RUL Prognostics: Recursive Bayesian Ensemble Prediction with Combining Artificial Degradation Patterns

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ABSTRACT

With the rising complexity of manufacturing processes, resulting from rapid industrial development, the utilization of remaining useful lifecycle (RUL) prediction, based on failure physics and traditional reliability, has remained limited. Although data-driven approaches of RUL prediction were developed using machine learning algorithms, uncertainty-induced challenges have emerged, such as sensor noise and modeling error. To address these uncertainty-induced problems, this study proposes a stochastic ensemble-modeling concept for improving the RUL prediction result. The proposed ensemble model combines artificial degradation patterns and fitness weights, which incorporate formulas reflecting failure patterns and various reliability function data with the observed degradation factor. Furthermore, a recursive Bayesian updating technique, reflecting the difference between expected and observed remaining life sequentially, was leveraged to reduce the prediction uncertainty. Moreover, we comparatively studied the predictive performance of the proposed model (recursive Bayesian ensemble model) against an existing baseline method (exponentially weighted linear regression model). Through simulation and case datasets, this experiment demonstrated the robustness and utility of the proposed algorithm.

1. INTRODUCTION

As production processes become increasingly complex and advanced, the increasing reliance on equipment necessitates efficient maintenance practices (Salunkhe et al., 2014). Currently, the preventive maintenance method, a conventional method for preventing equipment failure, is used to manage equipment conditions periodically according to the planning procedure (Hashemian, 2010). However, because each production process line operates under a different environment, the maintenance point is inaccurate and unstable. Therefore, maintaining the efficiency of the production process is a challenging task (Carvalho et al., 2019).

Recently, predictive maintenance has emerged as a state-of-the-art reliability management strategy for predicting equipment failures; predictions are made based on the current and historical conditions of the equipment. Through predictive maintenance, equipment downtime can be reduced, and optimal maintenance decisions can be realized. Furthermore, this maintenance mode enhances the efficiency of production processes. To detect faults or malfunctions in the manufacturing equipment and determine the exact maintenance point, certain predictive maintenance techniques have been developed that take into account the information obtained via multiple sensors (Sipos et al., 2014).

In predictive maintenance, prognostics is essential as it allows for the identification of future equipment conditions in advance. Prognostics is used to predict the remaining useful lifecycle (RUL) by assessing the degradation of equipment and deviation of their operating conditions from expected normal operating conditions. Specifically, RUL prediction is a key technology for state-of-the-art maintenance techniques, and this technology is drawing increasing interest and implemented in various manufacturing sites (Si et al., 2011; Chen et al., 2017).

RUL prediction can be classified into three main approaches: reliability-based approaches, physics-based approaches, and data-driven approaches (Heng et al., 2009). The reliability approaches, which are traditional approaches of RUL prediction, estimate the RUL based on the mean time-to-failure of reliability distributions (e.g. Weibull distribution, exponential distribution, and lognormal distribution) to historical time-to-failure data basically (Nannapaneni et al., 2020). Moreover, in physics-based approaches, the RUL is

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predicted using a mathematical model based on the equipment's life-cycle loading and failure mechanisms (Pecht & Gu, 2009). Furthermore, data-driven approaches predict the RUL via curve fitting on the degradation process and monitor environmental conditions in real time (Liu et al., 2012; Benkedjouh et al., 2012). However, reliability-based approaches have a drawback: the current equipment condition cannot be reflected because the RUL is predicted based on the mean time-to-failure. In addition, physics-based approaches are difficult to implement in complex systems because each system requires specific models for certain environments (Ahmad et al., 2017). Thus, as the aforementioned drawbacks hinder the feasibility of reliability-based and physics-based approaches, data-driven approaches have been extensively studied and characterized in the literature, which can be readily implemented in complex systems, reflecting the current equipment condition (Zhang et al., 2018; Peng et al., 2018; Lei et al., 2018). Regarding the research of the data-driven approaches, various models have been implemented in the prognostics field, such as machine learning, deep learning, ensemble learning, and similarity-based model.

In the field of machine learnings, Zhu et al. (2022) used support vector regression (SVR) to predict the RUL of a turbine engine. In the study, a genetic algorithm is applied to optimize the hyperparameters of the SVR model. Subsequently, SVR model is verified by using a small sample dataset of turbine engine data. The experiment shows that SVR outperforms the CNN and CNN-LSTM. As another machine learning model, Bienefeld et al. (2022) utilized the random forest model with various feature engineering methods to predict the RUL of rolling bearings. Through experiments with rolling bearing data, this method significantly improved the quality of RUL prediction.

Recently, with the advancement of computing power, deep learning models capable of handling large volumes of high-dimensional data have become extensively used. In particular, methods such as long short-term memory (LSTM) and gated recurrent unit (GRU) that address the long-term dependency issue of RNN are extensively employed in various applications. With respect to the state-of-the-art deep learning research, Tian et al. (2023) proposed an LSTM model that takes into account the spatial and temporal correlation of the components. This method was verified using turbofan engine data, and the experimental results showed it outperforms the other deep learning models such as BI-LSTM and CNN-LSTM. In the context of another deep learning model, Zhou et al. (2022) presented the reinforced memory GRU (RMGRU). This model enhances the RNN's long-term memory in several ways: by leveraging human forgetting laws, by combining state information from two prior moments, and by employing an attention mechanism. RMGRU was verified with the IEEE PHM 2012 bearing datasets, and the experimental results showed that RMGRU has a stronger predictive ability than other deep learning methods such as GRU and LSTM.

Despite extensive research on machine learning and deep learning, enhancing prediction performance in prognostics remains challenging. This is because the data that indicates the condition of the equipment exhibits complex characteristics, such as nonlinearity and time-varying phenomena (Atamuradov et al., 2017; Keizers et al., 2021). Therefore, ensemble learning has emerged to achieve better performance by combining multiple models (Radaideh et al., 2023). In related work on ensemble learning, Wang et al. (2022) proposed a feature fusion-based ensemble method for RUL prediction. In the study, the different characteristics of the features are extracted by signal analysis and deep learning methods. Subsequently, SVR based improved random subspace is constructed and combined with the mean-rule. This method was validated using the bearing datasets from the PROGNOSTIA platform and it improved the RUL prediction performance. As another method of ensemble model, Ma et al. (2021) presented ensemble deep learning with multi-objective optimization prediction. This method employs Deep belief network (DBN) as base model. Then, populations of DBNs are generated by the Non-Dominated Sorting Genetic algorithms II (NSGA-II) based on prediction accuracy and diversity measure. Subsequently, RUL is predicted using the mean-rule. The effectiveness of this method was evaluated in bearing cases, and it outperforms SVR and single DBN.

Additionally, the forgetting factor with recursive least square algorithm is widely used in RUL prediction. This methodology has two key advantages in RUL prediction. Firstly, the forgetting factor takes into account the equipment's latest condition by responding more sensitively to recent data and diminishing the influence of older data MA et al. (2022). Secondly, the recursive updating allows for real-time tracking of degradation curves that change over time Chang & Wu (2021). Related study with forgetting factor recursive least square algorithm, Lont et al. (2023) proposed a variable forgetting factor recursive least square algorithm with double extended Kalman filtering based on global mean particle swarm optimization for the state of energy (SOE) and state of health (SOH) estimation of lithium-ion batteries. Through experiments, they achieved stable and accurate estimates for both SOE and SOH. In addition, Hong et al. (2023) employed a recursive least square algorithm and an improved particle filter for SOH and RUL prediction. The accuracy of this method was validated using a lithium-ion battery dataset and, it yielded stable prediction results.

Unlike machine learning and deep learning models that are trained based on supervised learning, another kind of data-driven model is the similarity-based model. This model employs similar run-to-failure degradation profiles as references to predict RUL. For example, Lin et al. (2023) proposed a Gaussian process-based similarity model. The Gaussian process model is adopted to generate similar reference degradation trajectories. Subsequently, similarity is calculated using an exponential similarity measure, which then serves as the similarity weight. Based on these weights, RUL is predicted as the weighted average of the similar reference degradation trajectories. The performance of this model is verified with turbine engine data and GaAs laser data. For another similarity model, Catelani et al. (2022) employed the double exponential-based similarity model for Battery RUL prediction. The dynamic time warping (DTW) algorithm is used for calculating similarity between reference degradation profiles and actual degradation. Based on similarity, 45 nearest trends are extracted. Then, RUL is estimated as the median of the extracted trends. The effectiveness of this method has been tested using a battery degradation dataset and it achieved good prediction accuracy.

In this study, we employed exponentially weighted linear regression (EWLR) which is a simple linear regression using the forgetting factor recursive square algorithm, as a benchmark model. Due to the similarity of its recursive prediction method, EWLR was compared with the proposed methodology.

EWLR is a weighted linear regression model that incorporates exponential weight. Weighted linear regression is expressed as follows:

$$arg_{\beta_t} min \ \sum_{t=1}^{N} w_t \, (y_t - \beta_t x_t)^2 \qquad (1)$$

where w_t $(t = 1,2, \dots, N)$ denotes the weight assigned to the observation at time t, x_t represents, input data corresponding to multi-channel signals, y_t symbolizes the degradation factor, and β_t indicates the coefficient of the linear degradation curve. In the field of prognostics, as the volume of data increases, historical data decreases the predictive performance. Thus, an exponential weight is used to enhance predictive performance by reflecting refresh data proximate to failure conditions. The exponential weight is formulated as:

$$w_t = \alpha(1-\alpha)^{N-t}, \qquad 0 \leq \alpha \leq 1 \qquad (2)$$

where α denotes the forgetting factor that describes the reflecting level of the past. The lower the α, the higher will be the level of reflection of the past. Accordingly, weighted least square estimates, $\hat{\beta}$, can be expressed as:

$$\hat{\beta} = (X^T W X)^{-1} X^T W y \qquad (3)$$

where the matrix W denotes a diagonal matrix comprising the weight w_t, X and y are matrices comprising x_t and y_t, respectively.

EWLR offers several advantages: it is suitable for tracking time-varying problems in signal processing, and as EWLR does not require any parameters except the forgetting factor, the computational cost is relatively low. Thus, it is feasible in the field of prognostics field. However, EWLR has disadvantages: it is challenging to apply in nonlinear degradation patterns and features predictive uncertainty problem. A more detailed explanation of the predictive uncertainty problem is presented in Section 2.

This study proposes a new concept to overcome the uncertainty problem encountered in EWLR. This proposed idea is named recursive Bayesian ensemble model (RBEM). RBEM is an ensemble model integrating four different steps: (1) generation of artificial degradation patterns reflecting reliability information, (2) calculating the fitness weight, (3) RUL prediction using a mixture of artificial degradation patterns, and (4) updating the prediction result with Bayesian inference. The working principle of RBEM is demonstrated in Section 3.

The remainder of this study is organized as follows. Section 2 presents a limitation of the EWLR methodology when applied in real cases. RBEM methodology is demonstrated in Section 3. Section 4 presents a simulation study to examine the performance of RBEM under various scenarios. Section 5 illustrates a case study using a real case of bearing dataset that evaluates the performance of RBEM methodology. Finally, based on this study's findings, insights and conclusions are drawn and reported in Section 6.

2. MOTIVATION

The motivation for this study comes from the EWLR prediction in the NASA bearing dataset. This dataset was reported by the Center for Intelligent Maintenance System (IMS), University of Cincinnati and is publicly available at the NASA Ames Prognostics data repository (Lee, et al., 2007). Regarding IMS bearing dataset, Section 5 provides a more detailed description.

Figure 1 shows the RMS curve of two bearing cases in the IMS bearing dataset. In Figure 1, as the bearing approaches failure, the sensor signal gradually increases.

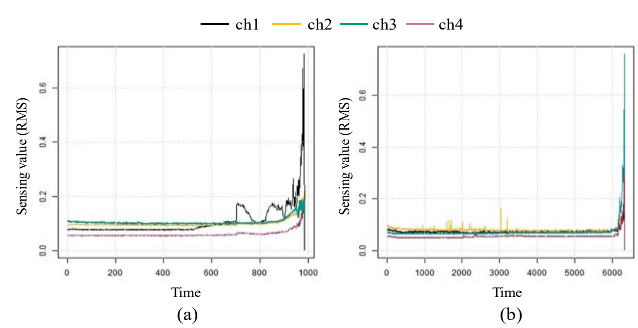


Figure 1. The RMS curve of bearing cases:
(a) case 2 and (b) case 3.

The RUL can be predicted via four major steps: 1) through signal processing methodology, 2) adoption of anomaly detection methodology, 3) by transforming the anomaly score to degradation factor, and 4) by using fitted degradation curve and predefined failure threshold. We used the root mean squared (RMS) value for signal processing, multivariate state estimation technique (MSET)-based linear regression for anomaly detection and transformed anomaly score to degradation factor via the residual-based degradation model.

MSET estimates equipment health by analyzing residuals, which depict the deviation of observed data from expected values. Subsequently, the degradation factor which represents the cumulative health estimated by MSET using multi-channel data, is utilized for RUL prediction. In this regard, Cheng and Pecht verified the utility of MSET and the residual-based degradation model for RUL prediction (Cheng & Pecht, 2007). Finally, EWLR methodology is used for RUL prediction.

Figure 2 describes the results of EWLR prediction of bearing cases. Observably, EWLR prediction fluctuates considerably implying a high degree of prediction uncertainty. The cause of uncertainty is that EWLR basically assumes linearity and is difficult to reflect overall degradation behavior of the bearings, resulting in non-linear characteristics and inefficient bearing dataset problems that provide single degradation behavior. Moreover, since the EWLR prediction captures the most recent pattern, it tends to overestimate the actual RUL. If this EWLR model is applied in industry, this high fluctuation of the EWLR prediction will lead to catastrophic failure of equipment.

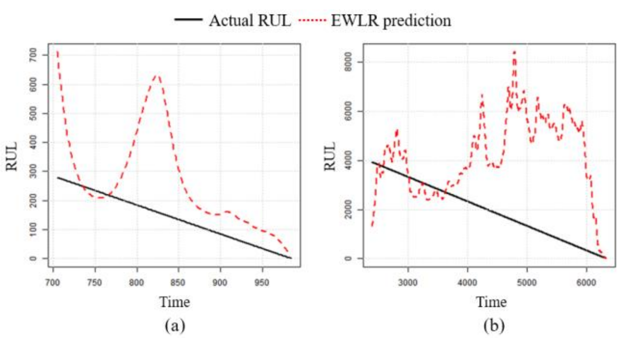


Figure 2. Bearing cases of RUL prediction using EWLR method (a) case 2 and (b) case 3.

3. PROPOSED METHOD

In this paper, we proposed a novel stochastic ensemble model for RUL prediction, referred to as RBEM. The main ideas of RBEM are Artificial Degradation Pattern, ensemble modeling, and recursive Bayesian update method. First, an Artificial Degradation Pattern (ADP) denotes empirical degradation curve that incorporates reliability information. In the context of ADP, reliability information represents the probability distribution for the equipment's overall lifespan.

Second, the ADPs are adopted as mixture components for ensemble prediction to achieve stable performance.

Finally, the Bayesian updating technique is a probabilistic method that refines probability of event based on data. This technique relies on Bayes' theorem, computing posterior probability from prior probability and likelihood. By iteratively incorporating new data, Bayesian updating allows us to continuously refine the beliefs or estimates about the event, making it a powerful tool (Star & McKee, 2021). In the present research, the recursive Bayesian updating technique is applied to mixture weights, which are the main components for ensemble prediction.

The RBEM has the following advantages:

- The reliability information aids in reducing prediction uncertainty by incorporating the overall lifespan information, unlike general prognostics modeling that reflects only the individual degradation pattern of equipment.

- The Ensemble modeling enhances result stability by integrating multiple patterns for prediction. Furthermore, it can avoid overfitting encountered by single models.

- The Recursive Bayesian update method utilizes time-based updates to track data changes over time. Additionally, it facilitates robust predictions by dampening the influence of new data with prior information.

To briefly summarize the procedure of RBEM Prediction, RBEM predicts the RUL through a combination of ADPs and fitness weights via the method of recursive updating. The RBEM generates ADPs in advance through mathematical equations and existing reliability information.

Once an adequate number of ADPs are pre-drawn, RBEM identifies the direction that the degradation curve tends toward in the future by combining pre-drawn ADPs with fitness weights.

After RUL prediction, the fitness weight is recursively updated to reduce predictive uncertainty. Considering the characteristic that the RUL is predicted after detection of failure precursors, the overall process of RBEM is activated when the degradation factor exceeds the control limit.

The RBEM procedure consists of four major steps: (1) ADP generation, (2) Fitness weight calculation, (3) Ensemble prediction, and (4) Recursive Bayesian updating. The overall procedure of RBEM is represented in Figure 3.

3.1. ADP Generation

In this study, a simple quadratic equation was employed to generate ADPs in order to capture the nonlinearity of the degradation curve. The quadratic equation is expressed as:

$$f(t) = at^2 + bt + c \tag{4}$$

where, a, b, and c are the coefficients of degradation curve. The reliability information is defined as $RI \sim N(\mu, \sigma)$, where

μ denotes the mean of lifespan and σ indicates the standard deviation of lifespan. Notably, any distribution can be used as reliability information. Subsequently, in the process of ADP generation, lifespan information is randomly sampled from the reliability distribution. Thereafter, the parameters a, b, c for the quadratic equation, which are determined by the following two points, $(trigger\ index, control\ limit)$ and $(sampled\ lifespan, failure\ threshold)$, are estimated. In terms of the trigger index, it represents the time when RUL prediction starts. Accordingly, the estimated quadratic equation denotes the ADP.

3.2. Fitness Weight Calculation

For calculating the fitness weight, Kolmogorov Smirnov (K–S) test was conducted. This test is widely used as fitness test in statistics (Massey, 1951; Berger & Zhou, 2014). For the K–S test, the maximum value of each difference is used that corresponds to the empirical cumulative probability distribution. The K–S test can be calculated as:

$$D = \max[F_t(x) - G_t(x)] \tag{5}$$

where $F_t(x)$ denotes the empirical cumulative distribution function of the actual degradation factor, which is calculated by multi-channel data, and $G_t(x)$ symbolizes the empirical cumulative distribution of ADP. RBEM contains an exponential weight to reflect the latest condition of the equipment in addition to the K–S test. The combined equations, exponential weight, and K–S statistic can be re-written as follows:

$$\pi_t = w_t \max[F_t(x) - G_t(x)] \tag{6}$$

where w_t denotes the exponential weight and π_t represents the stochastic fitness weight of ADP. Exponentially weighted K–S statistics of actual degradation factor and ADP are transformed to fitness weight along with the constraint $\sum \pi_m = 1$. In this study, exponentially weighted K–S test was utilized as the fitness weight; nevertheless, any methodology could be used.

3.3. RUL Prediction

The ensemble RUL prediction can be expressed as:

$$RUL = \sum_{m=1}^{M} \hat{\pi}_m RUL_m \tag{7}$$

where $\hat{\pi}_m$ $(m = 1,2,\ldots,M)$ indicates the fitness weight with prior knowledge reflected and RUL_m denotes the RUL for each ADP. RUL can be predicted using the weighted sum of the RUL with fitness weight.

3.4. Implementation of Recursive Bayesian Updating

This study proposes a recursive updating technique under a fitness weight with Bayesian inference to reduce the prediction uncertainty. This Bayesian inference is expressed as follows:

$$Pr\left(\hat{\pi}_{m,t} \middle| x_{m,t}, \hat{x}_{m,t}\right) \propto \prod_{t=1}^{N} Pr\left(\pi_{m,t}\right) L\left(\pi_{m,t} \middle| x_{m,t}, \hat{x}_{m,t}\right) \tag{8}$$

where $x_{m,t}$ $(t = 1,2,\ldots,N)$ represents the actual degradation factor, $\hat{x}_{m,t}$ denotes the ADP, and $Pr\left(\pi_{m,t}\right)$ symbolizes the prior of fitness weight. As the prior is unknown, it is allocated uniformly with $\frac{1}{m}$. Herein, $L\left(\pi_{m,t} \middle| x_{m,t}, \hat{x}_{m,t}\right)$ indicates the likelihood of fitness weight, and $Pr\left(\hat{\pi}_{m,t} \middle| x_{m,t}, \hat{x}_{m,t}\right)$ denotes the posterior of fitness weight with uncertainty reduced. Based on the aforementioned Bayesian inference, the fitness weight is updated sequentially.

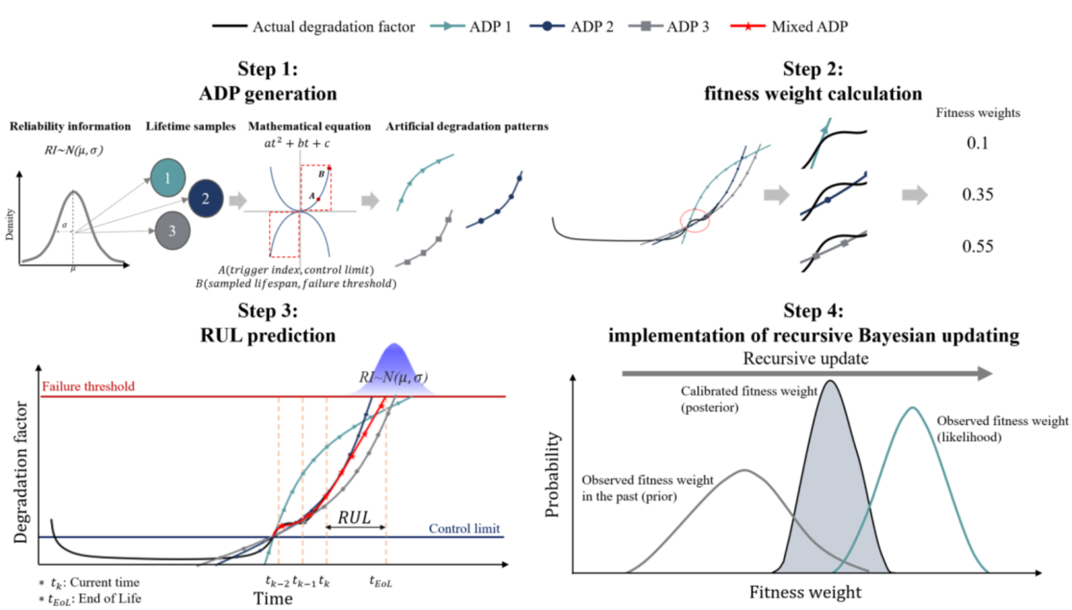


Figure 3. Overall procedure of recursive Bayesian ensemble model.

4. SIMULATION STUDY

4.1. Simulation Setup

We performed a simulation study to examine the properties of RBEM and demonstrate its usefulness. Simulation data was generated considering the bathtub curve, a typical aspect used in reliability engineering. The bathtub curve explains a particular form of the hazard function, which comprises three periods: decreasing failure, constant failure, and increasing failure (Hjorth, 1980). Figure 4 illustrates the generation method of simulation data. For generating simulation data, we assumed that the bathtub aging curve of equipment corresponded to the degradation curve.

Although the bathtub aging curve describes failure rate of entire population of equipment, whereas the degradation curve characterizes the stress of individual equipment. However, they possess a commonality: they are representations of failure through stress accumulation over time. When combining the patterns of a bathtub curve, the Weibull distribution is used to characterize failure distributions in all three phases of the bathtub curve.

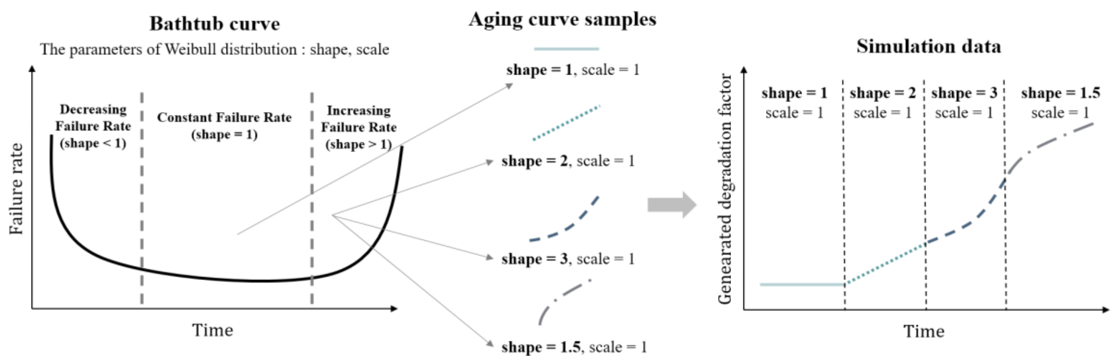


Figure 4. Generation method of the simulation data.

Figure 5 shows three scenarios of simulation data that represent a bathtub curve. Simulation data for each case features 1000 observations, and each case represents the typical failure pattern observed in reliability engineering.

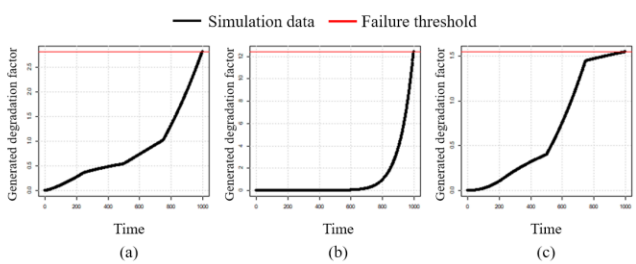


Figure 5. Three simulation scenarios generated via bathtub curve patterns: (a) scenario 1, (b) scenario 2, and (c) scenario 3.

To evaluate the usefulness of RBEM, we performed 100 replications to determine the average values and standard deviation of the root mean squared error (RMSE). The RMSE is expressed as:

$$RMSE = \sqrt{\frac{1}{t}\sum_{t=1}^{T}(y_t - \hat{y}_t)^2} \tag{9}$$

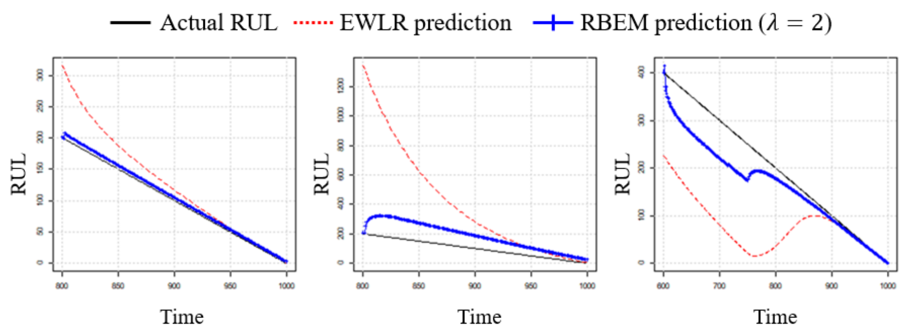
where t indicates the number of observations, y_t symbolizes actual RUL at time t, $\hat{y}_t$ represents predicted RUL at time t. Considering that the data-driven model required sufficient data to predict the RUL, prediction was performed under the assumption that failure precursor appeared in periods of 800, 800, and 600 for each simulation data. Thereafter, the failure threshold was predefined as the degradation at 1000 period arbitrarily by the user, thereby allowing for comparative performance evaluations of EWLR and RBEM. As the simulation data was generated, reliability information for RBEM was undetermined. Therefore, we used a non-centrality parameter (λ) to measure the statistical power of RBEM. In this study, the non-centrality parameter was used to quantify the magnitude of the shift in the reliability information. Reliability information is defined as $RI \sim N\left(EoL, \frac{EoL \times \lambda}{10}\right)$, where $\lambda = 1,2,$ and 3 is the non-centrality parameter. In this study, 30 ADPs were generated, and the number of patterns was determined heuristically.

4.2. Simulation Results

This section presents the simulation results for RBEM. Table 1 lists the RMSEs of the RBEM and EWLR predictions applied to simulation data. The mean and the standard deviation of the RMSE corresponding to RBEM are lower than those corresponding to EWLR. These results suggest that RBEM was more efficient in terms of RMSE. Figure 6 denotes the prediction results of simulation data implemented by the two models: RBEM ($\lambda = 2$) and EWLR. The more the line approaches the black solid line, the higher is the model efficiency. As illustrated in Figure 6, the RBEM prediction is more proximate to the actual RUL than the EWLR prediction. This visualization indicates that RBEM yields a higher performance than EWLR.

Scenario	EWLR	RBEM					
		Small ($\lambda = 1$)		Medium ($\lambda = 2$)		Large ($\lambda = 3$)	
		MEAN	SD	MEAN	SD	MEAN	SD
Scenario 1	37.6587	5.0793	4.4363	13.2865	7.8367	22.6024	13.3327
Scenario 2	430.9468	46.4724	12.5174	91.9238	13.7915	106.6536	17.5907
Scenario 3	153.5609	26.4842	16.6514	52.0305	20.8824	47.9843	27.2714

Table 1. Simulation results of EWLR and RBEM predictions with RMSE measures.



(a) (b) (c)

Figure 6. RUL prediction result based on the three simulation scenarios corresponding to RBEM ($\lambda = 2$) and EWLR: (a) scenario1, (b) scenario 2, and (c) scenario 3.

5. CASE STUDY

5.1. The Description of IMS Bearing Dataset

As reported in this section, we utilized the IMS bearing dataset. This dataset features three fault bearings cases, representing run-to-failure data. As displayed in Figure 7, four double-row bearings (Rexnord ZA-2115) are installed on the shaft. The rotation speed is maintained at 2000 RPM using an AC motor coupled to the shaft through rub belts. The bearings are force lubricated and radially loaded with a 6000-lbs load via a spring mechanism. The vibration acceleration of bearings is measured using high-sensitivity accelerometers (Quartz ICP®), and data are recorded via a NI DAQcard-6062E.

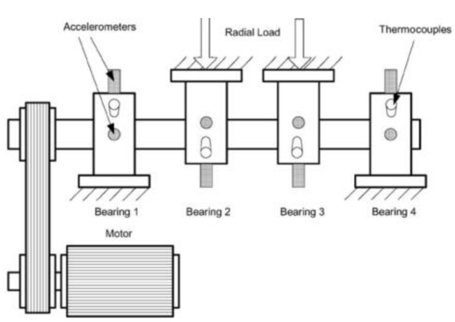


Figure 7. Bearing test rig and sensor (Qiu et al., 2006).

The vibration data were collected with an individual file consisting of 20,480 points (sampling rate: 20 kHz) from each accelerometer (Eren et al., 2019). Each dataset represents a test-to-failure experiment and the bearing defect that occurred at the end of the test-to-failure experiment. Extensive details pertaining to the IMS bearing dataset are presented in Table 2.

5.2. Setup of Case Study

In this study, we adopted the RUL prediction process presented in section II. For predicting the RUL, the RMS was implemented to transform 20,480 points of each file into a single cycle.

Subsequently, MSET-based linear regression and the residual-based degradation model were employed sequentially. Figure 8 illustrates results of three fault bearing cases of the degradation factor in the IMS bearing dataset. Observably, the red solid line indicates the predefined failure threshold, which is the degradation factor at time of failure corresponding to each case of fault bearing. The blue solid line represents the control limit, which is defined according to in-control observations (significance level: 0.05) via bootstrapping. In accordance with the control limit, RUL prediction was performed under the assumption that failure precursor occurred in the periods of 1700, 705, and 2400 for each case of the IMS bearing dataset. As the IMS bearing dataset features only three cases of failure, reliability information in RBEM is unknown. Thus, the non-centrality parameter was leveraged to define the reliability information.

Additionally, to test RBEM, 30 ADPs were generated for RUL prediction.

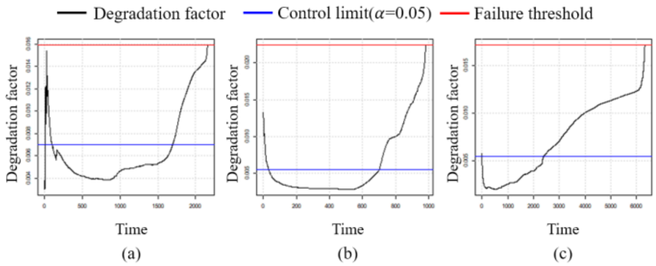


Figure 8. Three fault bearing cases of the degradation factor in IMS bearing dataset: (a) case 1, (b) case 2, and (c) case 3.

5.3. Results of Case Study

The RBEM performance is evaluated against that of EWLR based on the three cases fault bearing dataset. Table 3 summarizes the case results of EWLR and RBEM predictions with corresponding RMSE measures. The RMSE of RBEM is lower than that of EWLR, validating that RBEM is more efficient than EWLR for processing the IMS bearing dataset. In addition, although λ rises, the RMSE is not always high, indicating that the approach of ADP mixture is valid for RBEM.

Case	Endurance duration	Number of files	Number of channels	Data gathering time	Fault bearing & fault type
Case 1	34 days 12 hours	2156	8	Every 5 minutes (43 files), 10 minutes (2113 files)	Bearing 3: inner race, Bearing 4: roller element
Case 2	6 days 20 hours	984	4	Every 10 minutes	Bearing 1: outer race
Case 3	43 days 22 hours	6324	4	Every 10 minutes	Bearing 3: outer race

Table 2. Details of the IMS bearing dataset.

Case	EWLR	RBEM					
		Small ($\lambda = 1$)		Medium ($\lambda = 2$)		Large ($\lambda = 3$)	
		MEAN	SD	MEAN	SD	MEAN	SD
Case 1	110.8473	43.7252	14.1422	33.1425	16.2865	36.8453	24.4483
Case 2	183.103	26.2396	7.8459	25.7971	10.5977	23.7503	16.5252
Case 3	3081.316	148.0494	56.1389	153.6058	71.1334	212.7098	153.1416

Table 3. Case results of EWLR and RBEM predictions with RMSE measure.

Figure 9 denotes the three fault bearing cases of RUL prediction results, implemented via RBEM ($\lambda = 2$) and EWLR. EWLR prediction has a considerably fluctuating result in the three failure cases of bearing datasets, which is a clear manifestation of the uncertainty problem. In contrast, the RBEM prediction appears smooth, thereby representing relatively stable RUL prediction. As RBEM uses reliability information and the recursive updating method, it yields stable results in terms of RUL prediction. Specifically, RBEM is more stable and offers a higher performance than EWLR in terms of the RMSE and visualization.

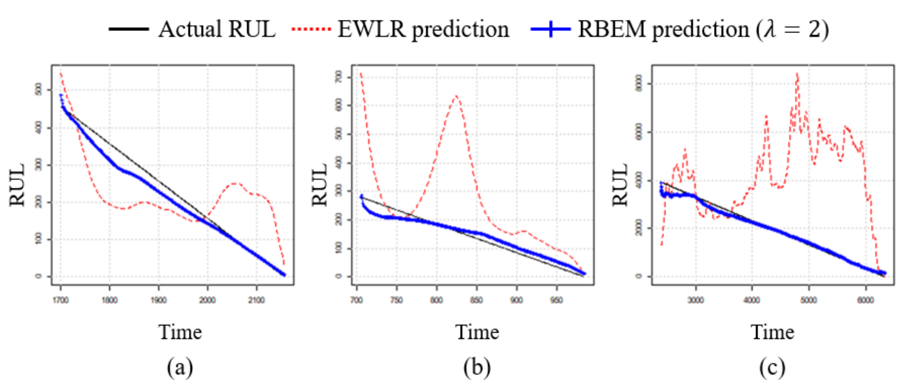


Figure 9. RUL prediction result of three fault bearing cases via RBEM with $\lambda = 2$ and EWLR prediction: (a) case 1, (b) case 2, and (c) case 3.

6. CONCLUSION

To address the uncertainty problem encountered in EWLR prediction, this study proposed RBEM, which could reflect reliability information. RBEM could predict the RUL using a mixture of ADPs and the fitness weight. For generating ADPs reliability information and mathematical equations were used. Finally, the method of recursive Bayesian updating was adopted sequentially to improve the robustness of the RUL prediction. As revealed by the results of the simulation and case study based on the IMS bearing dataset, RBEM yielded a more stable predictive performance than EWLR. Furthermore, this stable result could be of great importance for formulating maintenance decisions. However, RBEM had limitations: Firstly, to implement the proposed model in real-world applications, it is necessary to have access to historical failure data. The RBEM leverages historical failure data to establish reliability distributions, which are subsequently employed for predicting the RUL. The second constraint relates to the absence of incorporating physical characteristics. In the field of RUL prediction, having an understanding of the failure physics is crucial. Physical factors contribute to a better understanding of performance deterioration and failure mechanisms in equipment. Moreover, variables like environmental conditions, operational conditions, and component interactions, which exert substantial influence on the equipment, can affect its physical attributes. As the future research direction, to further improve the robustness of RUL prediction, physical characteristics will be incorporated into the proposed model.

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