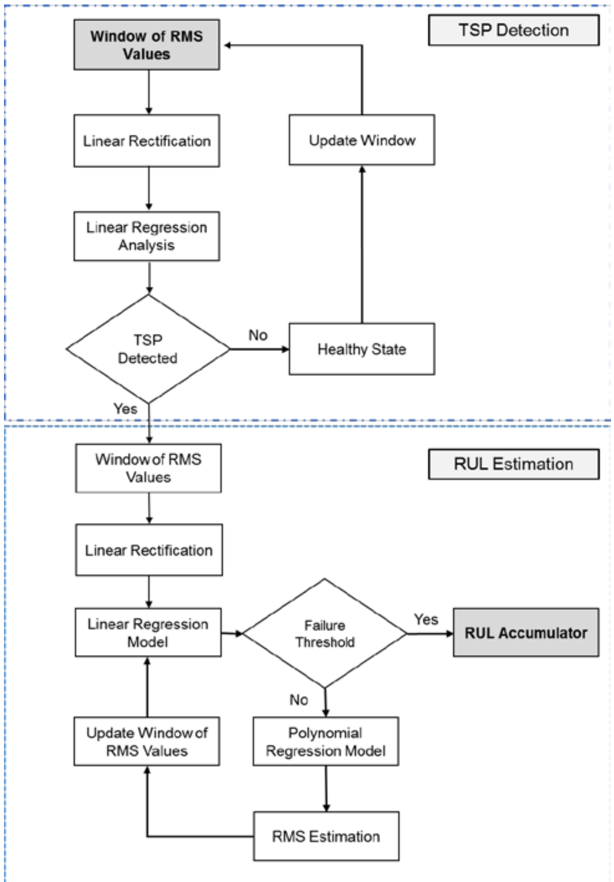

Fig. 3. The proposed adaptive predictive model based approach for the RUL estimation of bearings.

B. Health Indicator (RMS sample) estimation and RUL Prediction

Once the TSP is determined, the proposed algorithm is set to

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estimate the RUL of the bearing afterwards, at any point during its operation. When a bearing starts to deteriorate, the health indicator can follow either a linear or a higher degree polynomial trend. Based upon the historical data shown in Fig. 3, the health indicator almost always shows higher order behavior after TSP, especially when a bearing approaches its end of life (EOL). In this study, a quadratic regression model is constructed after the TSP is determined, which can be used to predict the future values of the health indicator (i.e., RMS). The model is constructed for a window of size n. The parameters of the model, including w_1, w_2, and b, as given in Eq. (5), are determined using the ordinary least squares approach by solving the minimization problem in Eq. (6).

$$y = w_1 x^2 + w_2 x + b \tag{5}$$

$$\begin{aligned} &\arg_{w_1, w_2, b} \min \{Q(\mathrm{w}_1, \mathrm{w}_2, \mathrm{b})\} = \\ &\arg_{w_1, w_2, b} \min \left\{ \sum_{i=1}^{n} (y_i - w_1 x^2{}_i - w_2 x_i - b)^2 \right\} \end{aligned} \tag{6}$$

The future values of RMS are therefore predicted using the quadratic regression model fitted over the set of the n most recent data points $(x_{1..n}, y_{1..n})$. The RUL is calculated based upon the number of steps taken by the algorithm until it reaches the failure threshold and the duration between two successive values of the RMS, as shown in Fig. 3.

C. Dynamic Failure Threshold

In existing approaches, the failure threshold is usually a constant value taken as the average value of the health indicator for all the bearings in a run-to-failure test. In this study, a new method is proposed to dynamically determine the failure threshold of a bearing. The failure threshold is determined based upon the gradient of the linear regression model fitted over a window of n RMS values (a gradient $\geq$ 0.0005 for a window of size 50 signals a bearing's failure). When the future RMS values are predicted using the quadratic regression model, the window is moved forward to include these predicted values. In order to determine whether the health indicator has reached the failure threshold or not, the proposed algorithm builds a linear regression model over the updated window. The gradient of this linear regression model is used to determine whether or not the bearing has reached its failure threshold. With each estimation step, the window is updated and moved forward. A linear regression model is constructed on the latest window to obtain the updated gradient of the current sequence of RMS samples. The moving window and the use of only the most recent values of RMS make the proposed approach adaptive to changes in a bearing's degradation behavior. When a bearing has reached its failure threshold, the algorithm stops predicting new RMS values and outputs the estimated RUL.

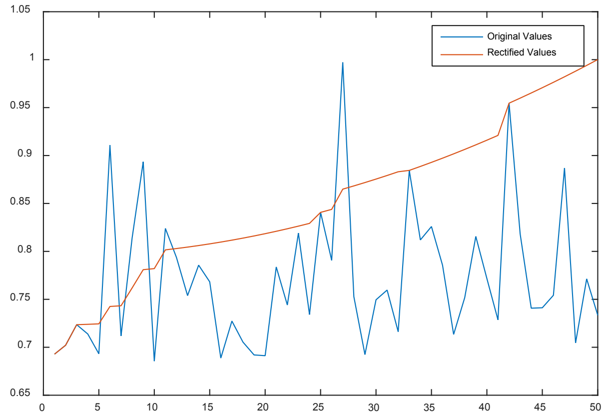

Fig. 4. Correction of random errors in stochastic process using LRT.

D. Fixing Random Errors using LRT

Although bearing degradation progressively worsens with time, nevertheless, the health indicator can show fluctuations that might indicate an improvement. From a modeling perspective, it is impractical to model these random fluctuations in the health indicator, which are uncharacteristic of a bearing's degradation. Hence, these random fluctuations in the health indicator are removed through the proposed linear rectification technique. After LRT, the health indicator shows bearing degradation as a monotonically increasing function. If the value of the health indicator at time t_i is less than its value at time t_{i-1} or it is greater than what is suggested by the recent growth trend η of the health indicator, then at time t_i, its value is determined using Eq. (7), which uses the current growth trend, η, of the health indicator to decide its value at t_i. The smoothing of the health indicator through the linear rectification process is illustrated in Fig. 4.

$$y_i = \begin{cases} y_i & \forall y_{i-1} \leq y_i \leq (1+\eta) y_{i-1} \\ y_{i-1} + \eta & \forall y_i < y_{i-1} \vee y_i > (1+\eta) y_{i-1} \end{cases}, \tag{7}$$

where η is the growth rate of the health indicator, which is calculated as follows:

$$\eta = \frac{1}{n} \sum_{i=1}^{n} y_{i+1} - y_i \,. \tag{8}$$

III. Experimental Setup and Data

For this study, the run-to-failure test data of the Center for Intelligent Maintenance Systems, University of Cincinnati, was used [26]. The data is publicly available at the NASA Ames Prognostics data repository [27]. The schematic sketch of the experimental testbed used to collect this data is shown in Fig. 5. This testbed is used to carry out three run-to-failure tests. In each test, four double row Rexnord ZA-2115 bearings are used. These four bearings are installed on a shaft that is rotating at a constant speed of 2000 revolutions per minute (RPM). The shaft is driven by an AC motor that is coupled to the shaft through rub belts. The bearings are force lubricated and radially loaded with a 6000 lb. force through a spring mechanism. The

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vibration acceleration of each of the four bearings is measured using high sensitivity quartz integrated circuit piezoelectric (ICP) accelerometers. The data is collected using a National Instruments data acquisition card 6062E (NI DAQ) at a sampling rate of 20 KHz.

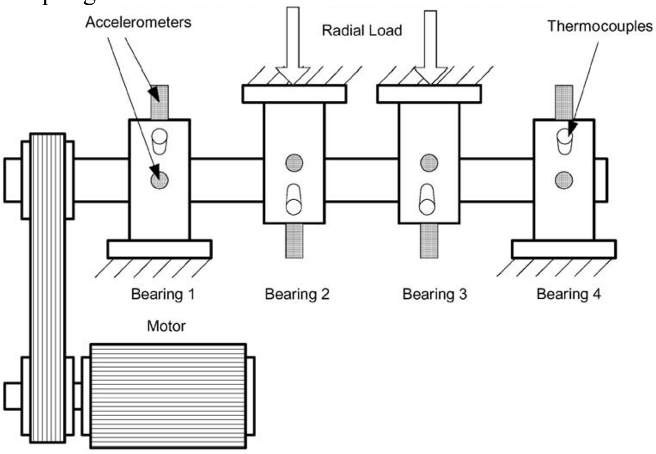

Fig. 5. Schematic sketch of the testbed for collecting the run-to-failure test data [26].

Three datasets have been published by [27], one for each of the three run-to-failure tests. Each dataset contains data for each of the four bearings in the form of 1 sec snapshots of the vibration acceleration signal for a total of 20,480 samples. These measurements are recorded at regular intervals (e.g., every 10 minutes) for all the datasets except for the first 43 files of dataset 1 [27].

IV. Results and Discussion

The results of the proposed approach for bearing health prognosis are presented in this section, using the run-to-failure test data for experiment no. 2 [27]. As discussed in Section II, new methods are proposed to resolve important issues in bearing health prognosis, i.e., TSP detection, determining the failure threshold, and removing spurious fluctuations in the health indicator. A bearing's RUL is estimated after the TSP is determined. The RUL is estimated by predicting new values of the health indicator using the quadratic regression model. The RMS window is shifted one step forward by appending the newly estimated value. The algorithm then generates a linear model for the updated window, in order to determine whether the health indicator has surpassed the failure threshold or not. The performance of the proposed approach is then measured using the $\alpha-\lambda$ performance metric, where α specifies the error bounds on the estimated RUL and λ specifies the relative distance, in time, of a given point from a bearing's EOL, i.e., a $\lambda = 0.5$ means that it is half way away from the EOL [22].

As mentioned in Section II, the proposed method does not rely on large amounts of historical data, but instead uses a window of n RMS values to determine the TSP and construct the regression model for estimating RUL. For the selection of TSP, a fixed size window of $n = 50$ samples is used, whereas for predicting RMS values and detecting failure thresholds, the averaged results for windows of size $40 \le n \le 60$ are provided. The values of the health indicator (RMS) are first rectified using LRT, as discussed in Section II. The calculated values of TSP for bearings 1, 2, 3, and 4 are 5100 minutes, 6900 minutes, 6800 minutes, and 6050 minutes, respectively.

The proposed algorithm uses a quadratic regression model to predict the future values of RMS, while it uses linear regression models for determining both the TSP and the failure threshold. For all the models, a window of n RMS samples is utilized (n = 40 − 60). This window is a sliding or moving window, which is moved forward to include the latest predicted values of the RMS. The RMS values are predicted until the gradient of the linear regression model reaches the failure threshold. At a given time index, the RUL is calculated using Eq. (9):

$$\hat{r}(t_i) = k \cdot \Delta T \quad , \tag{9}$$

where k is the number of predicted RMS values before reaching the failure threshold and ΔT is the sampling period of the RMS values. The sampling period for the given dataset is 10 mins [27].

TABLE I
Estimated and Calculated Values of RUL

Measurements	Calculated RUL (min)	Estimated RUL (min)
1	4725	5075
2	4585	4585
3	4550	4375
4	4270	4270
5	3150	2800
6	2695	2730
7	2625	2520
8	2485	2310
9	2170	2268
10	1575	1589
11	910	805
12	700	917
13	175	147
14	105	112
15	70	84

Table I shows the mean of the RUL estimates obtained by the proposed method and the RUL values calculated directly from the experimental data. Prognostic methods based on various techniques such as particle filters [8] and Kalman filters [11] report the median RUL estimates obtained after different runs of Monte-Carlo simulations. In the proposed method, however, the estimated RUL value is the mean of the RUL values obtained after using different window sizes for the regression models. The predicted RULs in Table I are therefore the average values obtained for windows of 40 to 50 RMS values.

The predictive performance of a prognostic algorithm can be affected by the TSP selection criterion, particularly for $\lambda < 0.5$, i.e., when the bearing is in the earlier stages of degradation. Figure 6 shows the prognostic performance of the proposed algorithm using the $\alpha-\lambda$ metric. The estimated and calculated RUL values are plotted for λ ranging from 0 to 1, where 0 corresponds to the time of the first prediction and 1 corresponds to a bearing's EOL. The error bound for the RUL estimates is 30%. From Fig. 6, it can be observed that almost all values of the estimated RUL lie within the specified error bounds of the calculated RUL, i.e., $\left[(1-\alpha)r(t_i)\right] \le \hat{r}(t_i) \le \left[(1+\alpha)r(t_i)\right]$, where $r(t_i)$ is the calculated RUL and $\hat{r}(t_i)$ is the estimated RUL.

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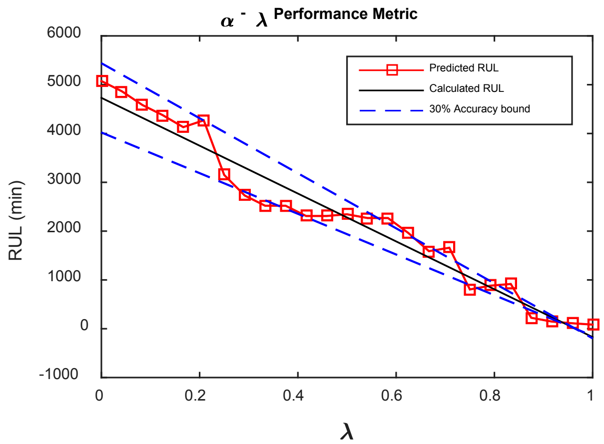

Fig. 6. The RUL prediction performance of the proposed approach.

The proposed algorithm makes reasonably accurate estimates of the RUL at all times, whereas most of the existing techniques do not provide good RUL estimates for smaller values of λ. This is because the predictive performance of traditional algorithms [7, 8, 11] improves when more information about a bearing's degradation becomes available, which usually happens when the bearing enters severe degradation towards the end of its operational life. This particular behavior of the prognostic algorithm is measured using the convergence metric [28]. In terms of the convergence, the behavior of the proposed algorithm is illustrated in Fig. 7. It can be observed that from the very beginning when the algorithm starts estimating the RUL, i.e., after TSP, the estimates of the RUL are fairly close to their calculated values. Hence, in contrast to traditional techniques [7, 8, 11], the proposed algorithm exhibits good convergence behavior from the very beginning. This is in part due to the appropriate selection of TSP and the use of an adaptive predictive model, which uses only the most recent values of the health indicator to predict its future values, thus adapting to the evolving trend.

Figure 8 shows the trajectories for a bearing's health indicator (i.e., the RMS value). These trajectories have been generated by the proposed algorithm starting at different points in time, specifically when the bearing was operated for 8250 minutes, 8450 minutes, 8550 minutes, 8900 minutes, 9000 minutes and 9200 minutes. It can be easily observed that the bearing's health indicator closely follows the trajectory generated by the proposed algorithm, which explains its predictive performance shown in Fig. 6.

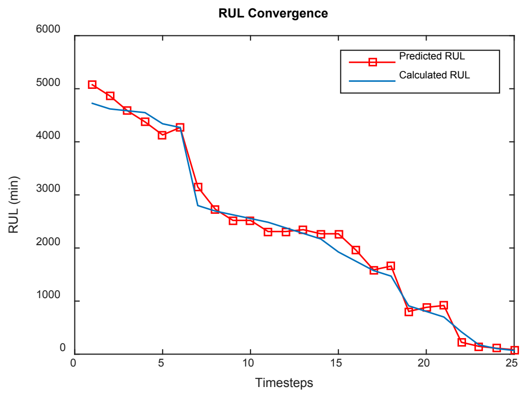

Fig. 7. Convergence of the predicted RUL values.

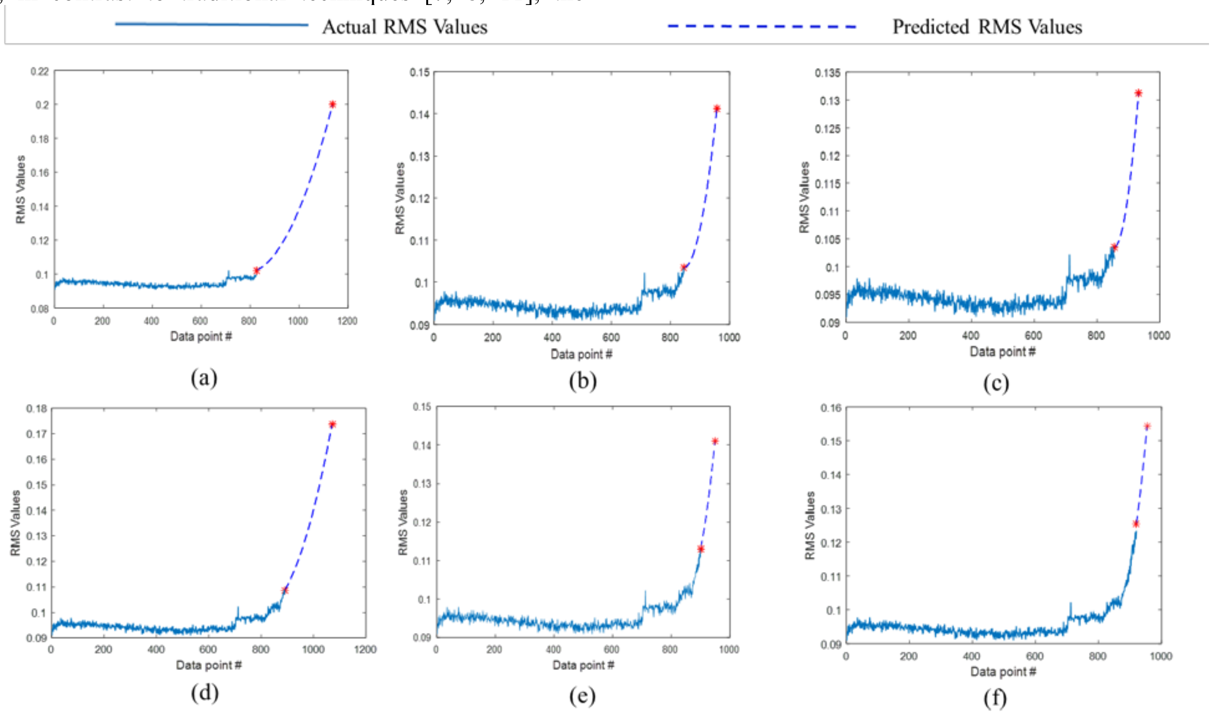

Fig. 8. The predicted trajectories for the health indicator of a bearing. The predictions start at (a) 8250 minutes, (b) 8450 minutes, (c) 8550 minutes, (d) 8900 minutes, (e) 9000 minutes and (f) 9200 minutes.

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In RUL estimation, setting a failure threshold is an important issue. Existing methods mostly use a constant value of the health indicator as the failure threshold. This value is usually calculated by finding the average value of the health indicator for all the bearings when they approach their EOL. The failure threshold has also been determined using clustering techniques, where the distance from a cluster of values determines the failure of a bearing or otherwise. This cluster usually contains values of the health indicator corresponding to the severe degradation state of the bearing. The proposed algorithm uses the gradient of the linear regression model, derived from the window of the health indicator, to determine its failure threshold, as discussed in Section II. The gradient, being the ratio of two numbers, makes it relatively independent from both the magnitude of a particular health indicator and the size and power of the motors. The gradient values determined as failure thresholds through the proposed method can be used as failure thresholds for systems with no significant historical data available. The results are expected to be relatively better than constant values for failure thresholds.

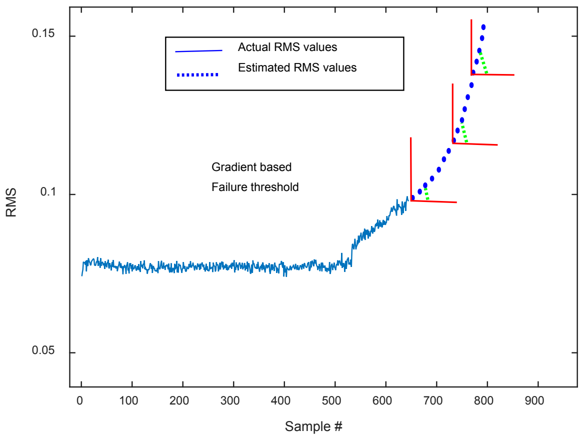

Fig. 9. The gradient based method for determining the failure threshold applied at different points.

The failure threshold is determined by utilizing a linear regression model over the sliding window and finding its gradient. A new linear regression model is derived each time the algorithm estimates a future RMS value, hence the gradient is updated at each step. The calculation of the failure threshold using this gradient based method is illustrated in Fig. 9, where the green lines give an indication of the steepness of the trajectory of the health indicator at a particular point. A steeper trajectory implies a higher gradient and hence an approaching failure. The calculated gradient is compared with a preset value, 0.0005, which is determined from the available historical data. When the gradient of the sliding window exceeds this preset value, then a bearing is declared to have failed.

The prognostic performance of the proposed method is compared with two state-of-the-art methods for RUL estimation, i.e., the improved exponential model based method [8] and the extended Kalman filtering (EKF) based method [9]. These techniques have been validated on the PRONOSTIA dataset [29]. Therefore, in order to provide a fair comparison with these techniques, the proposed method has also been validated on the PRONOSTIA dataset. The detailed description of the PRONOSTIA platform is provided in [29]. Li et al. improve the standard exponential model for estimating RUL by using particle filters [8]. The RMS is used as the health indicator, whereas the predictive performance of the algorithm is measured by calculating the cumulative relative accuracy (CRA) of the estimated RUL values for four bearings [28]. Table II presents a comparison of the proposed algorithm with the model based methods presented in [8], which clearly indicates that in almost all cases, the proposed method provides better CRA scores.

TABLE II
CRA SCORES FOR THE PROPOSED METHOD AND DIFFERENT MODEL BASED METHODS FOR RUL ESTIMATION [8]

Test	Paris model	Exponential model	Improved exponential model	Proposed method
Bearing 1	0.6967	0.7111	0.8696	0.9362
Bearing 2	0.6074	0.5311	0.7623	0.9003
Bearing 3	0.6317	0.5420	0.8712	0.9608
Bearing 4	0.7443	0.7463	0.9324	0.7790

Singleton et al. [9] use an extended Kalman filtering (EKF) based method to estimate the RUL of the bearings while utilizing the variance and Renyi entropy as health indicators. The EKF based approach is validated using all the eleven PRONOSTIA test datasets [29]. The prediction performance is measured in terms of the percentage RUL estimations that fall within +/- 20% of the true RUL in the last 500 seconds. Table III presents a comparison of the proposed method and the EKF based approach in terms of the performance measure proposed in [9]. Results for the proposed method are also provided when employing variance as the health indicator.

TABLE III
COMPARISON OF THE PROPOSED METHOD WITH THE EKF BASED APPROACH FOR RUL ESTIMATION [9]

Test set	Proposed Method		EKF	
	RMS	Variance	Variance	Renyi Entropy
1	89%	93%	96%	0%
2	100%	100%	100%	0%
3	53%	60%	46%	0%
4	60%	83%	54%	0%
5	58%	81%	40%	0%
6	20%	0%	0%	4%
7	64%	0%	0%	70%
8	87%	0%	0%	24%
9	90%	0%	0%	36%
10	20%	0%	0%	0%
11	58%	80%	56%	0%
Average	64%	45%	35.64%	12%

The results in Table III indicate that the proposed approach generally yields better results across all test sets compared to the EKF based method. Moreover, RMS appears to be more effective as a bearing health indicator compared to the variance or Renyi entropy [9].

V. CONCLUSIONS

In this paper, an adaptive predictive model based approach is proposed to determine the health of rolling element bearings by estimating their remaining useful lives (RULs). This approach employs a gradient based method to determine the time to start prediction (TSP) using linear regression analysis. Accurate detection of the TSP contributes to relatively more accurate

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RUL predictions with the proposed method, especially during the early stages of bearing degradation. The random errors or spurious fluctuations in the health indicator are removed using a linear rectification technique (LRT). After detecting the TSP, the proposed approach constructs a quadratic regression model over the same window of RMS samples that was used earlier for determining the TSP to learn the evolving trend of the health indicator and predict its future values. With each prediction of the future RMS values, the window is updated. The gradient of the linear regression model is then calculated based on the updated window. This gradient is then checked against a pre-determined value in order to determine whether a bearing has reached the failure threshold or not. The prognostic performance of the proposed method is evaluated using the $\alpha - \lambda$ metric. In most cases, the estimated RULs fall within the prescribed error bounds. The proposed method yields better RUL estimates than existing methods, especially, when a bearing has not entered a severe state of degradation.

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