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Predicting the Deterioration Trend of Rolling Element Bearings through an Adaptive Relevance Vector Machine Utilizing Limited Historical Data

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ABSTRACT: Rotating equipment, akin to human systems, necessitates diligent care and monitoring to ensure optimal functioning. Given that nearly half of rotating equipment failures can be attributed to bearing malfunctions, it is crucial to develop effective predictive solutions. One promising approach is developing a model capable of forecasting bearing deterioration once it enters the degradation stage. With the rise of artificial intelligence, numerous studies have sought to estimate bearing lifespan or detect deterioration. However, these methods often rely on continuous data collection, which is frequently unavailable in industrial settings. This paper introduces a relevance vector machine (RVM) model that effectively provides predictions utilizing limited historical data while also offering results with a defined confidence level. To validate this model, run-to-failure tests are conducted in the laboratory, complemented by vibration analysis of two electro-fans in an industrial environment. The model is developed through three stages: identifying the optimal health indicators marking the onset of degradation, determining the best indicators for describing the deterioration trend, and configuring the RVM through hyperparameter optimization. The model's robustness is further evaluated against data reduction and measurement intervals, demonstrating superior predictive capabilities with accuracies exceeding 92.4% in laboratory data and over 91.1% in industrial data.

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1- Introduction

Rolling element bearings (REBs) are critical components in the operation of rotating machinery across various industrial sectors. They account for approximately 45% of failures in rotating equipment. REBs possess a finite lifespan, necessitating their replacement after a certain period of use. A key challenge lies in identifying the optimal replacement time. Premature replacement leads to an increase in inventory costs due to unused bearing life, while delayed replacement can result in secondary damage or catastrophic failure, compounding the risk of operational disruptions. Both scenarios are associated with significant financial losses for industries. Consequently, accurately predicting the remaining useful life (RUL) and monitoring the deterioration trends of REBs are essential for enhancing the reliability of industrial rotating equipment, enabling timely interventions.

With advancements in technology and the emergence of artificial intelligence, a significant number of studies have been published concerning the prediction of RUL for REBs. Notably, Qin et al. (2020) [1] introduced a novel approach known as the Gated Dual Attention Unit (GDAU) neural network for RUL prediction. The GDAU model incorporates dual attention gates to forecast the health indicator sequence of an REB utilizing vibration data, achieving a mean absolute percentage error (MAPE) of 14.8% on the PRONOSTIA public dataset. Additionally, Wu et al. [2] implemented a long-term cascading convolutional memory network for RUL prediction, which effectively captures spatio-temporal correlations among features. To enhance the stability of the prediction results, they also employed a smoothing technique based on multiple averaging operations.

In their 2021 study, Zeng et al. [3] employed an online transfer learning-based approach to predict the RUL of REBs. Their methodology effectively addressed several challenges, including the scarcity of run-to-failure data, the variability of deterioration trends under differing conditions, and the incorporation of unlabeled online data. This approach integrated a deep learning model during the offline phase and fine-tuning with unlabeled data during the online phase to enhance the accuracy of RUL estimations. Consequently, their method achieved a maximum cumulative relative accuracy (CRA) of 84% on the PRONOSTIA dataset. Additionally, She et al. [4] proposed a bidirectional gated recurrent unit (BiGRU) method, utilizing the bootstrap technique to predict RUL and to compute the confidence interval (CI) of RUL, thus capturing prediction uncertainty. The results indicated that the BiGRU model attained the lowest MAPE of 6.1% for a bearing tested in their laboratory.

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In 2022, Liu et al. [5] introduced a data-driven approach for predicting the RUL of REBs in air engines. This method employed a deep convolutional neural network in conjunction with a particle filter. Validation of the approach was conducted using experimental data, resulting in a mean absolute error (MAE) of 2.2%. Similarly, Zhang et al. [6] developed a bearing life prediction method leveraging digital twin technology to enhance the accuracy of RUL predictions. Their approach incorporated unsupervised classification and an attention mechanism for feature extraction, culminating in the formation of a comprehensive digital twin dataset. The method's validity was established using the authors' testing setup.

In 2023, Li et al. [7] introduced a method for predicting the RUL that employs the GRU-DeepAR model with an adaptive failure threshold. Their experimental investigations and validations utilized the XJTU dataset and an accelerated test bench featuring an internal roller bearing. These experiments demonstrated the effectiveness of their proposed method compared to other predictive models, such as a convolutional neural network (CNN) and a long short-term memory (LSTM). Concurrently, Zhang et al. developed a new model comprising three components: a multiscale entropy-based feature selection for health index (HI), a Hodrick-Prescott filter process to ensure optimal performance with minimal fluctuations in HI. The model also includes an LSTM neural network combined with a particle filter algorithm for RUL prediction. The resulting root mean square error (RMSE) on the PRONOSTIA dataset was approximately 0.88.

In 2024, Guo et al. [8] introduced a novel hybrid method that constructs a nonlinear health index using full ensemble empirical mode decomposition with adaptive noise and kernel principal component analysis. Additionally, the 3σ criterion was employed for the health assessment of bearings. Deterioration modeling and probabilistic predictions of RUL were executed using a nonlinear Wiener process with random effects, guided by the authors' laboratory test data. Meanwhile, Wen et al. [9] proposed a method combining the envelope spectral index, extended Kalman filter, and bearing fault frequency analysis, using Bayesian regression to estimate RUL. This approach effectively predicts early RUL with few observations, making it valuable for early-stage bearing health management. However, it is important to note that the primary focus of the research mentioned above was on RUL prediction, while the emphasis of the present paper is on predicting the deterioration trend.

In conclusion, the literature review highlights that research aimed at predicting the lifespan of rotating equipment bearings typically necessitates the collection of online data. It also requires the application of sophisticated models to ensure accurate predictions using extensive historical datasets. However, the practicality of online data collection within industrial settings is frequently limited, underscoring the necessity for an RUL prediction model that requires minimal data. This study is centered on proposing an innovative method for developing a predictive model targeting bearing deterioration based on limited vibration history. The desired features of this model encompass not only effective performance under limited historical data but also the capability to predict the upcoming deterioration trend with a defined level of confidence. Additionally, it is designed for seamless application in both online and offline condition monitoring systems. To achieve these objectives, a machine learning-based algorithm, relevance vector machine (RVM), characterized by a probability distribution that ensures responses reflect the specified confidence level (CL), is employed. The distinct contribution of this research lies in its unique approach to training the model for the prediction of vibration conditions during subsequent data acquisition, thereby enhancing its applicability in a variety of monitoring contexts. Best HIs are strategically selected to detect the onset of fault (start of degradation stage of REB) and to articulate the deterioration trend, while the optimal quantity of data is meticulously determined to maximize the algorithm's accuracy. To evaluate the efficacy of the proposed algorithm, laboratory experiments are conducted to record the vibration behavior of a bearing through run-to-failure tests. The developed model subsequently serves as the basis for assessing the model's performance using industrial data samples.

This paper is structured as follows: Section 2 provides an overview of the test rig and details the run-to-failure tests conducted on the bearings under laboratory conditions. It also includes data from two industrial cases of vibration corresponding to the damaged bearings. Section 3 is dedicated to a description of the methodology and the development of the predictive model. Then, it emphasizes the selection of the optimal HIs for identifying the onset of the REB degradation stage and predicting deterioration trends. In Section 4, the results obtained from the laboratory dataset are presented, along with a determination of the optimal quantity of data required for accurate predictions. It also addresses the verification of the developed model using industrial data. Finally, a summary, conclusions, and suggestions for future research are provided.

2- Data Collection

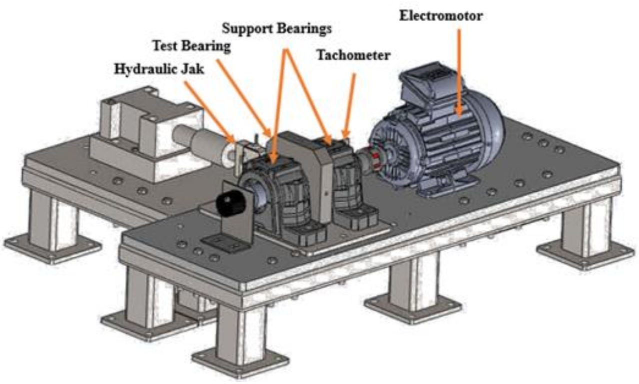
This section introduces the collected data in the laboratory through the run-to-failure test of four bearings for developing the appropriate deterioration trend model prediction, and the collected data in the industry to verify the developed model.

2- 1- Bearing run-to-failure test in laboratory

Developing an intelligent bearing deterioration prediction model requires laboratory data under controlled conditions by performing run-to-failure (highly accelerated life) tests (HALT). For this purpose, this research is conducted in the condition monitoring laboratory, using the bearing test rig, which is seen in Fig. 1. The test rig consists of an electromotor as a driver, a hydraulic jack for applying the pressure load on the test bearing, two support bearings of the shaft, a tachometer for recording the speed, and accelerometers for recording the vibrational signals. The magnetic accelerometer sensors are placed on the test bearing housing. Technical info of the

Table 1. Technical specification of the experimental test

Parameter	Unit	Value
Electromotor nominal power	kW	1.5
Electromotor nominal speed	RPM	3000
Applied pressure load on the test bearing	kN	1.2
Accelerometer sensitivity	mV/g	100
Accelerometer resonant frequency	kHz	30
Accelerometer range	g	±80
Test bearing type	-	Deep groove ball bearing
Test bearing bore diameter	mm	50
Test bearing outside diameter	mm	90
Test bearing width	mm	20
Test bearing dynamic load rating	kN	37
Test bearing static load rating	kN	23.2



a)

b)

Fig. 1. Bearing test rig in the condition monitoring center: a) Schematic view b) Real view

accelerometers, test bearing, and operating condition of the test are listed in Table 1. Run-to-failure tests are performed for four deep groove ball bearings. To speed up the test, a hole with a diameter of 3 mm is created in the outer rings of the bearings, as seen in Fig. 2. This hole is not an artificial defect, although it may cause nearby failures. The purpose was to induce vibrations for earlier failure in controlled laboratory conditions, a common practice in bearing failure testing.

Each test has been stopped in such a way that, in addition to a significant increase in acceleration, the noise of the test bearing has increased sharply. The vibration level at test termination varies between samples, and decisions for test stoppage are made by experts based on observed conditions. So, there is no fixed vibration amplitude threshold for stopping the test. The run-to-failure time for each test bearing is listed in Table 2. It must be noted that all bearings were tested under the same speed (3000 RPM) and load (1.2 kN), yet their failures occurred unpredictably at different times due to factors like microscopic defects, manufacturing variations, and uncontrollable operating environments.

As an illustration, Fig. 3 presents the time waveform of the bearing vibrations recorded at the start of the test and at the end, along with the corresponding kurtogram image. The time response reveals an increase in vibration amplitude of

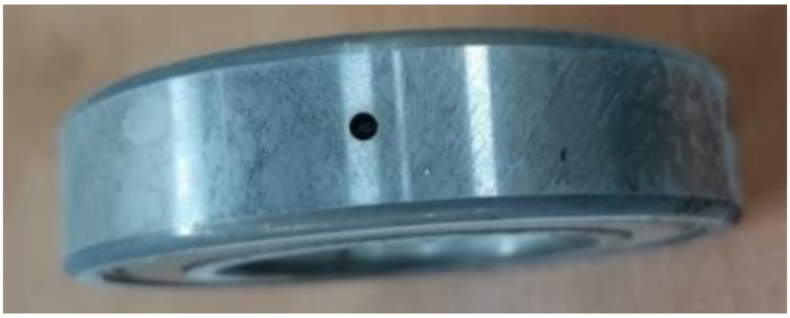


Fig. 2. The hole created in the outer ring of the bearing to speed up the run-to-failure test (highly accelerated life test: HALT)

Table 2. Run-to-failure time for each tested bearing (Speed = 3000 RPM, and Load = 1.2 kN)

Test Bearing Number	Run-to-Failure Time
1	3 days + 18 hr + 11 min
2	2 days + 15 hr + 25 min
3	22 hr + 34 min
4	1 day + 22 hr + 59 min

up to six times with highly impulsive behavior, as well as the progression of failure until the bearing reaches the fourth stage of its failure can be seen in the kurtogram, which has exposed the entire frequency range to random vibrations with a considerable increment in the kurtosis.

2- 2- Damaged bearing in industry

The industrial data used in this article is taken from a Petrochemical Company in Arak. The data collected is related to the bearing of electro-fans. Specifications of the machines and bearing information of them are given in Table 3. It has been observed that the geometric and load characteristics of industrial bearings differ significantly from those of laboratory bearings (Table 1). Consequently, it is anticipated that the developed model is expected to be capable of estimating the deterioration trend for various REBs. The trend of changes in vibration velocity and acceleration recorded for these bearings, from the onset of the degradation stage of REB through to the replacement and subsequent data, is illustrated in Fig. 4. The increase in the vibration amplitude of the bearings is clearly visible in the acceleration diagrams. Following the replacement of the bearings and their subsequent disassembly, it was observed that the first bearing exhibited an inner ring failure, while the second bearing demonstrated failures in both the inner and outer rings, as depicted in Fig. 5.

3- Prediction of Deterioration Trend

The focus of this section is to present a model for predicting deterioration trends in REBs utilizing vibration signals. This model becomes applicable after the onset of the degradation stage of the REB, at which point the bearing can no longer be classified as healthy, necessitating monitoring it to prevent catastrophic failure. Initially, a suitable HI is identified to determine the onset of the degradation stage. Subsequently, an appropriate feature is selected to effectively characterize the deterioration trend of the REB. In conclusion, this section describes the proposed model, which is based on RVM and is capable of providing results with a specified CL.

3- 1- Onset of degradation stage health indicator

The indices of root mean square (RMS), Peak, Crest Factor, and Kurtosis are calculated for four bearings tested in the laboratory throughout the entire data collection period (Fig. 6) using the vibrational acceleration signals. The separation between health and degradation stages for the trends of all aforementioned features is based on the outlier detection algorithm extracted from the normal distribution. This approach is a straightforward and effective method for identifying anomalies in the data. Since the initial unhealthy condition typically appears as an outlier compared to normal behavior, this algorithm is well-suited to detect it. The method works as follows:

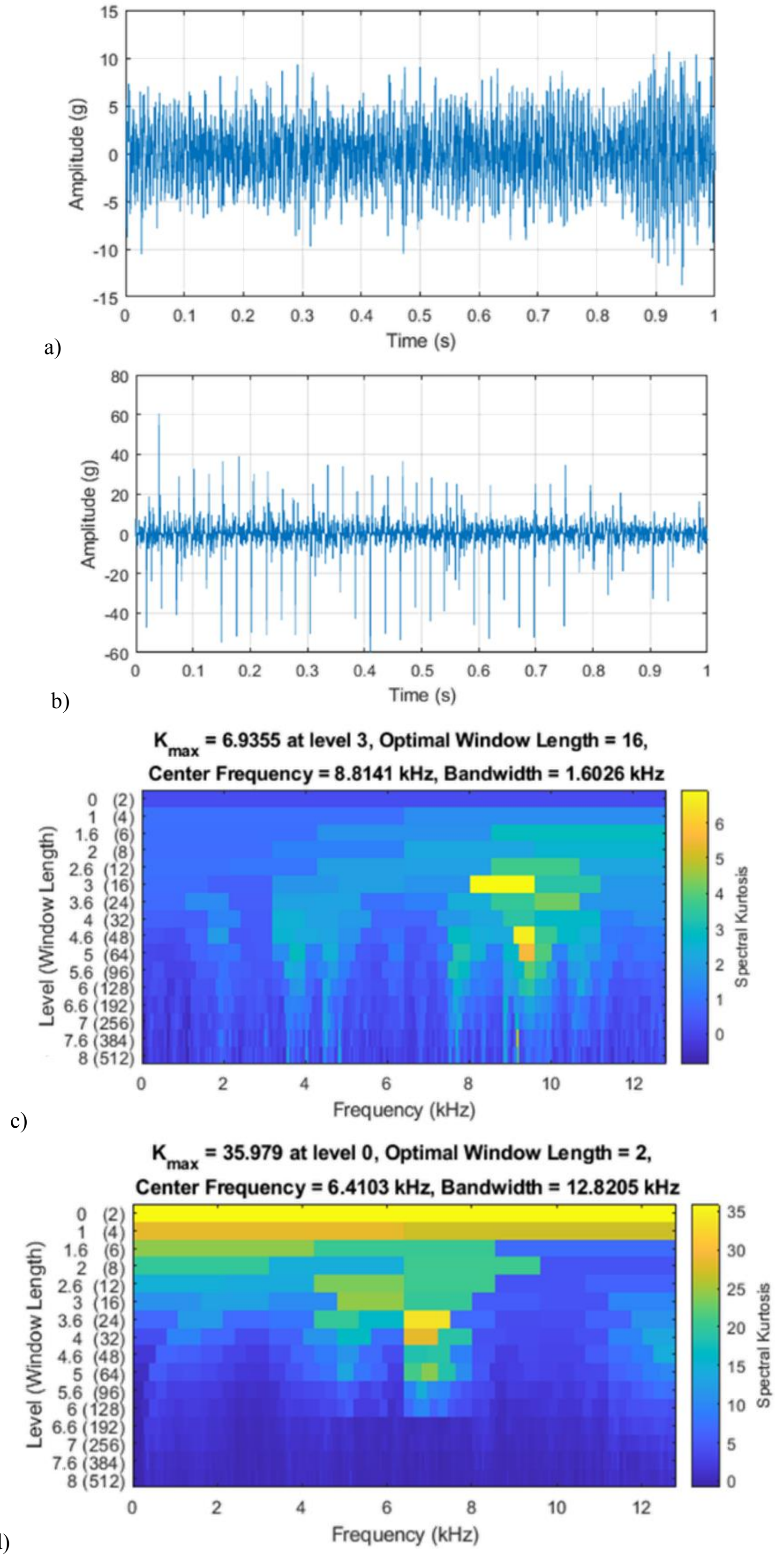
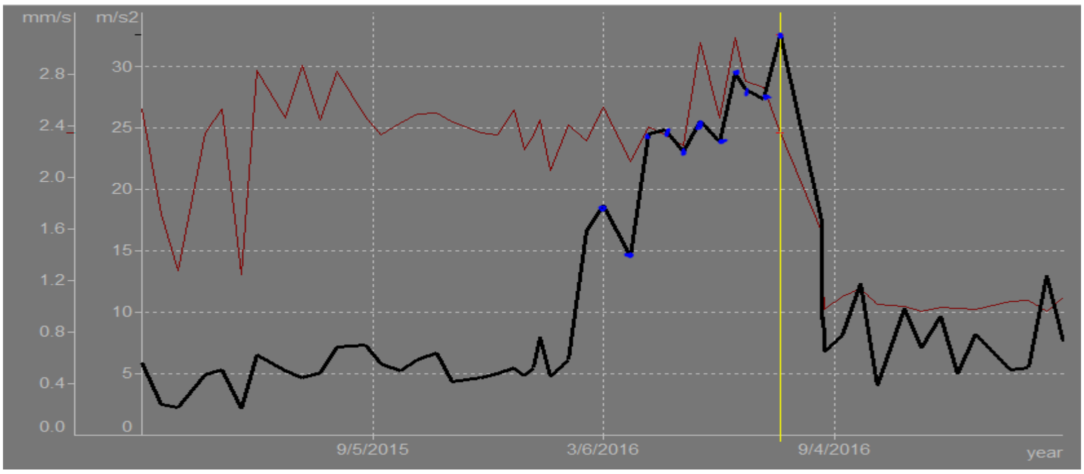


Fig. 3. Test bearing acceleration vibration signal: a) Time waveform at the start of the Degradation trend b) Time waveform at the end of the test c) Kurtogram at the start of the Degradation trend d) Kurtogram at the end of the test

Table 3. Technical specification of the industrial machines selected for model verification

Parameter	Unit	First Data	Second Data
Power	kW	132	132
Speed	RPM	1485	1485
Bearing type	-	Deep groove ball bearing	Spherical roller bearing
Test bearing bore diameter	mm	120	75
Test bearing outside diameter	mm	215	130
Test bearing width	mm	40	31
Test bearing dynamic load rating	kN	146	217
Test bearing static load rating	kN	118	240



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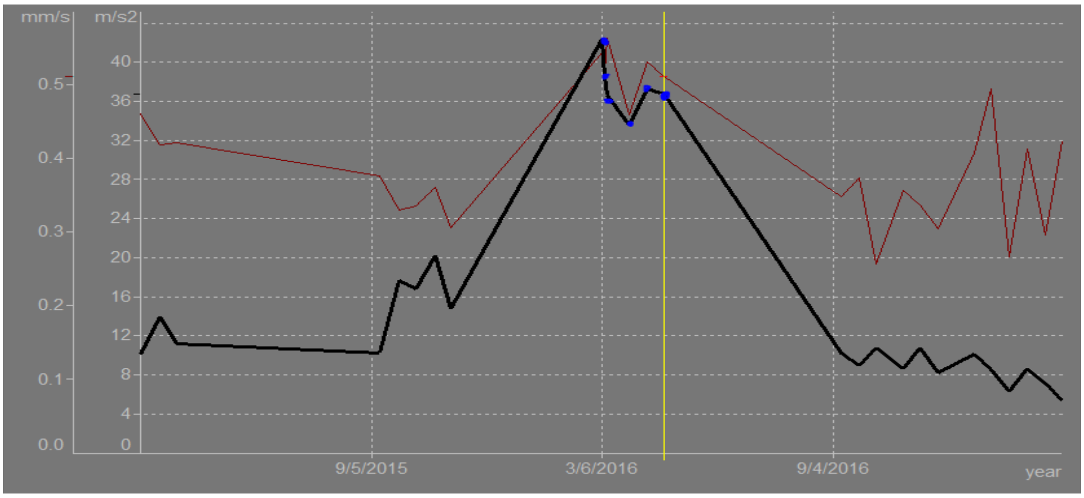

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Fig. 4. Vibration trend of the bearings selected from industrial data for model verification: a) First bearing b) Second bearing- red plot: velocity, mm/s, black plot: acceleration: m/s2

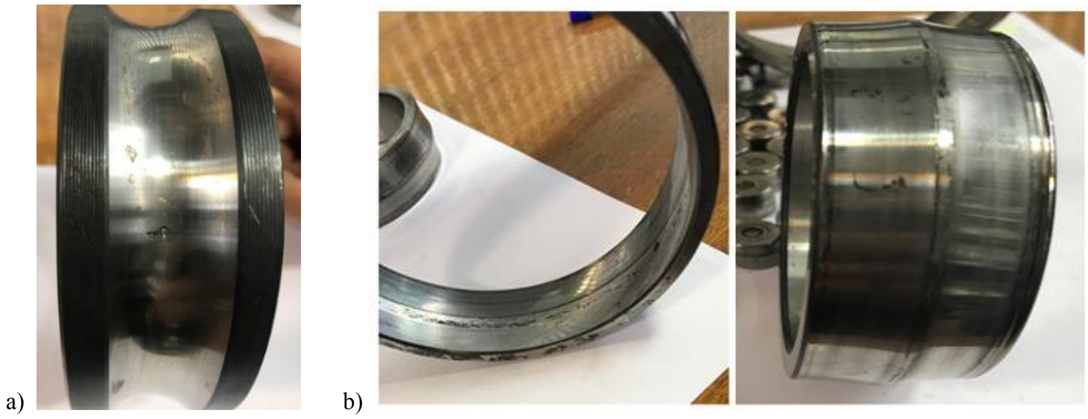


Fig. 5. Damaged elements the bearings selected from industrial data for model verification: a) First bearing b) Second bearing

- Assumption of Normality: We begin by assuming that data collected from a healthy bearing follows a normal (Gaussian) distribution.
- Dynamic Parameter Estimation: At each time step during data collection, we calculate the mean (average) and standard deviation of all the data recorded up to that point. These statistics represent the current estimated parameters of the healthy data's normal distribution.
- Outlier Evaluation: When a new data point is collected, its value is compared against the current mean and standard deviation. If the new data lies within three standard deviations of the mean (the typical range for about 99.7% of normal data), it is considered part of the healthy condition. However, if it lies beyond this range—meaning its distance from the mean is greater than three times the standard deviation—this data point is flagged as an outlier, suggesting a deviation from normal (healthy) behavior. Such a point is taken to represent the onset of an unhealthy state or early failure.

To identify the earliest onset of failure more reliably, several signal features derived from the vibration data, including RMS, Peak, Crest Factor, and Kurtosis, are evaluated. The red lines in Fig. 6 indicate the determined points marking the onset of degradation for each feature across the tested bearings. It can be observed that the Peak feature is the most effective indicator for determining the onset of degradation.

3- 2- Deterioration trend indicator

Given that the Peak, RMS, and Crest Factor indices are widely utilized in the industry, a comparison of these three indices is conducted to assess their effectiveness as degradation trend indicators. Ideally, the health index should exhibit an upward trajectory over time, indicating that the desired trend indicator is increasing. As illustrated in Fig. 5, the RMS index successfully fulfills this requirement, demonstrating a consistent increasing trend over time with less variability compared to the other indices.

3- 3- Deterioration trend predictor

Support vector machine (SVM) and RVM are two well-known machine learning methods with applications in regression that are effective in facing limited historical data. The key distinction between them lies in their underlying principles, with SVM being a modified version of the least squares method, while RVM is rooted in probabilities. RVM is a Bayesian sparse kernel technique that shares many of the characteristics of the SVM whilst avoiding its principal limitations, like representing decisions rather than posterior probabilities, owning more hyperparameters, and centering on training data points in kernel selection. RVM gives a sparser solution with shorter testing time and fewer required training samples [10]. Considering normal distribution (N), a conditional distribution (p) for a real-valued target variable t, given an input vector x, takes the form [11]:

$$p(t \mid x, w, \beta) = N(t \mid \sum_i w_i \phi_i(x), \beta^{-1}) \qquad (1)$$

in which β is noise precision and ϕ_i represents kernels. Detailed formulation of the RVM model can be found in [11]. Because the deterioration trend prediction of REBs is nonlinear in nature and the processes of erosion and failure are complex, accompanied by uncertainties, the CL is used for prediction. Two CLs of 95% and 68% are used in this research for presenting the results. It is important to note that, given that the output of the RVM model (Eq. (1)) follows a normal probability distribution, the model can yield outputs corresponding to various CLs obtained from this distribution. The hyperparameter of the RVM is achieved through the Grid Search optimization method. The best kernel is chosen

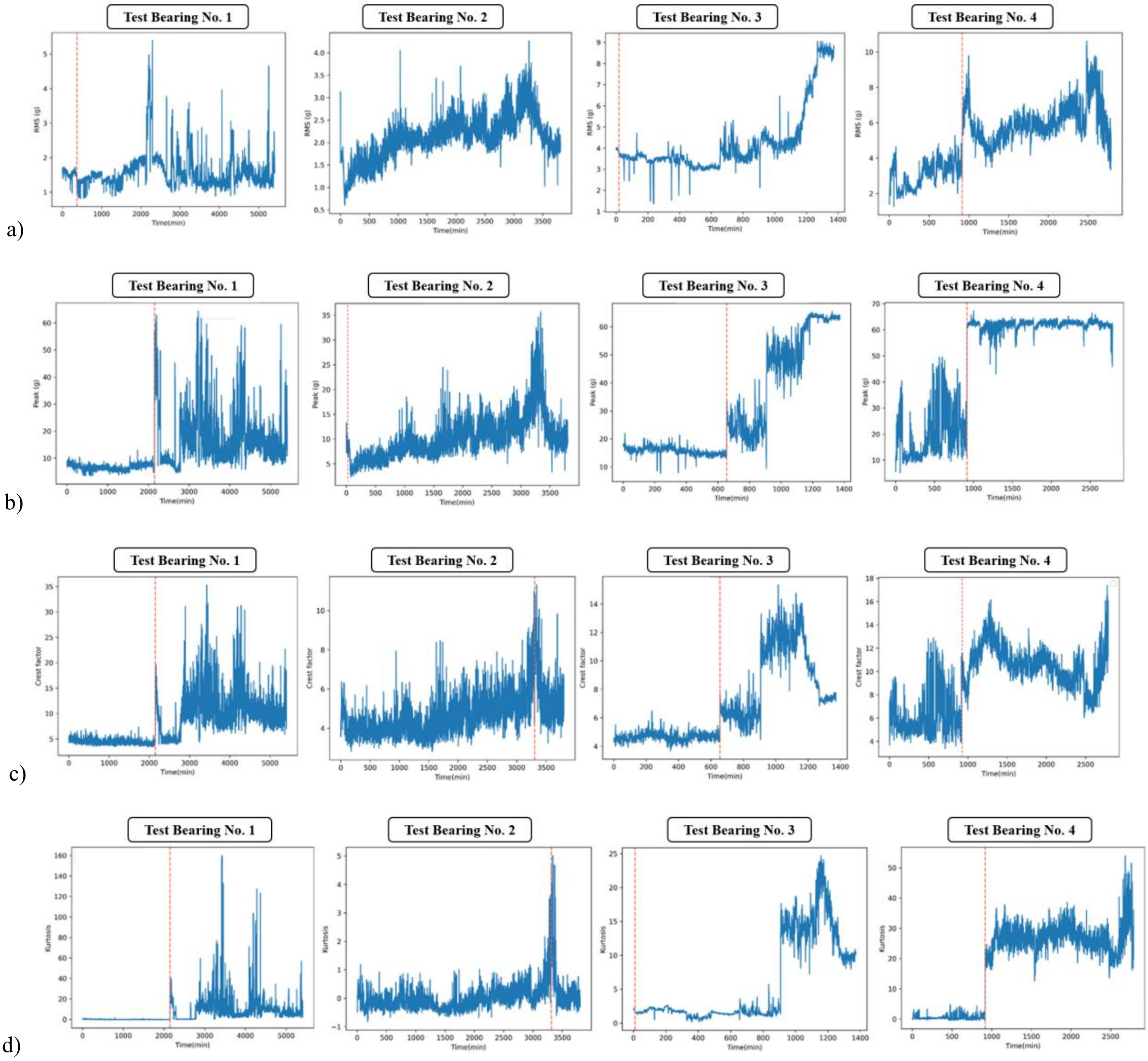


Fig. 6. Determining onset of degradation stage HI for four tested bearings based on: a) RMS b) Peak c) Crest Factor d) Kurtosis

among linear, polynomial, Sigmoid, and radial-basis function (RBF) kernels.

In prior studies addressing the prediction of deterioration processes, the conventional methodology involved fitting a curve to the recorded vibrational trend over time, subsequently utilizing this extrapolation to estimate the duration until the critical failure threshold is attained. This approach, illustrated schematically in Fig. 7.a, necessitated a substantial amount of data to adequately fit the curve, while failing to account for the inherent fluctuations in vibration responses over time, resulting in limited accuracy. In contexts where the dataset derived from equipment vibration history is sparse and the intervals between data collection are considerable, it is essential to recognize that alterations in the bearing failure stage will manifest distinct vibration trends compared to preceding stages. Consequently, applying a general curve to model the vibration trend is impractical. This highlights the imperative for an algorithm that is more responsive to variations in vibration behavior.

Fig. 7.b provides a visual representation of the functionality of the proposed adaptive algorithm. Following the identification of the onset of the degradation stage,

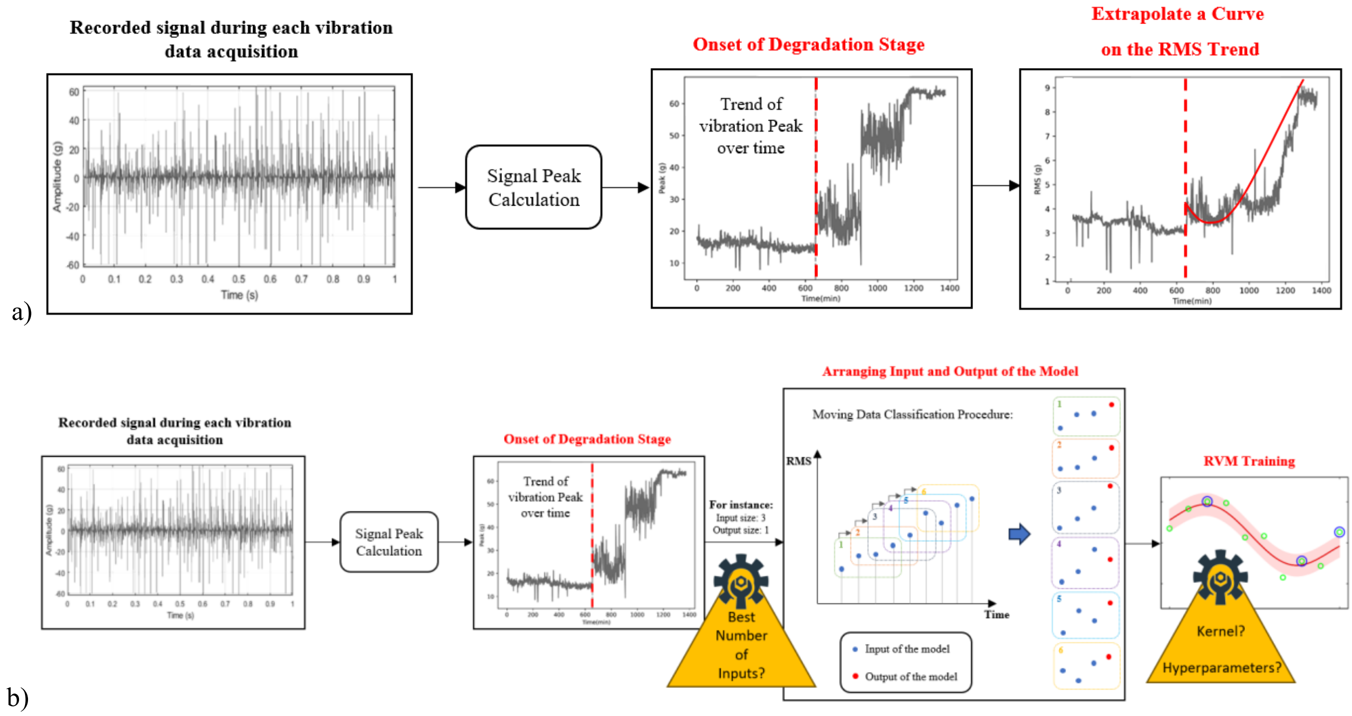


Fig. 7. Visual explanation of deterioration trend predictors: a) Classic mathematical extrapolation of historical vibration acceleration peak trends, b) Proposed adaptive algorithm that selects the optimal number of historical data points and employs an averaging method with optimized kernel and hyperparameters to improve prediction accuracy

the algorithm leverages a series of trend points to predict the response at the subsequent data acquisition point. This capability enables condition monitoring experts to anticipate the vibrations expected in the next data collection, thereby enhancing the precision of equipment condition assessments. The research aims to determine the minimum number of data points required to accurately predict the response for subsequent vibration data acquisitions. Moreover, the proposed RVM algorithm is designed to provide response prediction with a specified CL, thereby improving the robustness of predictive maintenance strategies.

In this research, the initial 80% of the data is used to train the model, while the remaining 20% is reserved for testing. After the model is trained with the training data, it employs the developed algorithm to make predictions on the test data. The model predicts future data points by considering both the data it has previously predicted and a specified amount of earlier data. It must be noted that the term “adaptive” is used to describe the proposed model because of how the input and output data are categorized during training (see Fig. 7. b). This data engineering classification allows the model to respond flexibly to changes in vibration levels.

According to Zeng et al.’s article [3], it seems that cumulative relative accuracy (CRA) is a good measure to evaluate the accuracy of the model. Because it calculates the relative accuracy between all real data and predicted data. For this reason, it is more appropriate to evaluate the accuracy of the prediction of the deterioration trend. This evaluation criterion is calculated using the following formula [3]:

$$CRA = \frac{1}{N}\sum_{i=1}^{N}\left(1 - \frac{\left|y^i - y_p^i\right|}{y^i}\right) \tag{2}$$

in which N is the number of data, y^i is the actual value of i th data, and y^i_p is the predicted value of i^{th} data.

4- Results and Discussion

The outcomes of implementing the proposed model in Section 3-3 are organized into six distinct subsections. Firstly, an appropriate kernel is chosen, and its hyperparameters are optimized. Subsequently, the model’s sensitivities to data reduction and data measurement interval are evaluated to develop a model that maintains acceptable performance with a limited historical dataset, thereby ensuring its applicability in industrial settings. Then, the superiority of the selected RVM model is demonstrated in comparison to the conventional SVM enhanced by the bootstrapping technique. Finally, the performance results of the optimized model on both laboratory and industrial data are presented and thoroughly discussed.

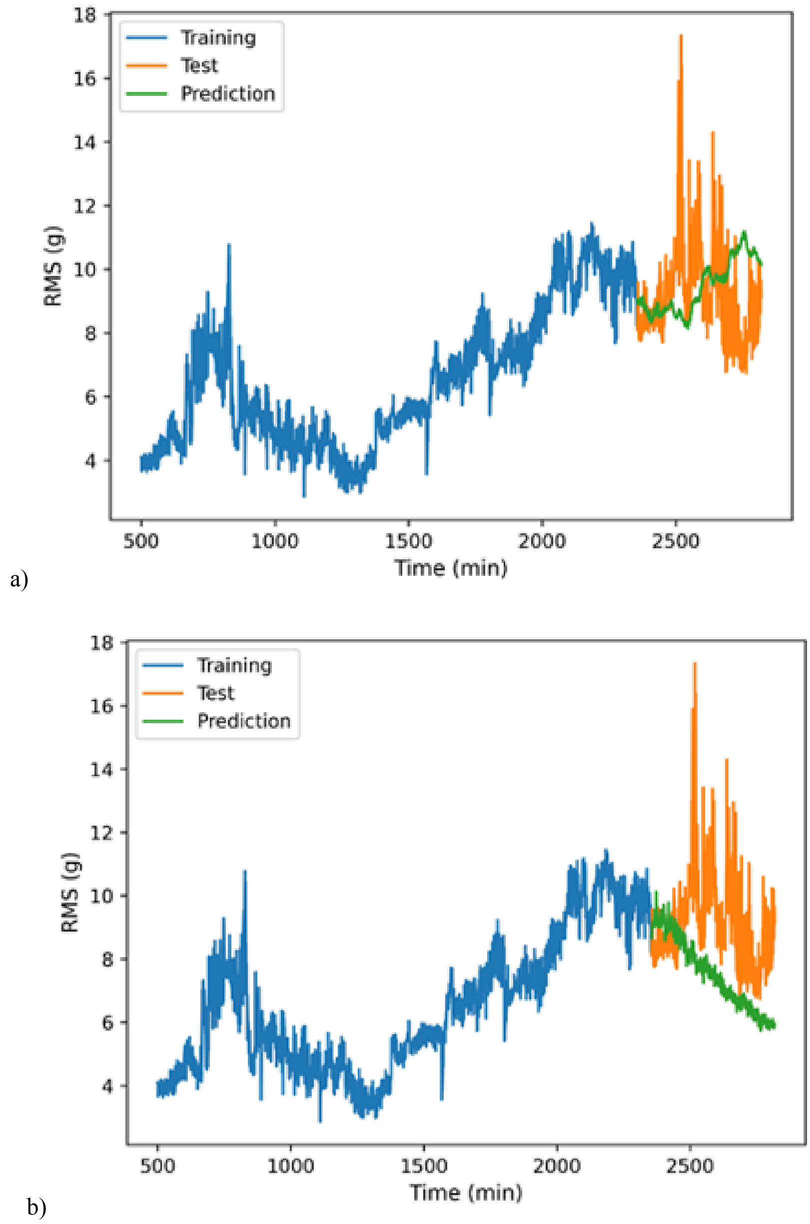


Fig. 8. Models' prediction by observing 500 previously recorded acceleration data using: a) Linear kernel b) RBF kernel

4- 1- Kernel Selection and Hyperparameters Optimization

Fig. 8 presents the results of the model's predictions, utilizing a dataset of 500 observations to predict the vibration response at subsequent time intervals, employing both linear and RBF kernels. In the graph, the blue plot represents the training data, while the orange plot corresponds to the testing data. The green line illustrates the model's predictions. It is noteworthy that the performances of the two polynomial and sigmoid kernels were found to be inadequate; consequently, their results have not been included. A comparison of the two graphs indicates that the RBF kernel demonstrates superior predictive capability for the deterioration process. Therefore, the subsequent sections of this article concentrate on optimizing the model through the selection of this kernel.

To ensure that the developed model achieves its optimal performance, it is essential to evaluate and adjust its hyperparameters until the most favorable outcomes are obtained. By employing the Grid Search optimization method, the model consistently achieves a measurement accuracy of approximately 93% and an R^2 score of 80% across various previous data observations. The maximum deviation observed in prediction accuracy is 0.09%, which can be considered negligible. The model's response after hyperparameter optimization is depicted in Fig. 9. In this figure, the blue and green plots represent the actual training and testing data, while the orange and red plots illustrate

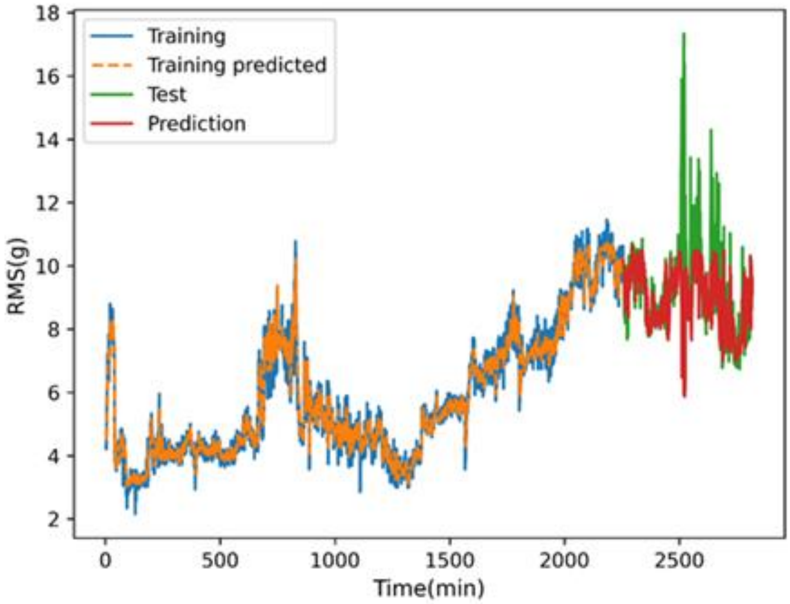


Fig. 9. Models' prediction using RBF kernel after hyperparameter optimization: acceleration vibration RMS vs. time

the model's predictions for these datasets, respectively. A comparison with Fig. 8. b clearly demonstrates a significant improvement in the model's prediction accuracy following the optimization process.

4- 2- Model sensitivity to data reduction

As illustrated in Fig. 8, the model's predictions are based on an analysis of 500 previous data points. However, in real-world industrial settings, such extensive datasets are often unavailable. For rotating equipment monitored offline, data collection intervals can vary significantly depending on the equipment's sensitivity; these intervals may occur weekly, monthly, annually, or even less frequently. In contrast, laboratory data in this research have been collected every minute. To align the laboratory data collection with industrial practices, a data reduction method is employed.

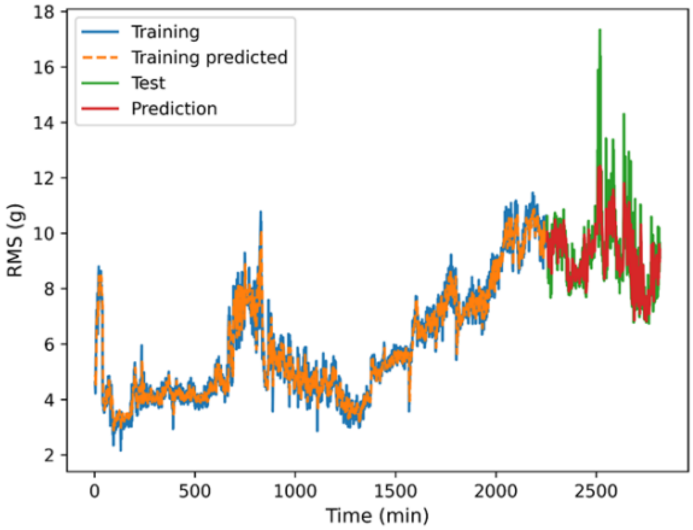
This paper approaches this challenge from two perspectives. First, by recognizing that the longer intervals between data acquisition in industrial settings result in fewer data points in the degradation stage of REBs available for predicting bearing deterioration. Thus, the model must be capable of making accurate future predictions with a limited amount of past data; this is the focus of this section. The second perspective addresses how the model can maintain accurate predictions even as data acquisition intervals increase, which is discussed in Section 4.3.

To address the question raised in Fig. 7. b regarding the optimal number of inputs for the model, Fig. 10 presents the results for models developed using three, four, and five input data points, achieving accuracies of 93.20%, 93.17%, and 93.11%, respectively. These results indicate that reducing the number of inputs enhances the model's ability to accurately track fluctuations in the response, compared to models with a greater number of inputs. Consequently, a model utilizing three data inputs has been selected for the next stage of development.

4- 3- Model sensitivity to data measurement interval

This section introduces a model designed to operate with the maximum measurement interval for data collection. To implement this approach, a specific time interval is established before training the model and making predictions. For example, if the chosen interval is every 10 minutes, the model computes the average of every 10 data points, replacing the original 10 data points with this average value. This averaging process is applied to the entire dataset, generating a new dataset that reflects the desired time interval. Predictions are then made based on this reduced dataset.

Fig. 11 presents the predictions generated by the RVM model using three previous data points across time intervals of 10 minutes, 30 minutes, 1 hour, and 5 hours. In this figure, the purple and green lines represent the actual training and testing data, while the orange and red lines signify the model's predictions, respectively. The model demonstrates strong predictive accuracy for the 10-minute and 30-minute intervals; however, it does not perform as well at the 1-hour and 5-hour intervals. It appears that the model utilizing a data collection interval of 30 minutes exhibits a delay in its predictions. As a result, a 10-minute interval has been selected as the preferred model for validation in the subsequent sections.



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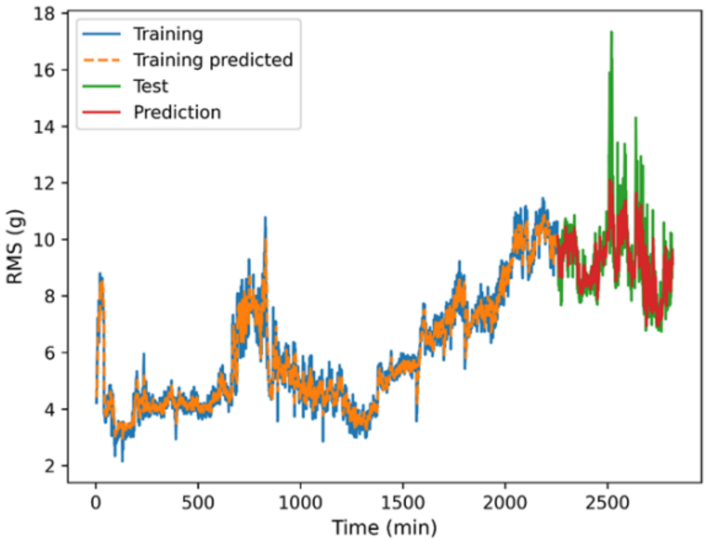

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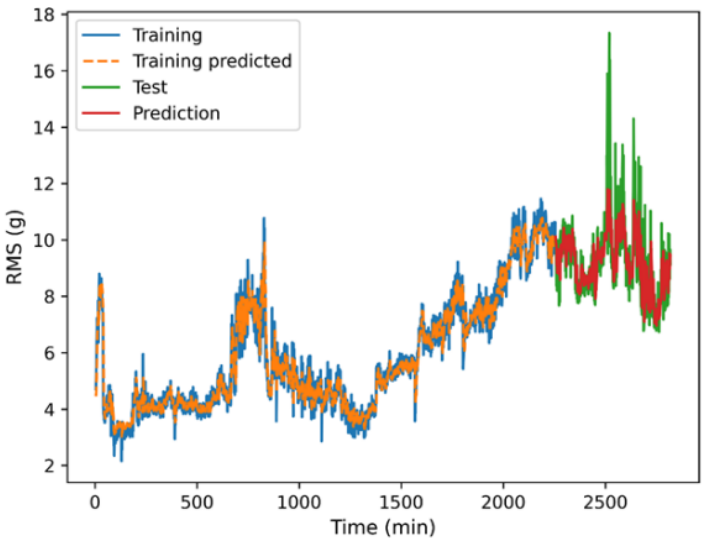

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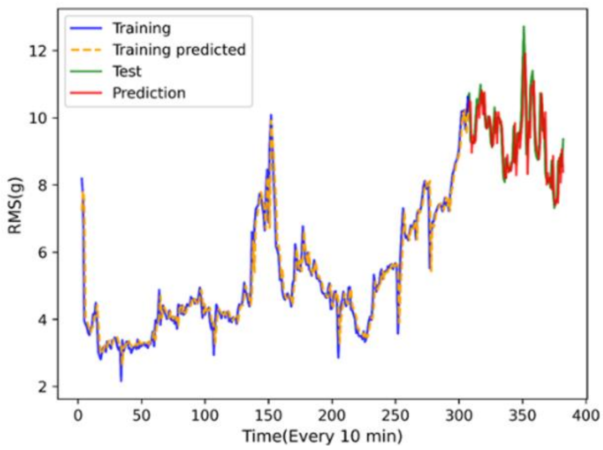
Fig. 10. Models' prediction (acceleration vibration RMS vs. time) using RBF kernel after hyperparameter optimization considering: a) three b) four c) five previously recorded vibration data.



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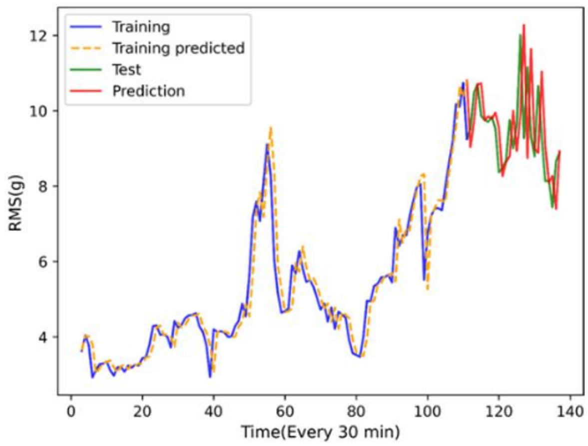

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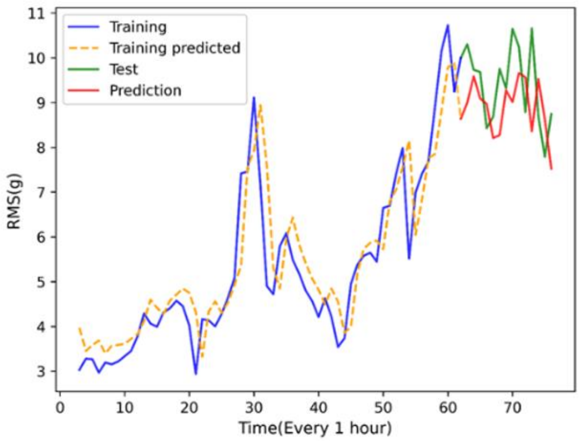

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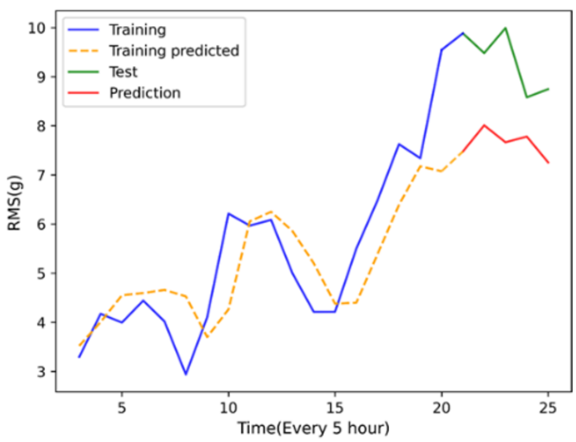


d)

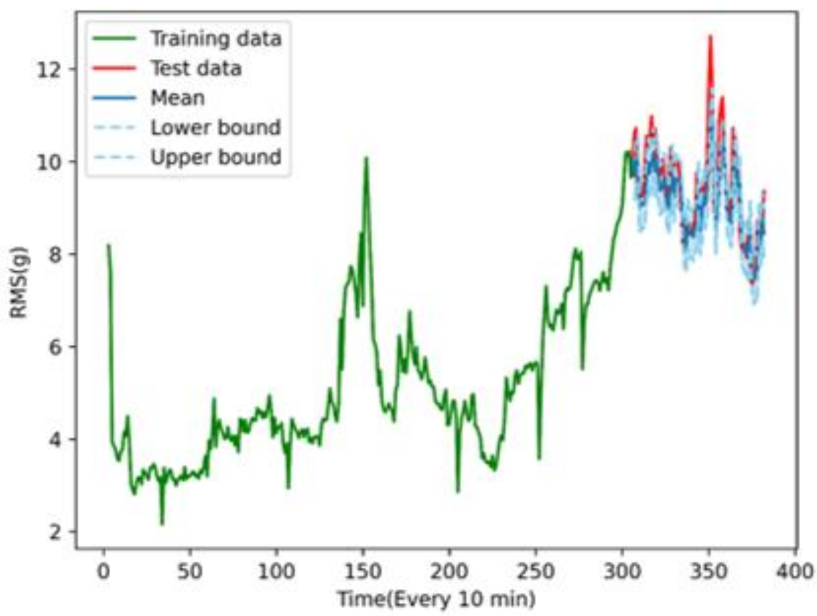
Fig. 11. Models' prediction (vibration RMS vs. time) using RBF kernel after hyperparameter optimization by observing three previously recorded vibration data in time intervals of: a) every 10 minutes b) every 30 minutes c) every hour d) every five hours

4- 4- Comparison of the model with other machine learning methods

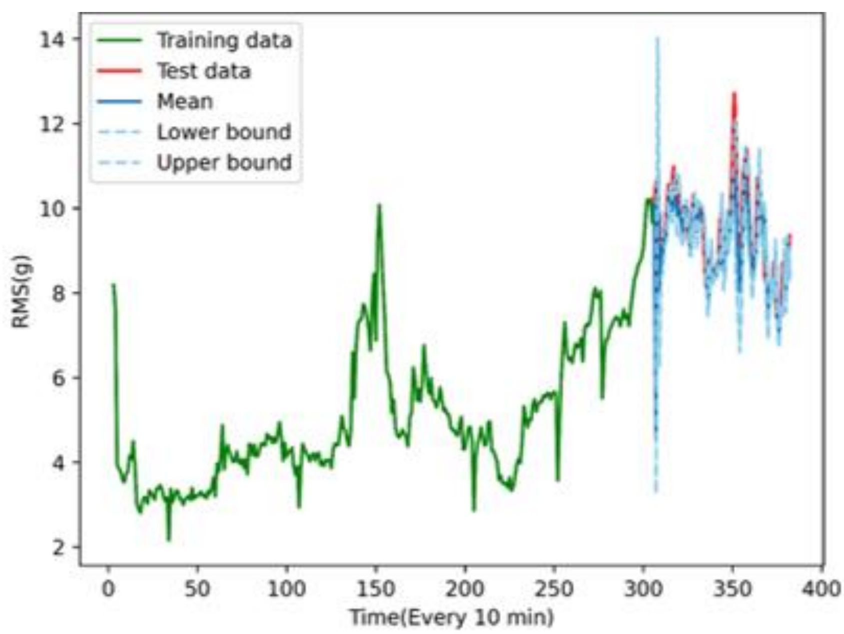
Section 3.3 outlined the rationale for employing the RVR model in this paper. This section illustrates the superior predictive capability of the RVR model compared to the SVR model, as depicted in Fig. 12, through the implementation of an alternative machine learning approach. Given that the SVR model does not yield a confidence level, it has been integrated with the bootstrapping method. The green and blue lines in the plots represent the training and testing data, respectively, while the blue line, accompanied by the confidence interval, denotes the predictions. It is obvious that the SVR model, which produces results with a CL of 68%, generates predictions over a wider range. In contrast, the RVR model offers greater certainty and higher accuracy in its predictions. Additionally, the RVR model has a lower computational cost, whereas the SVR model incurs a higher computational cost due to the combination with bootstrapping.

4- 5- Model verification using laboratory data

Fig. 13 presents the results obtained from the developed model for estimating the bearing deterioration trend, evaluated at two CLs: 68% and 95%. The model's accuracy in predicting the vibration response during subsequent data acquisitions, as assessed using the CRA criterion defined in Eq. (2), yielded values of 92.4%, 93.0%, 60.3%, and 93.9% for the four bearings tested under laboratory conditions. Notably, for bearing No. 3, the model demonstrated proficiency in accurately tracking the deterioration trend during a portion of the testing data; however, as the bearing transitioned into the fast degradation phase, the prediction model exhibited a lag in correlating with the observed increase in vibration amplitude. This observation underscores the necessity of delineating the bearing degradation into two distinct phases: slow and fast degradation. The results indicate that the model proposed in this study is effectively applicable to the slow degradation phase, achieving an accuracy exceeding 92.4% in this domain



a)



b)

Fig. 12. Comparison of models' acceleration vibration trend prediction: a) RVM b) SVM + Bootstrapping

of laboratory data.

Another observation from the deterioration prediction analysis of bearing No. 2 is that, in scenarios where the equipment is classified as critical within the factory, the upper bound of the response prediction at a specified confidence level can be reported as the predicted response. This approach enhances the accuracy of the deterioration estimate for this bearing, increasing it from 93.0% to 94.7%.

4- 6- Model Verification using Industrial Data

To complete the verification of the developed model's performance, the industrial data presented in Section 2-2 is utilized for the evaluation. Fig. 14 illustrates the prediction results for two industrial datasets, assessed at a CL of 68%. Given the inherent uncertainties associated with industrial data, it is not feasible to report a 95% confidence level. The prediction accuracies for the two datasets are 89.9%

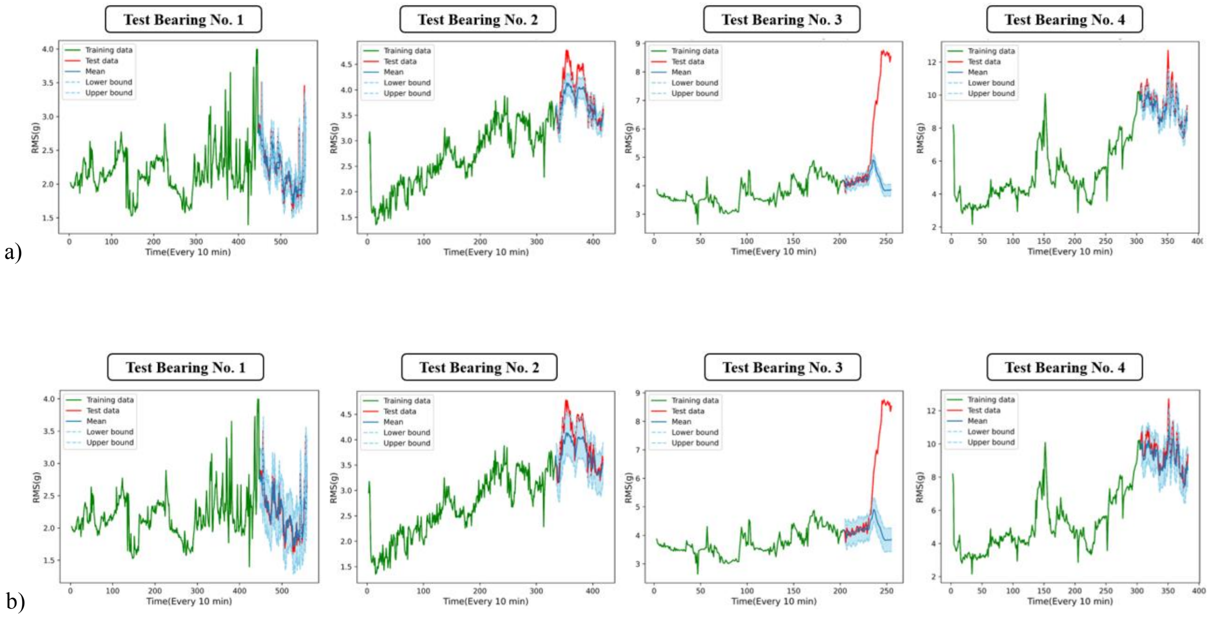


Fig. 13. Models' deterioration trend prediction with three previously recorded vibration data in 10-minute time interval, and RBF kernel using Grid Search optimization method for laboratory dataset for two confidence levels (CL): a) CL = 68% b) CL = 95%.

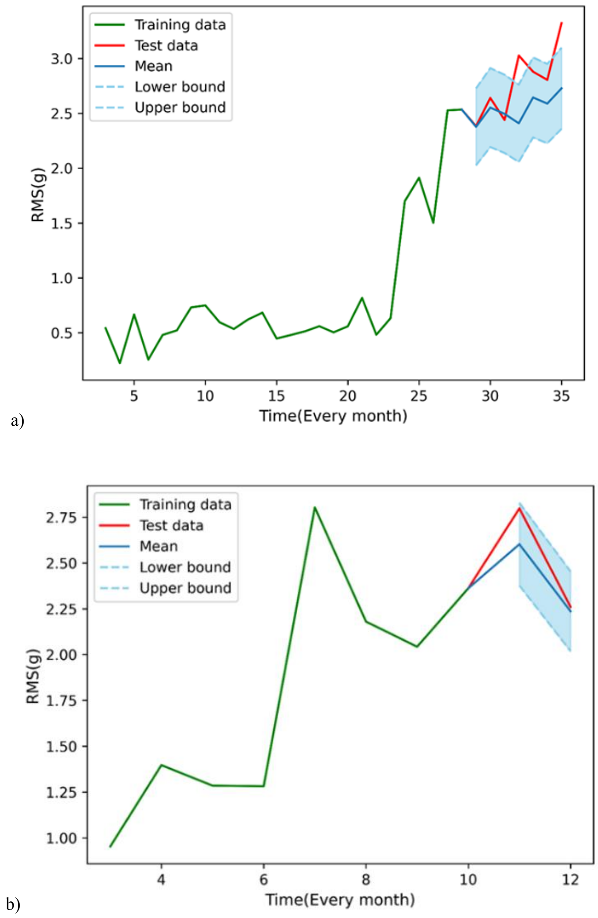


Fig. 14. Models' deterioration trend prediction with three previously recorded vibration and RBF kernel using Grid Search optimization method for industrial dataset, considering the confidence level of 68% for: a) 1st bearing b) 2nd bearing

and 95.7%, respectively, while the accuracies for the upper bounds are 91.1% and 95.5%. These findings confirm the effectiveness of the proposed model in accurately predicting the slow deterioration of bearings in an industrial setting.

4- 7- Model Strengths and Limitations

The model developed in this study aims to predict bearing deterioration in industrial environments, specifically designed to operate effectively with limited data. It has been trained to estimate the deterioration trend over time accurately by using minimal recorded data, capturing the largest possible intervals between offline/ periodic condition monitoring measurements. The model demonstrates strong performance in estimating bearing deterioration using online condition monitoring, effectively tracking the deterioration progression. However, for offline monitoring, it is crucial to have recorded at least the minimum required number of data points to ensure reliable estimation. Bearing degradation can be categorized into two phases: slow (gradual) and fast degradations. The model is best suited for monitoring slow degradation.

During fast degradation, the measurement intervals must be shortened to maintain the minimum data points needed for accurate modeling. To address fast degradation scenarios, it is recommended to integrate this model with a fast degradation detection algorithm. This integration can alert condition monitoring experts to reduce data acquisition intervals, ensuring sufficient data for continued accurate estimation. It is also important to note that in critical equipment, bearings are often replaced promptly upon detecting fast degradation, aligning with the model's primary purpose of estimating gradual wear. Additionally, the introduced model presents deterioration estimates with confidence intervals, allowing users to select appropriate confidence levels based on equipment sensitivity, thereby tailoring predictions to specific operational requirements.

Another challenge in model development pertains to the model's sensitivity to amplitude fluctuations in the vibrational trends of bearings. While the model generally operates independently of equipment type, it encounters difficulties with high-frequency vibration content found in gearboxes exhibiting gear mesh frequency or pumps and fans with blade pass frequency. In such cases, pre-processing is necessary to isolate the bearing-related components of the vibration signal. Following this processing stage, the developed model can be effectively utilized. Addressing this issue is a key objective for future enhancements to the model.

5- Summary/ Conclusion

This paper has focused on the development of a predictive model applicable for forecasting the deterioration trend of REBs after they enter the degradation stage. The objective has been to develop a robust model capable of functioning effectively with minimal data available following the onset of degradation, while also providing results accompanied by a confidence level, addressing the inherent uncertainties present in industrial environments. To achieve these objectives, the RVM model has been selected and its hyperparameters have been optimized. This model has been specifically designed to evaluate the slow degradation stage of REBs and can predict the vibrational amplitude for future data measurements. Key health indicators have been identified to determine the start of the degradation stage and facilitate trend prediction. The Peak and RMS values have been derived from the acceleration vibration signals. The RBF kernel has been determined to be the most effective for tracking vibration trends. Remarkably, the developed model requires only three input data points to generate predictions. Comparative analyses have demonstrated the proposed model's lower computational cost and higher accuracy relative to the SVM model. Validation through run-to-failure test data from the laboratory has yielded an average accuracy of 96.7%, indicating significant effectiveness. Additionally, when applied to industrial data from two electro-fans, the model has achieved an average accuracy of 93.3% using a confidence level of 68%, underscoring its practicality in real-world applications. Future research will focus on integrating the developed model into condition monitoring software for industrial use, incorporating continuous learning mechanisms to further enhance predictive accuracy by collecting data over time.

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