

New trend in enhancing bearing remaining useful life prediction

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Abstract

Generally the two main strategies taken in data-driven remaining useful life (RUL) prediction of a component/system can be summarized in 1) identifying a health indicator and predicting its trend until a predefined threshold; 2) mapping directly the health indicator (HI) to RUL by regression. Under the first category, traditional extracted features for RUL prediction usually show undesirable behaviors such as fluctuation, non-monotonicity and abrupt increase at the end which hampers the accuracy of the RUL prediction. To enhance the prediction accuracy, this paper brings a new feature selection method, based on preprocessing further the extracted features in a way that the identified prognostic feature results in an obvious trend quality. A set of established and proposed suitability metrics for the prognostic task are used to assess the identified features qualities. The Particle Filtering technique is adopted as a projection tool as well for the prediction of the RUL due to its capability to carry nonlinear systems in presence of non-Gaussian process/observation noise. Datasets from bearings run-to-failure experiments provided by FEMTO-ST Institute - IEEE PHM 2012 challenge- were used to validate our approach. A mean percentage error of 12.18% was achieved indicating that the model worked accurately and reliably on every tested bearing..

Keywords: Health Index; Prognostics and Health Management; Particle Filtering; Remaining Useful Life

1. Introduction

Downtime caused by premature failures of mechanical components, driven by bearings or gearboxes, challenges almost industrial processes and increases the maintenance cost. In this context, the Prognostics and Health Management (PHM), as an approach to system life-cycle support, seeks to reduce or eliminate inspections and time-based maintenance [1]. The prognostic, which is the key process of the PHM, focuses mainly on predicting the RUL of a component/system with a confidence interval [2]. Among various prognostic approaches namely model-based, data-driven, experience-based approaches or the hybridization of them, data-driven techniques are preferred and bring a compromise between precision and complexity when it is hard to understand the first principles of a component/system [3]. The strategies taken for RUL prediction in data driven case: can be categorized in these two main approaches 1) finding a health indicator and extrapolating the trend until a predefined threshold; 2) mapping directly the extracted features to RUL by regression [4]. Generally, statistical and artificial intelligent (AI) approaches are used under the first category. They aim to track some measure of degradation called a prognostic feature, even sensed or pre-processed, and extrapolating it to reach the failure threshold. A good prognostic feature should well capture the trend of the fault progression through the entire component/system

life. This leads to a simple and accurate RUL prediction model. Unfortunately, the trend of some prognostic features can occur right before the failure of the component, as shown in Figure 3.b which impairs the accurate prediction of the RUL.

Only few works attempt to address this issue. The authors in [5] have proposed an intelligent selection method to identify an appropriate feature from a population of features in an automated way using a set of qualitative metrics to assess the prognostic features for the prediction task, namely monotonicity, prognosability, and trendability. In the same way, [6] proposed Genetic Programming (GP) to discover an advanced feature highly correlated with the fault growth by randomly combining mathematical operators, analytic functions, constants, and state variables using the monotonicity as the only suitability metric. However, the difficulty lies in determining failure threshold of the discovered feature when different input features are involved by the GP. Therefore, keeping the original features for determining the threshold is essential. The authors in [7] instead, proposed selection method based on the separability measure of consecutive time segments to evaluate the suitability of the extracted features for RUL prediction.

Our approach to address this issue attempts firstly to acquire the trending shape of the prognostic feature by further preprocessing the extracted features transforming them to their cumulative form. Secondly, using the particle filtering (PF) technique as an extrapolating tool to predict

the RUL. Analytic expressions are often used to model the degradation process to fit the given data even linear, exponential or logarithmic. But in our case there is not such trivial case as the data exhibit a complex shape. To address this issue, we propose a Neuro-Fuzzy system (NFS) predictor that fit perfectly the degradation process.

This paper is organized in such a way that follows the steps of a typical health monitoring system. Starting from the methodology in which the framework of the RUL prediction approach is given. In next section we describe

the experimental setup. Followed by the feature extraction and processing step which is the cornerstone of our approach. After the identification of the appropriate prognostic feature, the prediction of the RUL is carried out using the particle filtering method adapted for the prognostic purpose with the integrated NFS. The validation step ends our approach by the commented results. Finally a conclusion is drawn in the last section.

2. Methodology

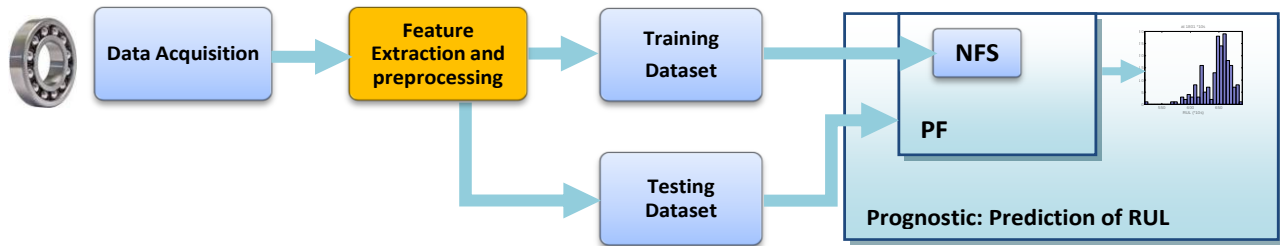


Figure 1. Framework of the RUL prediction approach

The flowchart of the proposed method for bearing RUL prediction, illustrated in Figure 1, includes two main phases: training phase and testing phase. The training phase conducted off-line, aims to generate firstly a health indicator by further preprocessing the extracted feature from raw vibration signals acquired by the sensors and secondly to train the evolution model used by particle filtering algorithm to fit the bearing degradation data. The testing phase is an on-line prediction that uses the generated model from the training phase to predict the RUL when a new sample is available.

3. Experiment setup

3.1. PHM case study (bearings datasets of IEEE PHM challenge 2012)

The choice of bearings and their condition monitoring to validate this study can be justified firstly, by the fact that these components are omnipresent in almost industrial processes using rotating elements and are subject to frequent failures. Secondly, when condition monitoring of bearings without altering their operation is considered, the vibrations is top ranked among the sensed data.

PHM challenge datasets were provided by FEMTO-ST Institute and are mainly composed of run-to-failure vibration signals related to ball bearings from an experimental platform PRONOSTIA. The datasets are recorded at a sampling frequency of acceleration and temperature of 25.6 kHz and 0.1 Hz respectively. The

experiments were stopped when amplitude of the vibration signal overpasses 20g limit. They provide 6 run-to-failure datasets in order to build prognostics models, and ask to estimate accurately the RUL of remaining bearings. Further details are given in [12].

Ber_{i-j} represents the bearing number j under the load condition i .

Figures 2a and 2b show the raw vibration signals of the bearing Ber_{1-1} on the horizontal and vertical axis respectively.

3.2. Feature extraction & exploring step

The feature extraction step aims to map the acquired data into a feature space which is relevant to the equipment health state using various signal processing techniques even in time domain, frequency domain or time-frequency domain [8]. The overall features extracted from vibration sensor for PHM case study are listed in [9]. Time-frequency domain is considered using the Daubichies wavelet of 5th order D5 and 5th decomposition level for the analysis of bearing vibration signals. Statistical features were performed on at different decomposition levels using detail coefficients. These features still show a low trending and present variation right before failure time which limits their prognostic capabilities. Figure 3b is an illustrating example..

We suggest transforming the extracted features into their cumulative form using the formula below.

Note that the extracted features are presented as time series.

$$cf(i) = \frac{\sum(data(1:i))}{\sqrt{|\sum(data(1:i))|}} \quad (1)$$

where $data(1:i)$ is the time series of any extracted feature up to time i .

cf is the cumulative form of the time series data

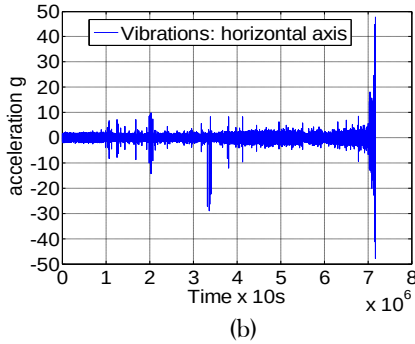
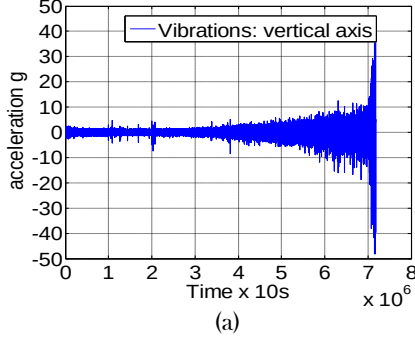


Figure 2. Vibration signals of the bearing Ber_{1-1}
a) horizontal and b) vertical axis.

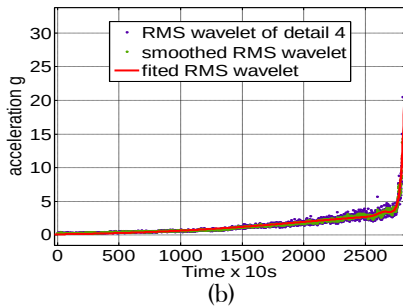
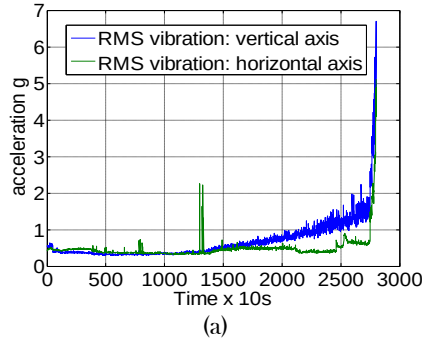


Figure 3. a) RMS vibration features of bearing Ber_{1-1} .
b) RMS of wavelet detail coefficients of level 4 of bearing Ber_{1-1} with its fitting curve (red).

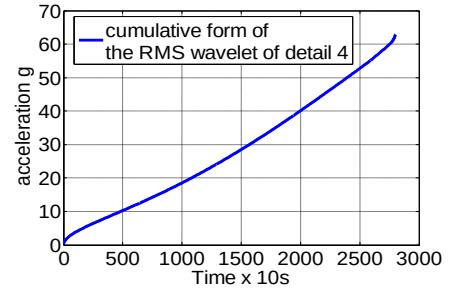


Figure 4. Identified feature for the bearing Ber_{1-1}

Suitability evaluation of the identified features for the prognostic task was made according to [5]. In addition to these metrics, we have also proposed the sum of the differential coefficients as another suitability measure. The differential coefficients are calculated after partitioning the degradation curve in equidistant time segments and using a linear regression for each part to calculate these coefficients. The identified prognostic feature presented in Figure 4 is better smoothed, trended and well adapted to the RUL prediction. This is substantiated by the result of the suitability metrics' comparison of the extracted feature vs. its cumulative form in table 1.

Table1: Results of the suitability comparison of the extracted feature vs. its cumulative form

	normalized cumulative feature	normalized Wrms_5
Monotonocity	1	0.8064
Trendddability	0.9934	0.8799
Prognosability	1	1
Sum of differential coefficients (proposed)	0.0328	0.0138

4. Remaining useful life prediction

The PF framework adapted for prognostic task works as follow. During the learning phase, we assume that the initial PDF $p(x_0)$ of the state is given. The posterior PDF $p(x_k | z_{1:k})$ is then obtained recursively in two steps:

Prediction step: the particles are propagated using the state evolution model $p(x_k | x_{k-1})$ (in our case the proposed NFS model). We obtain a new PDF.

Update step: the weights are update on the light of measurement according to the calculated likelihood $p(z_k | x_k)$.

$$w_k^i \approx w_{k-1}^i p(z_k | x_k^i) \quad (2)$$

A re-sampling step is needed to avoid degeneration by eliminating the particles with lower weights. At the end of this phase, when no measurement is available and the

likelihood is no longer calculated; starts the prediction phase; only the state x_k is propagated from one stage to another using the evolution model [10-11]. A Neuro-Fuzzy System predictor is proposed to fit the degradation process. The modified NFS is introduced with the process noise to represent the dynamics of the system, as shown below

$$\begin{aligned} x_{k+1} &= \hat{x}_{k+1} + \omega_k \\ \hat{x}_{k+1} &= g_{k+1}(x_k) \end{aligned} \quad (3)$$

Where $g_k(x_{k-1})$ is a nonlinear function used by the NFS.

The proposed NFS fit perfectly the degradation data Figure 5.

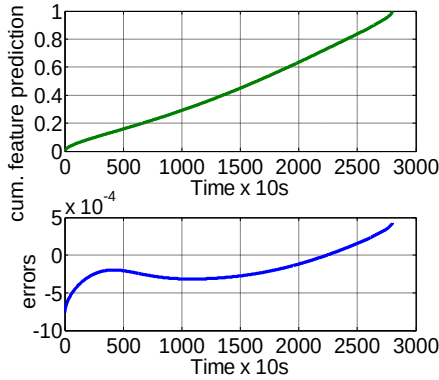


Figure 5. Results of NFS evolution model.

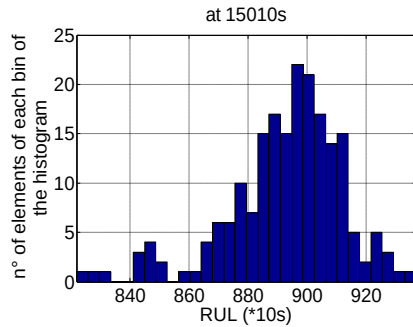


Figure 10. Example PDF RUL prediction at 15010s of Ber_{1-7} .

Table 2: Results of RUL at different prediction times.

	prediction time in (s)	Percentiles of predicted RUL			True RUL	%ER [13]	%ER proposed method
		5prct	median	95prct			
Ber_{1-3}	18010	5975	6520	6780	5730	37	-13,78
Ber_{1-5}	23010	510	1210	2280	1610	9	24,64
Ber_{1-6}	23010	145	1475	2415	1460	-5	-1
Ber_{1-7}	15010	7330	8275	7695	7570	-2	9,31
mean						13,25	12,18

The proposed method shows in general low percent errors, implying that the model works accurately and reliably on every tested bearing. Major deviation was found in bearing Ber_{1-4} as well as bearing Ber_{1-5} due to the lack of learning data. The bearing Ber_{1-4} was discarded. A mean percentage error of 12.18% was

5. Results and discussion

The given threshold for the vibration training set, 20g, correspond to 37.5 on the cumulative form which is kept for the test phase

The prediction results of the RUL are depicted in Table 2. For each tested bearing, the prediction is made at the end of test data. At late prediction time (23010s), the proposed model underestimates the RUL indicating an early RUL prediction which is less penalized compared to early prediction time (18010s) which gives an overestimate of the RUL prediction, but generally these predictions are often very close to the real one; we deal here with seconds.

The results of the proposed method are compared to those of [13], winner of the IEEE PHM 2012 Prognostic Challenge using the percentage error of RUL prediction as criteria calculated according to [12]:

$$\%ER = 100 \times \frac{actRUL - \widehat{RUL}}{actRUL} \quad (4)$$

where $actRUL$ is the actual RUL and $\widehat{RUL}$ the predicted one.

The RUL in [13] is predicted using frequency analysis-based anomaly detection, degradation feature extrapolation, and survival time ratios. The authors extracted a prognostic feature by taking averaging of five highest absolute acceleration values measured in each observation, realized degradation state recognition of bearings by anomaly detection when there was a change in the frequency of the peak vibration in the frequency spectrum and estimated RUL based on making comparisons on durations of degradation states between the training and the test bearings. However, the method has the disadvantage of defining the anomaly detection time point based on subjective criteria used to calculate the bearing survival time ratios.

achieved, indicating that the model worked accurately and reliably on every tested bearing.

The proposed method would be a good compromise if the goal is to decrease the computational requirements with an error that does not increase too much.

6. Conclusion

To overcome the problem of fluctuation, non-monotonicity and abrupt increase at the end of the component's life cycle of the extracted feature which impair the prediction accuracy, we have focalised to the identification of a new prognostic feature. This feature was performed by further preprocessing the extracted features transforming them to their cumulative form exhibits a monotonic trend that clearly reflects the evolution of machine degradation. The assessment of the identified features qualities was performed by a set of suitability metrics which show the superiority of the identified features over the extracted one. This leads to a simple and accurate prediction model. This claim is substantiated by the results of the RUL predictions which are quite close to the real ones.

A mean percentage error of 12.18% was achieved, indicating that the model worked accurately and reliably on every tested bearing.

The simplicity of the proposed method makes it a good compromise between accuracy and less computing in comparison with other complicated methods. The challenge remaining for the future work is to reduce the uncertainty of the RUL prediction.

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