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Investigation on the effects of measurement and temporal uncertainties on rolling element bearings prognostics

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ABSTRACT

Estimation of remaining useful life (RUL) of rolling element bearings (REBs) has a major effect on improving the reliability in the industrial plants. However, due to the complex nature of the fault propagation in these components, their prognosis is affected by various uncertainties. This effect is intensified when the recorded data is offline, which is very common for many industrial machines due to the lower cost rather than the online monitoring strategy. In the present paper, in order to overcome the shortcoming of the feed-forward neural network (FFNN) in REBs prognostics, a new method for considering two main uncertainties (caused by the measurement and process noises) is proposed, in the presence of offline data acquisition. In the proposed method, the primary RUL probability distribution corresponded to each offline measured data is predicted, utilizing the outputs of trained FFNNs. Then, the predicted RUL distribution will become more robust in confronting the temporal changes, by taking into account the approval of pervious stage predictions to the present prediction. As a result, the overall probability distribution of REBs RUL and also its confidence levels (CLs) are obtained. Finally, the evaluation of the proposed method is performed by utilizing bearing experimental datasets. The results show that the proposed method has the capability to express the estimated RUL CLs in the offline data acquisition method, effectively. By providing a probabilistic perspective, the proposed method can improve the reliability of the asset and also the decision-making about the future of the industrial plants.

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1. Introduction

Accurate functionality of the rotating machinery plays an important role in improving plant efficiency. In unexpected breakdowns, expensive costs of downtime are inflicted on the system, besides the repair costs[1]. To prevent the excessive costs and improve system reliability, condition-based maintenance (CBM) is applied to the critical industrial plants, as one of the newest and the most effective maintenance strategies in the last decades [2]. On the other hand, rolling element bearings (REBs) are widely used in rotating machinery, and their failure may lead to catastrophic damage in the machine. It should be noticed that almost 50 percent of failures in the rotating machines are because of REBs fault[3]. Therefore, they are known as critical components and implementation of the CBM strategy for their fault detection and remaining useful life prediction is a vital task.

The CBM strategy is generally divided into two main steps: diagnosis and prognosis[4]. The former detects faults, especially in the early stages of fault propagation. While the latter is mainly concerned about estimating the remaining useful life (RUL) of the asset. Predominantly, there are three different approaches for predicting the RUL, as follows[1]:

- Physical model-based methodology
- Knowledge-based methodology
- Data-driven methodology

Physical models are generally based on the defect growth description. Li *et al* [5] used a defect propagation model so as to estimate the RUL of REBs. In another work, Li and Lee [6] utilized Paris' law to model the crack evolution in gear. Mainly, it is difficult to develop an accurate physics-based model, due to the system complexity as well as the complicated nature of defect growth. Consequently, the aforesaid methodology has had limited application in practical cases. On the other hand, knowledge-based models which are mainly constructed based on expert knowledge, may not be restricted to the analytical theories. However, their low flexibility leads to their inability in the analysis of complicated processes[7]. As an effort, Lembessis *et al* [8] predicted the fault growth by implementing an online expert system (ES).

Data-driven models utilize the observation data, in order to recognize the underlying pattern between the input(s) and output(s)[1]. One of the most popular data-driven models in prognostics is a neural network (NN) model. NN models are the learning-based approaches and have considerable high flexibility in analyzing complicated dynamic systems, such as the REBs degradation process. Thus, utilizing the NN models is very common in the literature of REBs prognostics.

The feed-forward neural network (FFNN) method has been employed by researchers to predict the RUL of REBs [9, 10]. Gebraeel *et al* [11] have predicted the RUL of REBs based on experimental data, using vibration amplitude of defective frequencies and their harmonics as the input features. In another research, Mahammad *et al* [12] used kurtosis and RMS features as the inputs of FFNN. Tian [13] employed the FFNN method on the actual industrial data to estimate the RUL. Zhao *et al[14]* predicted RUL of REBs, utilizing linear regression model and time-frequency features. Vachtsevanos and Wang [15] presented a dynamic wavelet neural network (DWNN) for prognosis purposes. In another research, Cui *et al* [16] analyzed the defect growth, using a dynamic recurrent neural network (RNN). Satish and Sarma [17] developed a hybrid model by combining fuzzy logic with NN to identify conditions and RUL estimation.

The procedure of RUL prediction is full of uncertainties, due to the complex nature of defect initiation and propagation, especially in REBs. However, the NNs are unable to model different uncertainties and they cannot represent a probabilistic description for the predicted RUL, in spite of their merits and capabilities in predicting the complex dynamic behavior of REBs degradation. This shortcoming leads to a lack of confidence level (CL) for the prediction outputs and consequently affects the logical decision-making process [2]. On the other hand, the data acquisition in most industrial plants is performed in the offline method, regarding the imposed cost reduction strategies in the plant. In this situation, the existence of different uncertainties becomes even a more serious problem[7]. Therefore, in the presence of offline data acquisition, consideration of the main sources of uncertainties is essential in the REBs prognostics using NN models.

The main concern of the present paper is to overcome the NNs shortcoming in providing the CL in the estimation of REBs remaining useful life. In this way, the proposed algorithm considers two of the most important uncertainties in the prognostics with the offline data acquisition from the REBs; first, caused by the measurement and second, caused by process noises. Consequently, the resultant RUL prediction is represented through a probability distribution function that can describe the CL of any given RUL, contrary to the output of conventional FFNN models.

The remainder of this paper is organized as follows: The utilized experimental data is introduced in section 2. In section 3, the existent uncertainties in the NN-based prognostics are briefly discussed. The proposed method for modeling the measurement and the temporal uncertainties in the application of REBs prognostics is presented in section 4. In section 5, the model is evaluated, using run to failure datasets. Finally, conclusions are presented in section 6.

2. Experimental Data

An experimental dataset of REBs run to failure tests, named PRONOSTIA is utilized for studying the performance of the proposed method in this paper. The PRONOSTIA vibration data was published in the PHM2012 conference as a data challenge [18]. Many researchers used this dataset, in order to assess their proposed method [19-22]. This experiment includes seven run-to-failure tests of REBs in the first constant operating condition (4000 N radial force and 1800 rpm rotational speed). The vibration time signals have been recorded every 10 seconds with 25.6 kHz sampling frequency. The PRONOSTIA platform is shown in Fig 1.

As discussed in[23], bearings 2 and 4 of the first operating condition have unnatural behavior. Therefore, in the remainder of this paper, five datasets of the first operating condition will be utilized. The RMS of the vibration signal is employed as the REBs health indicator (HI) and the input of the data-driven model. The trends of RMS for the utilized REBs are shown in Fig 2.

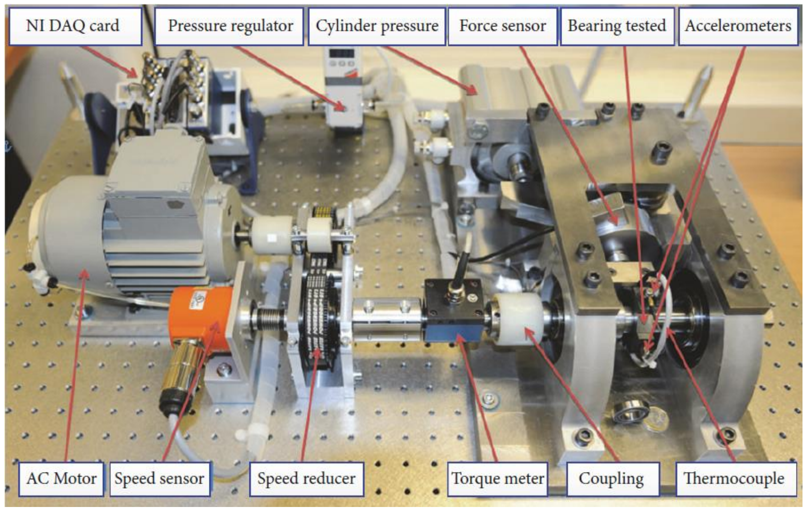


Fig 1: Overview of the experimental platform

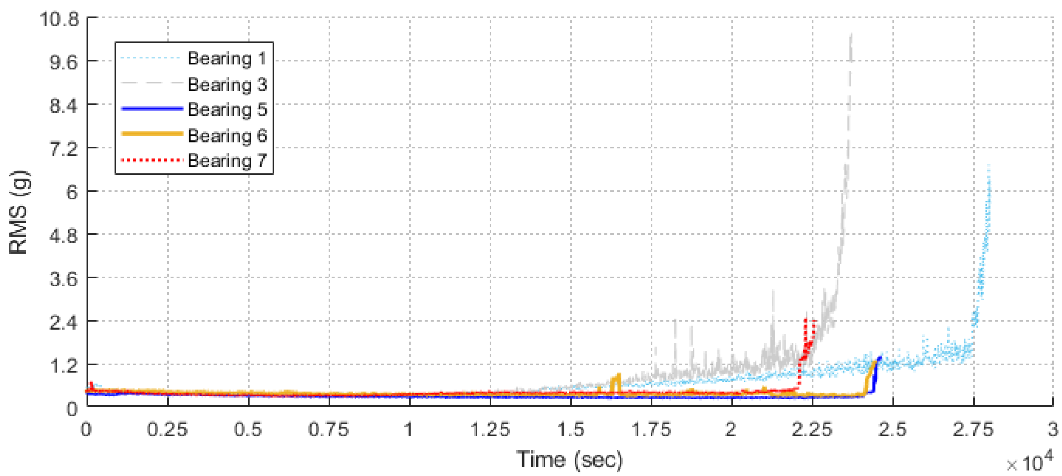


Fig 2: The trends of RMS for the utilized REBs

The data in the PRONOSTIA platform has been recorded online. Regarding the main concern of this research, offline CM data are required. Therefore, only a few measurements of the online recorded data are observed as the offline method in the mentioned run to failure tests. As can be seen in Fig 3, 2740 data points are available from online records. However, only 30 data points are selected in long intervals as offline data. In this way, the online data (with 2740 points) turns into the offline data (with 30 points); which could be further used in evaluating the performance of the proposed method.

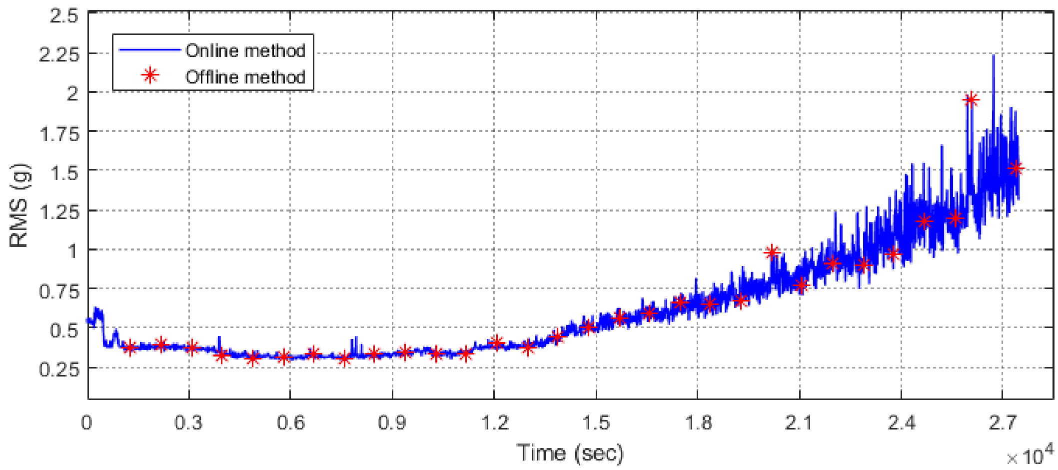


Fig 3: Turning the online data into the offline data

3. Uncertainty in NN-based Prognostics

The remaining useful life of REB is inherently a stochastic variable, due to the presence of uncertainties. In other words, the accuracy of RUL estimation through the NN-based methods are affected by different uncertainty sources; which the well-known ones are as follows[24]:

- The lack of an analytical model for the degradation process

- Measurement noises

- Process noises

Generally, it is impossible to derive an exact mathematical model that can explain the degradation process. So, it is common to consider some assumptions to make a practical model. However, the corresponded results are less accurate under these assumptions. In NN-based methods, the desired mathematical pattern is made through a black-box structure. Thus, the hidden underlying assumptions in this structure may lead to inaccurate results (similar to the other methods).

Measuring the real values of the HI in the component is costly or practically impossible. This is due to the presence of noises, disturbances, and imperfection of the data acquisition equipment, which all are considered as measurement noises in the acquired signal. The measurement noise affects the prediction result, so it is considered as the second source of uncertainty[25].

The third source of uncertainty is process noise, which can be observed through the temporal changes in the trend of HI. These changes are not due to the change in the real condition of the asset and consequently, the HI value will go back to the normal state, after a while. As these local changes are not expected to influence the prediction result, the utilized prognostics algorithm has to be capable of comprehending the aforesaid uncertainty[26].

For instance, the online trend of the RMS feature has been illustrated in Fig 4. This trend could also be acquired through limited offline measured points which can be seen in the figure. In an arbitrary stage of the offline data acquisition process, it is possible to record any of the existing points, as the offline measured data (Fig 4). It should be noticed that every data around this point, had also the chance of being chosen as the current machine condition. Therefore, the measuring instance could somewhat vary the measured value of the signal. Furthermore, as an input of the prediction model, it affects the accuracy of the estimated RUL. The source of prescribed variability is the measurement and process noises.

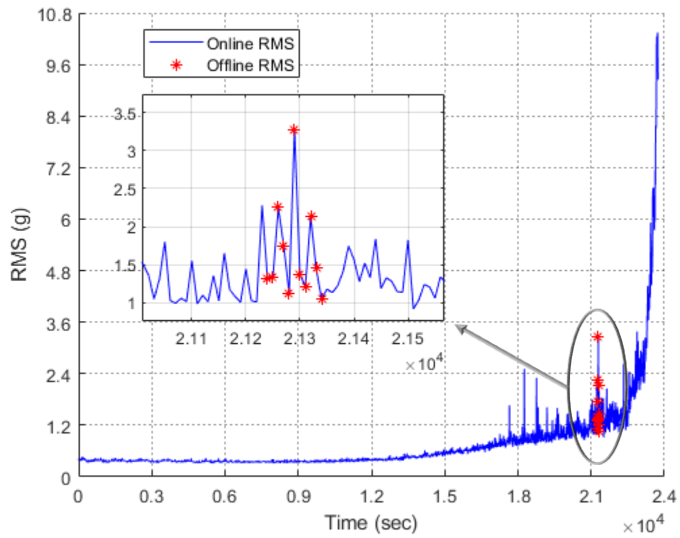


Fig 4: The variability in offline data acquisition, caused by measurement and process noises

The last two uncertainties caused by the measurement and process noises are more significant when the measurements are acquired with the offline method. Therefore, considering the prescribed uncertainties in the prognosis procedure is essential in the presence of offline data acquisition, which is the main concern of this paper.

4. The Proposed Method

In the present research, to estimate the RUL of REBs with the offline data, the measurement and temporal uncertainties are considered in the NNs structure. Note that in the offline CM data, only one measurement is recorded in each stage. Therefore, in the prediction step, only one single measurement is used for the RUL prediction. However, in the training step, the prescribed uncertainties cannot be effectively modelled through one CM data in each stage. To overcome this shortcoming, here it is assumed to have ten measurement points in each stage of training data, instead of one.

The proposed framework can be implemented as the following steps:

Train step 1: Preparing the stages. Firstly, the average value of the given ten sample points is calculated in each offline measurement stage. Secondly, a curve is interpolated on the average RMS values. Fig 5 depicts the described process. Note that the weighted means of the data above and below of the interpolated curve are the same.

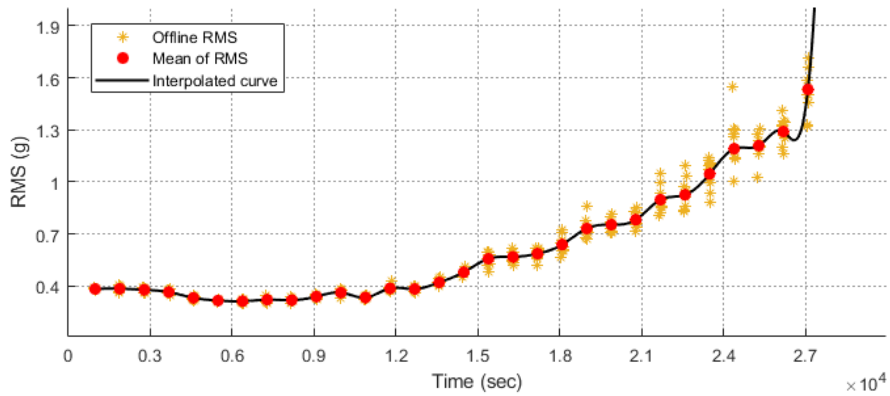


Fig 5: Data interpolation process

Train step 2: Calculating mean and standard deviation of RULs in each stage. For every ten available points in each offline measurement stage, the corresponded RUL is calculated by means of the interpolated curve and Eq 1. In other words, ten different RULs for ten RMS values are determined in each stage. For instance, Fig 6 shows the variation amount of the calculated RUL in the existence of two offline RMS data for a short period.

$$\overline{RUL}_A = t_{end} - \bar{t}_A$$
$$\overline{RUL}_B = t_{end} - \bar{t}_B \tag{1}$$

where $\bar{t}_A$ and $\bar{t}_B$ are the elapsed lives corresponded to the projected RMS values of points A and B onto the interpolation curve, respectively. $\overline{RUL}_A$ and $\overline{RUL}_B$ are the calculated values of RULs corresponded to points A and B, respectively; and t_{end} represents the REB's end of life. Then a normal distribution is fitted to the RULs of ten recorded RMS (which have been obtained through Eq 1) in each stage of the offline measurements. Further, the mean and standard deviation of the fitted distributions are calculated.

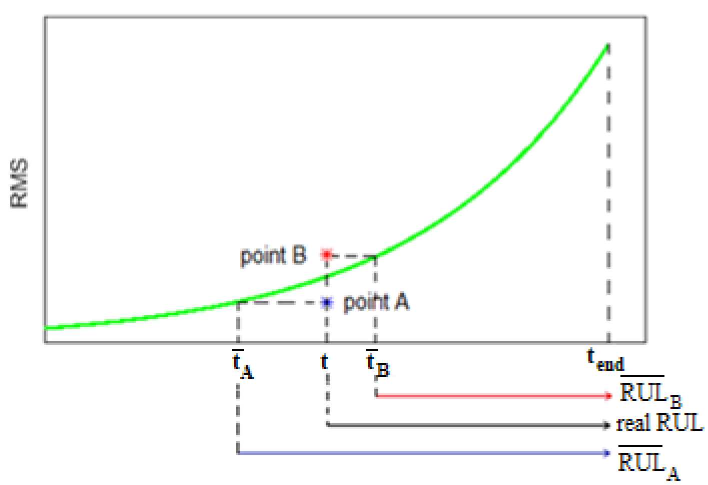


Fig 6: Procedure of the corresponded RUL calculation, for each record

Train step 3: Constructing NNs. The calculated means and standard deviations of RUL distributions in the previous step are utilized as the desired targets in two FFNNs. The inputs of both FFNNs are elapsed life and the mean RMS value at the present and previous stages. The constructions of the implemented FFNNs are shown in Fig 7.

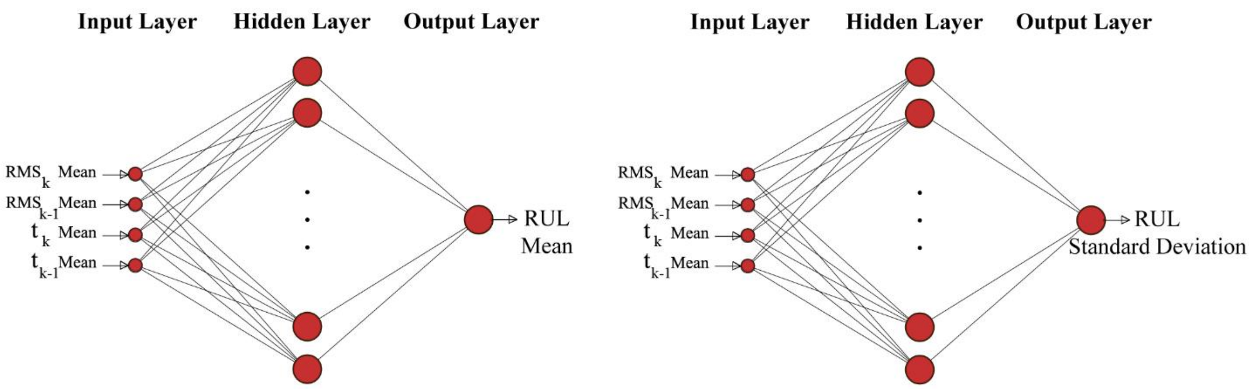


Fig 7: The structure of the proposed FFNNs

Prediction step 1: Calculating the primary RUL distribution. In the prediction step, only one data point is available for each stage, due to the offline measurement strategy. In each stage, the mean and the standard deviation of RUL distribution are estimated by the given values of RMS and elapsed life to the trained FFNNs. Therefore, the RUL normal distribution is obtained via its estimated mean and standard deviation.

Prediction step 2: Considering temporal uncertainty. Following the described steps, the measurement uncertainty is considered in the obtained RUL distributions. However, the resultant RULs cannot comprehend the effect of temporal uncertainty (which is due to the process noises). As discussed in section (3), temporal changes affect the signal HI locally and it disappears after a while. So, the temporal changes can only affect the RUL accuracy in the corresponding stage and not the others. Accordingly in the present paper, it is proposed to combine the estimated RUL at the current time with the previous RUL predictions. In this way, the effect of temporal uncertainty in the RUL results will be reduced.

As the elapsed time in different stages (t_k) are not the same, the corresponding RUL distributions cannot be combined directly. Accordingly, the comparable parameter "time at End-of-Life (EoL)" in every stage is utilized, instead. The estimated time for the End-of-Life (EoL_k) can be obtained for each prediction of RUL in kth step (RUL_k) as follows:

$$P(EoL_k) = t_k + P(RUL_k) \tag{2}$$

where $P(\cdot)$ denotes the probability distribution.

Note that when the model estimation about the future remains unchanged during the time, the EoL_k distribution for all stages will be the same. However, in the predictions by prognosis approaches, EoL is different in each stage, due to the prediction variations. The variation of EoL distribution from previous stages can be seen, especially in the occurrence of temporal change in the signal.

Thus, in this paper, the effect of temporal changes on the prediction results is reduced, by combining the estimated EoL distribution at the present stage k ($\mathrm{P}(\mathrm{EoL_k})$) with the last two previous ones ($\mathrm{P}(\mathrm{EoL_{k-1}})$, and $\mathrm{P}(\mathrm{EoL_{k-2}})$). Here, the overall probability distribution of EoL at t_k ($\mathrm{EoL_{Overall,k}}$) is assumed to be a linear combination of the estimated $\mathrm{P}(\mathrm{EoL_k})$, $\mathrm{P}(\mathrm{EoL_{k-1}})$ and $\mathrm{P}(\mathrm{EoL_{k-2}})$; which includes both measurement and temporal uncertainties.

$$P(EoL_{Overall,k}) = \frac{\sum_{i=k-2}^{k} w_i \, P(EoL_i)}{\sum_{i=k-2}^{k} w_i} \tag{3}$$

where $\mathrm{P}(\mathrm{EoL_i})$s are the last three PDFs of estimated RUL up to present time stage k obtained from "Prediction step 1"; and $\mathrm{w_i}$s represent their corresponding weights. The weights define the relative contribution of each prediction in the linear combination and lie within the interval [0,1]. The denominator term is also utilized to normalize the calculated output so that the total under area equals to one as in probability distributions.

The calculated EoL probability distribution at the present time ($\mathrm{P}(\mathrm{EoL_k})$) contains much more valuable information than the others because it is based on the last observation of the component condition. Therefore, the weight of corresponded prediction ($\mathrm{P}(\mathrm{EoL_k})$) is considered to be one ($\mathrm{w_k} = 1$). On the other hand, since the main goal in this step is to resist being affected by the temporal changes, the $\mathrm{w_{k-1}}$ is defined as follows:

$$w_{k-1} = 1 - \left(P(EoL_k) \cap P(EoL_{k-1}) \right) \tag{4}$$

By this definition, w_{k-1} is increased, as the conflict of the prediction in the present stage k and its previous prediction k-1 arises. In another word, w_{k-1} for the prediction at the present stage k is interpreted as a measure of not being approved by the previous prediction. In the same way, by the occurrence of a temporal change in the signal, the conflict between two prediction results arises and consequently, w_{k-1} will be increased. By increasing w_{k-1}, the contribution of the present step is reduced, simultaneously. Thus, a slight change in the prediction results will be observed, instead of a sudden significant change. The definition of w_{k-1} is illustrated in Fig 8.

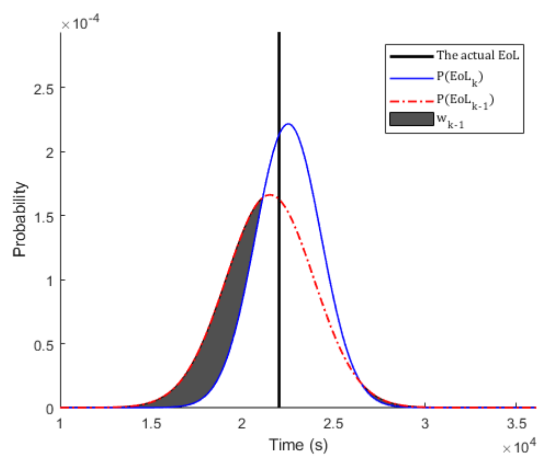


Fig 8: The definition of w_{k-1} based on Eq 4

Similarly, as it can be seen in Fig 9, w_{k-2} increases in the case which second previous prediction (k-2) does not approve the predictions in present and previous stages (k and k-1). So, w_{k-2} is defined as follows:

$$w_{k-2} = 1 - \left(P(EoL_{k-2}) \cap (P(EoL_{k-1}) \cup P(EoL_k)) \right) \tag{5}$$

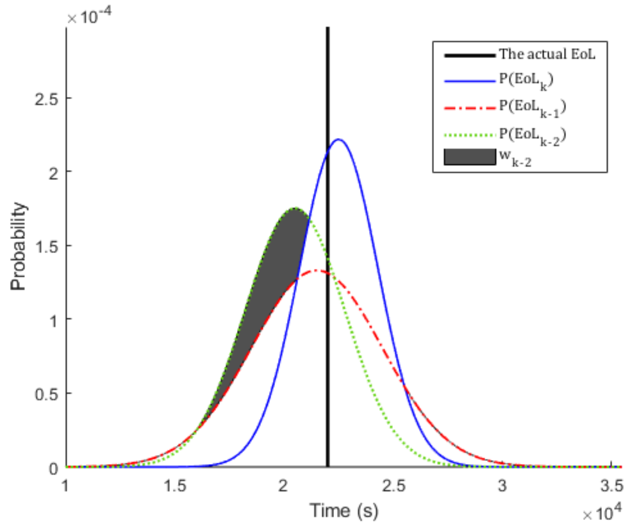


Fig 9: The definition of w_{k-2} based on Eq 5

By knowing the w_is at each time stage (k), the resultant probability distribution of $EoL_{Overall,k}$ is calculated by Eq 3. Then, $P(RUL_{Overall,k})$ is obtained, through the equation below.

$$P(RUL_{Overall,k}) = P(EoL_{Overall,k}) - t_k \tag{6}$$

The presented algorithm aims to control the effect of temporal changes on the estimated RUL results. If the observed change remains in the next stages of RMS, it cannot be considered as a temporal change anymore and it is a sign of the change in the real state of the component. In this case, the estimated prediction of EoL by the last two previous stages approves the present prediction at k. Thus, the assigned weights to previous predictions are reduced based on Eqs (4) and (5). Therefore, the estimated RUL will be adapted to the real condition of the component.

Finally, the CLs of the total RUL distribution ($P(RUL_{Overall,k})$) at each stage k are calculated, considering both measurement and process uncertainties in the results. A schematic view of the proposed method is shown in Fig 10; which consists of two main steps, training, and prediction.

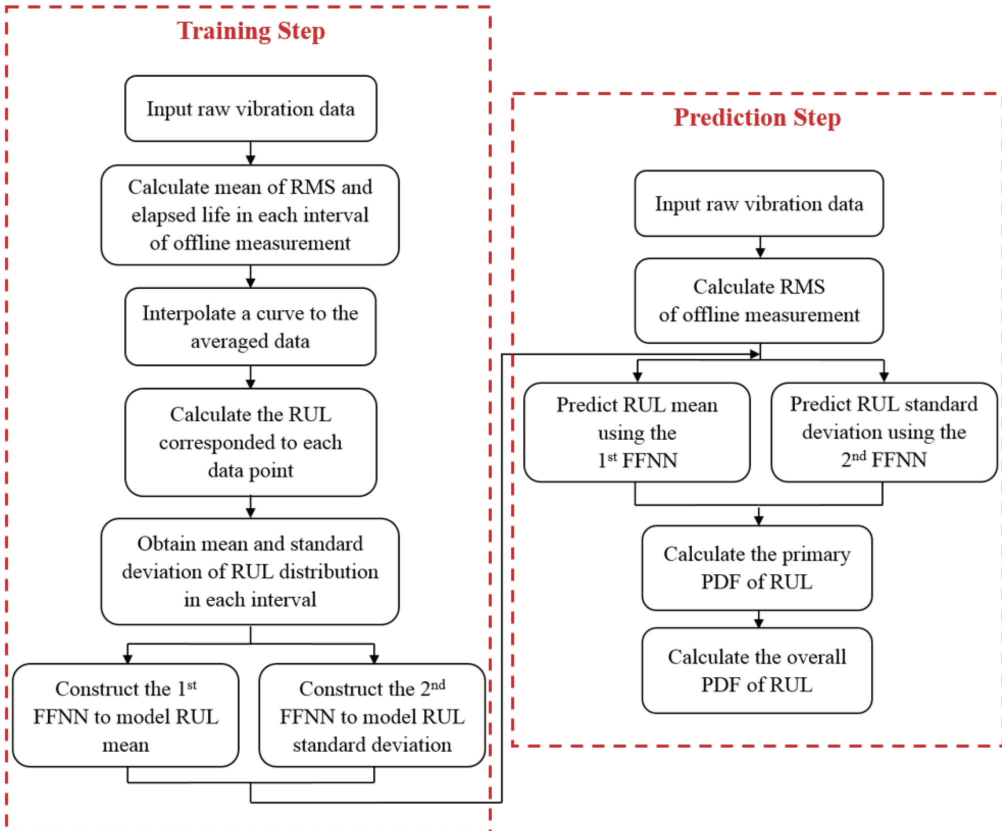
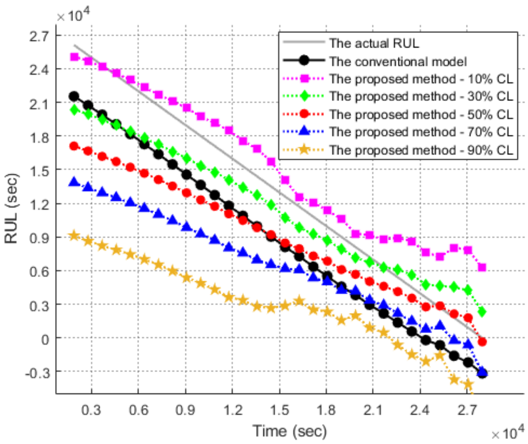


Fig 10: Flowchart of the proposed method

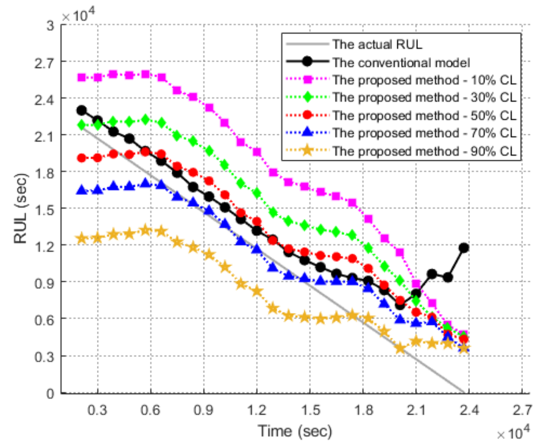
5. Results

To evaluate the effectiveness of the proposed algorithm on REBs prognostics, the well-known PRONOSTIA dataset is utilized in this section. For achieving this purpose, the proposed algorithm will be applied in different cases. In each case, four bearings in the same operational condition are considered. Three of them, are used in the FFNNs training step, and the other one is considered as a test bearing in the prediction step. In the prediction step, the trained NNs are employed in predicting the RUL of the test REB.

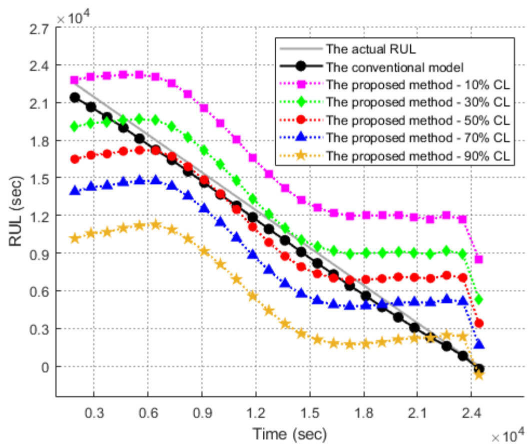
The estimated RUL results through the proposed method are shown in Fig 11, versus the conventional FFNN model outputs 12-13 in four different cases. Note that the conventional prediction results are expressed as deterministic values at each prediction stage. On the contrary, the proposed algorithm has predicted the RUL through a probability distribution (including measurement and temporal uncertainties). As it can be seen in the figure, the RULs are presented by the specified CLs of the probability. The mentioned CLs are the upper one-sided confidence intervals; so it may be interpreted as the minimum expected RUL for different given probabilities. As a result, the main advantage of the proposed algorithm is to overcome the lack of probability distribution in the prediction output of FFNNs, which is considered as a serious shortcoming in REBs prognostics via NNs models.



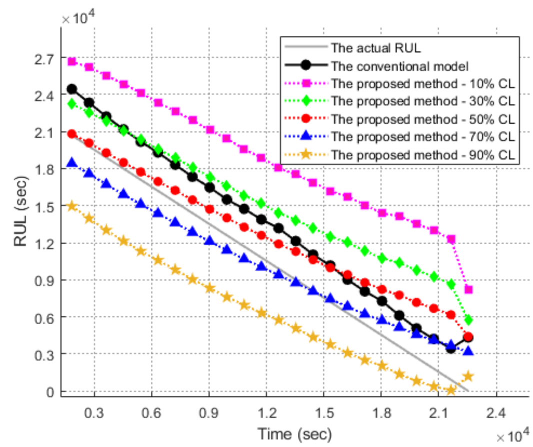
Case 1) training REBs: 3–6–7, prediction REB: 1



Case 2) training REBs: 1–5–7, prediction REB: 3



Case 3) training REBs: 3–5–7, prediction dataset: 6



Case 4) training datasets: 1–5–6, prediction REB: 7

Fig 11: Comparison of the RUL prediction results between the proposed method and the conventional model (four different cases)

In Fig 11, as can be seen in the third case, the conventional model has predicted the RULs with high accuracy. However, in other cases, this model deviates from the actual RUL in numerous prediction stages. This implies that the conventional model does not provide confident results, and the RUL outputs are required to be quantified as a probability distribution, in order to express the corresponding reliability of each prediction. Accordingly, the proposed method has the capability of representing the prediction reliability through the corresponding CLs, by considering two main sources of uncertainties including measurement and temporal.

To quantify the resultant RUL predictions by the proposed method, the parameter $RD_{CL\%}$ is introduced. This parameter is defined as the mean value of the relative distance from the estimated RUL (with CL% confident) to the actual RUL along the prediction lifetime:

$$RD_{CL\%} = \frac{1}{n}\sum_{k=1}^{n}\frac{RUL_{CL\%,k} - RUL_{actual,k}}{RUL_{actual,k}} \tag{7}$$

where n indicates the total number of stages. $RUL_{CL\%,k}$ is the minimum expected RUL for the given probability (CL%) at stage k, and $RUL_{actual,k}$ is the actual RUL at stage k.

The defined metric is calculated for different CLs (including 10%, 30%, 50%, 70% and 90%) in each case. The corresponding results of all cases are presented in Table 1.

Table 1. The $RD_{CL\%}$ of the proposed method in all cases

datasets Training	datasets Prediction	$\mathbf{RD_{10\%}}$	$\mathbf{RD_{30\%}}$	$\mathbf{RD_{50\%}}$	$\mathbf{RD_{70\%}}$	$\mathbf{RD_{90\%}}$
1 − 3 − 5	**6**	0.931	0.537	0.264	−0.008	−0.402
	7	1.133	0.739	0.467	0.195	−0.197
1 − 3 − 6	**5**	0.856	0.497	0.249	0.001	−0.357
	7	1.238	0.781	0.465	0.148	−0.308
1 − 3 − 7	**5**	0.690	0.378	0.162	−0.053	−0.366
	6	0.723	0.391	0.161	−0.067	−0.401
1 − 5 − 6	**3**	0.866	0.526	0.303	0.061	−0.307
	7	1.320	0.793	0.427	0.062	−0.464
1 − 5 − 7	**3**	0.981	0.658	0.435	0.212	−0.114
	6	0.997	0.535	0.215	−0.105	−0.569
1 − 6 − 7	**3**	0.788	0.465	0.252	0.027	−0.313
	5	1.350	0.652	0.169	−0.313	−1.011
3 − 5 − 6	**1**	0.359	−0.071	−0.358	−0.638	−1.037
	7	1.250	0.708	0.333	−0.040	−0.581
3 − 5 − 7	**1**	0.186	−0.145	−0.373	−0.601	−0.937
	6	0.944	0.495	0.183	−0.127	−0.578
3 − 6 − 7	**1**	0.324	−0.031	−0.278	−0.524	−0.881
	5	1.002	0.432	0.037	−0.356	−0.926
5 − 6 − 7	**1**	0.803	0.007	−0.490	−0.975	−1.708
	3	0.840	0.121	−0.365	−0.849	−1.544
$[\boldsymbol{Min}, \boldsymbol{Max}]$		[0.186 , 1.350]	[−0.145 , 0.793]	[−0.490 , 0.467]	[−0.975 , 0.212]	[−1.708 , −0.114]
Average		**0.879**	**0.423**	**0.113**	**−0.198**	**−0.650**

According to Eq 7, the $RD_{CL\%}$ will be lowered by decreasing the estimated RUL at each time step ($RUL_{CL\%,k}$). On the other hand, it is known that the decrease in the estimated $RUL_{CL\%,k}$ can be due to the considering higher percentage of confidence levels (CL) in the prediction. Thus, the trend of $\mathrm{RD_{CL\%}}$ must be decreasing over the CL, which is evident in each row of the table. Note that the negative sign of $RD_{CL\%}$ shows that the estimated RUL (with corresponding CL) is lower than the actual RUL, and vice versa.

The performance of the proposed method is not the same in different cases. As an instance, the $RD_{50\%}$ is positive (50% CL line is above the actual RUL) in most of the cases. On the other hand, it is negative in some other cases; as in training datasets 5-6-7 on the prediction datasets 1 and 3. As an overall view for each CL, the $[Min\ ,Max]$ interval and also the average $RD_{CL\%}$ are represented, correspondingly. It can be seen from the average row that the $\mathrm{RD}_{50\%}$ is about 0.113. This value means that the estimated 50% CL is 11.3% upper than the actual RUL, on average. As another expression, the corresponding estimation is a little optimistic about the RUL of REB. On the other hand, the average of $\mathrm{RD}_{90\%}$ is -0.650; which can be interpreted as a pessimistic view about the RUL of the asset. In this way, the proposed method provides a new perspective in NN-based prognostics about the future of an asset.

As discussed in section (4), the proposed algorithm provides the capability to comprehend the temporal changes in the REB's RMS. In order to investigate the effect of temporal changes on the prediction results, Fig 12-a represents the acquired data through the offline method in the bearing dataset 3 (the red points in this figure). Following the measured data, it can be seen that the system experiences a temporal change at the moment $\mathrm{t} = 1.8 \times 10^4\ (\mathrm{s})$ of the degradation signal. Consequently, as can be seen in Fig 12-b, the prediction of the conventional model at this moment deviates from the actual RUL, significantly. On the contrary, the proposed method can comprehend the temporal change (which is caused by the noises) and considers its effect on the estimated RUL results. So, instead of a sudden change in the RUL prediction results, the estimated trend of RUL CLs experience slight changes at the corresponding moment. And after a while, the RUL results returns to its normal condition. Therefore, the results of the proposed algorithm become more robust to the temporal changes.

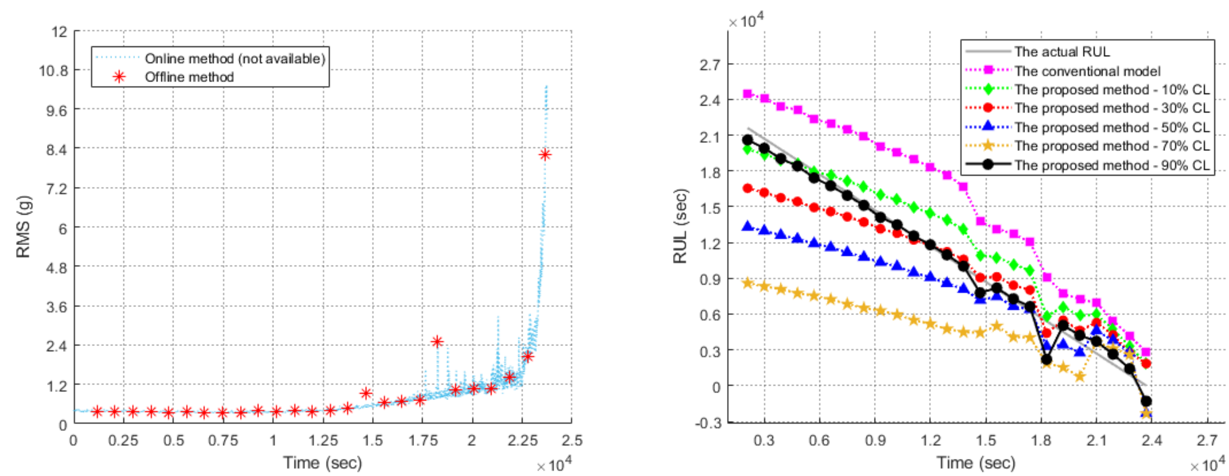


Fig 12: Investigation of the temporal change effect on the prediction results

a) The acquired RMS data through the offline method

b) Comparison of the estimated RUL between the proposed method and conventional model

6. Conclusion

This paper has proposed a probabilistic method so as to improve the NN-based prognostics of REBs, in the presence of the offline data acquisition. The main concern is to take into account the measurement and temporal uncertainties. For achieving this purpose, two FFNNs have been employed in order to estimate the mean and standard deviation of the primary RUL distribution at each stage. Then, the temporal uncertainty has been considered in the RUL distribution based on the degree of approval by the previous stage predictions.

The method has been evaluated by using the experimental results of the bearing accelerated run to failure tests. The superior property of the presented method over the conventional model is providing a probability distribution and its CLs for the estimated RUL, by considering different uncertainties. It has also illustrated in the results that the method can comprehend the temporal changes in the HI signal, and consequently consider its effect on the corresponding predictions. According to the proposed probabilistic perspective, the NN-based prognostics can be more practically used in improving the system reliability and also the industrial decision-making about the future of plants.

There are several important directions for future research, as follows:

- Identifying the real state of the system by other methods may improve the results.
- Other types of the probability distribution for RUL could be utilized in further studies.
- Utilizing other types of NN may affect the results.

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