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New Trend in Enhancing the Remaining Useful Life Prediction

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***Abstract*— In situation where the development of degradation model based on first principles is difficult or the extracted features from data-driven model do not exhibit an obvious trend in order to enhance the prediction of the Remaining Useful Life (RUL), we must, therefore, be addressed to the identification of new features having an obvious trending quality. In this context, this paper brings a new feature selection method, based on preprocessing further the extracted features in such a way that the identified prognostic feature results in an obvious trending quality. This method was validated on a set of experimental data collected from bearings run-to-failure tests.**

***Index Terms*— Fuzzy neural networks; Prognostics and health management; Remaining Useful Life; Particle Swarm Optimization; Particle Filters.**

I. Introduction

THE prognostic is the key process of Prognostics and Health Management (PHM). Its main goal is to predict the Remaining Useful Life (RUL) with a confidence interval during which the failure is expected to occur [1],[2] in order to decide plan of maintenance interventions for the most convenient and inexpensive times.

Among various prognostic approaches, data driven techniques are easier to deploy when it is hard to understand first principles of an equipment to build a prognostics model. In such case, degradation-based prognostic algorithms involve trending some measure of degradation, even sensed or pre-processed, called a prognostic feature. A good prognostic feature should well capture the trend of the fault progression through the entire component/system life. If the trend of the prognostic feature is not obvious or if it occurs right before a failure of the component as shown in Fig. 4 , it is difficult to make an accurate prediction [3].

Few authors attempt to address this issue like [3]-[4] who have proposed a genetic algorithm method to identify an optimal set of prognostic features from a population of features. This method was based on a set of metrics for the fitness function to evaluate the suitability of the identified feature for the prediction task namely monotonicity, prognosability, and trendability.

In the same context, [5] proposed an optimization approach that uses Genetic Programming (GP) to discover the advanced features highly correlated with the fault growth by randomly combining mathematical operators, analytic functions, constants, and state variables using the monotonicity as the only metric. However, the difficulty lies in determining failure threshold of the identified feature when different input features are involved by the GP. Therefore, keeping the original features for determining the threshold is essential.

On the other hand, the authors in [6] instead, proposed to use a fitness function based on the separability measure of consecutive time segments to evaluate the suitability of features extracted from raw signals to RUL prediction.

Taking the advantage of these previous endeavors, we have proposed to address this issue by further preprocessing the extracted features using an intelligent selection method or transforming them to their cumulative form. Again, the technique used to predict the RUL is a recursive Bayesian estimation technique called particle filtering (PF). Analytic expressions are often used to model the degradation process in this technique 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. Giving a brief theory for the technique used, Starting from feature extraction step in section, then the selection step which is the cornerstone of our approach. After the identification of the appropriate prognostic feature, the prediction of the remaining useful life (RUL) is carried out using the particle filtering method with the integrated NFS in section 3. The validation step ends our approach by the description of the experimental setup and the comments of the results which are given in section 4.1, and 4.2 respectively. A proposition of the embodiment aspect of this approach is given in section 5. Finally a conclusion is drawn in section 6.

II. Methodology

A. Data acquisition step

The choice of bearings to validate this study can be explained by the fact that these components are considered as

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the most common mechanical elements in industry and are present in almost all of industrial processes, especially in those using rotating elements and machines. Moreover, bearings are the main components which most frequently fail in rotating machines. Vibrations occupy a privileged position among sensored data to be considered when monitoring the condition of rolling bearings without effecting their operation.

B. Feature extraction 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.

Vibration signals can be processed in time domain, frequency domain or time-frequency domain [7].

More signal processing methods can be employed to extract features in this step as well [7]. The overall features used in this paper are listed in table I.

There are 153 features extracted from vibration sensor for both PHM case studies shown in table I, none of them exhibits an obvious trend.

III. Remaining Useful Life Prediction

The Particle filtering is an emerging and interesting technique for sequential signal processing based on the concepts of Bayesian theory and Sequential Importance Sampling (SIS). It is very suitable for nonlinear systems and in presence of non-Gaussian process/observation noise [8].

A. Bayesian estimation and resolution by particle filter

In The objective of the tracking is to estimate recursively the state probability distribution at time k by constructing the probability density function $p(x_k \mid z_{1:k})$ from:

Firstly, the state model describing the evolution of the system state (in our case, the state is the bearing degradation feature).

$$x_k = f(x_{k-1}, v_{k-1}), \quad for\ k > 0 \qquad (1)$$

where f is the transition function from the state x_{k-1} to next state x_k generally nonlinear, v_{k-1} is non-Gaussian distributed noise.

Secondly, the measurements introduced by the second equation; the observation model

$$z_k = h(x_k, \varepsilon_k), \quad for\ k > 0 \qquad (2)$$

where h is the observation function and ε_k is non-Gaussian distributed noise. We assume that the initial PDF $p(x_0)$ of the state is given. So, $p(x_k \mid z_{1:k})$ is obtained recursively in two steps:

Prediction:

$$p(x_k \mid z_{1:k-1}) = \int p(x_k \mid x_{k-1}) | p(x_{k-1} | z_{k-1}) dx_{k-1} \qquad (3)$$

Update:

$$p(x_k \mid z_{1:k}) = p(z_k \mid x_k).p(x_k \mid z_{1:k-1}) / p(z_k \mid z_{1:k-1}) \qquad (4)$$

The recursive computation of the posterior state pdf $p(x_k \mid z_{1:k})$ is more conceptual than practical, since there is no analytical solution to the integrals in equation (3). As a result, several estimation approaches have been developed to address this issue using filtering framework such as Kalman filter or particle filter depending on the hypotheses of the problem [8]. In this paper, a particle filtering method is employed to approximate the solution.

B. Particle Filtering Approach

Particle filtering employs a Sequential Importance Sampling algorithm. The posterior PDF can be approximated by a swarm of random samples named particles with associated weights representing the discrete probability masses, [9]-[11]:

$$p(x_k \mid z_{1:k}) \approx \sum_{i}^{N} w_k^i \delta(x_k - x_k^i) \approx \frac{1}{N} \sum_{i}^{N} \delta(x_k - x_k^{i*}) \qquad (5)$$

where w_k^i is the weight of the i^{th} particle at time k, x_k^i is the i^{th} particle at time k, N is the total number of particles and $\delta(\,)$ is the Dirac delta measure.

The weights are updated as follow:

$$w_k^i \approx w_{k-1}^i \frac{p(z_k \mid x_k^i) p(x_k^i | x_{k-1}^i)}{q(x_k^i | x_{k-1}^i, z_k)} \qquad (6)$$

where $q(x_k^i | x_{k-1}^i, z_k)$ is called an importance density. If we take.

$$q\left(x_k^i | x_{k-1}^i, z_k\right) = p\left(x_k^i | x_{k-1}^i\right) \qquad (7)$$

We obtain

$$w_k^i \approx w_{k-1}^i\, p(z_k \mid x_k^i) \qquad (8)$$

The state evolution model $p(x_k \mid x_{k-1})$ is used to draw the particles.

TABLE I: List Of Extracted Features For First And Second PHM Case Study.

Index	Feature	Sensor	Index	Feature	Sensor
1	RMS		21-25	Strongest Frequency Energies	
2	Standard Deviation		26	VHF Band Energy	
3	Mean Value		27	HF Band Energy	
4	Max Value		28	MF Band Energy	
5	Min Value		29	LF Band Energy	
6-10	Quantiles		26	VHF Band Energy	
11	Skewness		27	HF Band Energy	
12	Kurtosis		28	MF Band Energy	

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13	Crest Factor		29	LF Band Energy	
14	Clearance Factor		30-35	Percentages of Energy corresponding to the detail wavelet coefficients	
15	Shape Factor	Vertical and Horizontal Vibrations	36	Percentages of Energy corresponding to the approximation wavelet coefficients	Vertical and Horizontal Vibrations
16	Impulse Factor		37-66	RMS, Mean, Max, Min, Standard Deviation, Median of the detail wavelet coefficients	
17	BPFO Energy				
18	BPFI Energy				
			67-71	RMS , Mean, Max, Min, Standard Deviation, Median of the approximation wavelet coefficients	
19	BSF Energy		72-107	Inverse Hyperbolic Sine of the above wavelet statistical features	
			108-142	Inverse Tangent sine of the above wavelet statistical features	
			143-148	Histogram of detail coefficients	
20	FTF Energy		149-153	Cumulative Histogram of detail coefficients	

C. Adapting particle filter for prognostics purpose

The prognostic process is presented in Fig. 2.

During the learning phase, the filter works as described above. But at the end of this phase, when no measurement is available and the likelihood is no longer calculated; only the state x_k is propagated from one stage to another using the evolution model [9]-[10], [13].

D. Integration of NFS in particle filtering

Linear, exponential or logarithmic analytic expressions are often used to model the degradation process to fit the given data. These expressions are first-order Markov models where the system state x_k depends only on the previous state x_{k-1} and a process noise ω_{k-1}. But usually there is not such trivial case, as in our situation. To address this issue, we add a degree of complexity to the PF technique by proposing a neuro-fuzzy system predictor to fit the degradation process. The proposed NFS is a fuzzy logic system combining the human-like reasoning style of fuzzy systems with the learning and connectionist structure of neural networks. The modified NFS is introduced with the process noise to represent the dynamics of the system, as shown below

$$\begin{aligned} x_k &= \hat{x}_k + \omega_{k-1} \\ \hat{x}_k &= g_k(x_{k-1}) \end{aligned} \qquad (9)$$

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

The NFS consists of five layers, wherein the signal is processed throw, namely input layer, Membership Function (MF) layer, rule layer, normalized layer and output layer, respectively [11], [13].

The adopted NFS predictor is a single input-single output (SISO) Neuro-Fuzzy System. Its architecture is shown in Fig. 1.

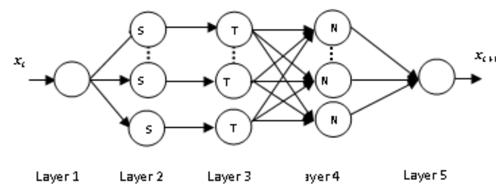

Fig. 1: SISO NFS predictor Architecture.

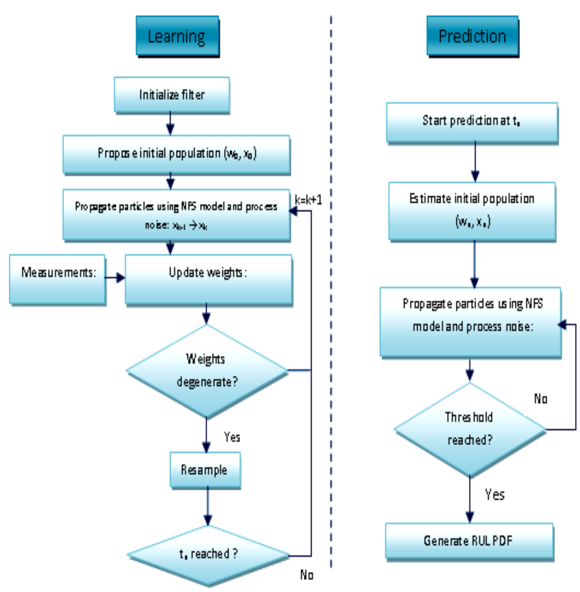

Fig. 2: Particle filter framework for prognostics

IV. Experiment Setup

A. PHM case study (Bearings datasets of IEEE PHM Challenge 2012):

PHM challenge datasets were provided by FEMTO-ST Institute and are mainly composed of run-to-failure

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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 11 remaining bearings. Further details are given in [14].

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

Fig. 3a and 3b show the raw vibration signals of the bearing Ber_{1-1} on the horizontal and vertical axis respectively.

1) *Feature extraction & exploring*

Following the steps of the prognostic scheme and in addition to the extracted features in time and frequency domains, features in time-frequency domain is also considered, using the Daubichies wavelet of 5^{th} order D5 and 5^{th} decomposition level for the analysis of bearing vibration signals.

Statistical features were performed on at different decomposition levels using detail coefficients, Fig. 4 is illustrating example. These features still show a low trending and present variation right before failure time which limits their prognostic capabilities; Fig. 4a and 4b.

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

$$cdf(i) = sum(data(1:i))/sqrt(abs(sum(data(1:i))));$$

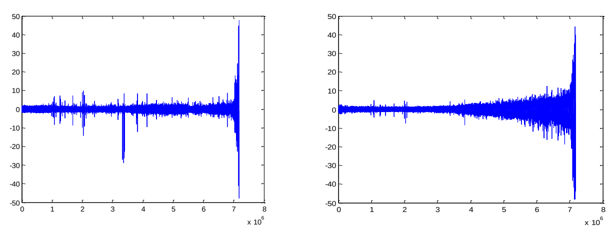

Fig. 3: Vibration signals of the bearing Ber_{1-1} - Horizontal and Vertical axis.

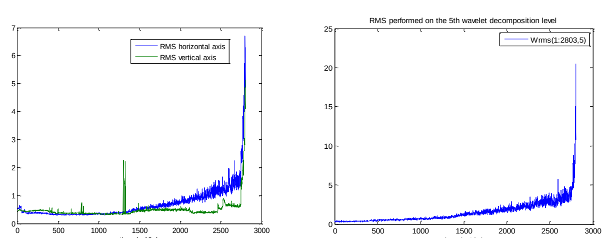

Fig.4: a) RMS vibration features of bearing Ber_{1-1}
b) RMS of wavelet detail coefficients of level 5 of bearing Ber_{1-1}

The result, Fig. 5, is better smoothed and trended characteristic and well adapted to the RUL prediction.

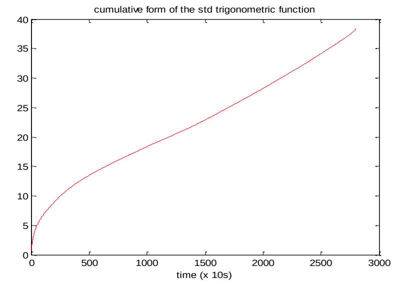

Fig. 5: Identified features for the bearing Ber_{1-1}

The given threshold for the training vibration, 20g, correspond to 37,5 on the cumulative form which is kept for the test phase.

Fig. 6 shows the NFS evolution model to be integrated to particle filtering algorithm for RUL prediction; it represents with fidelity the evolution of the identified feature.

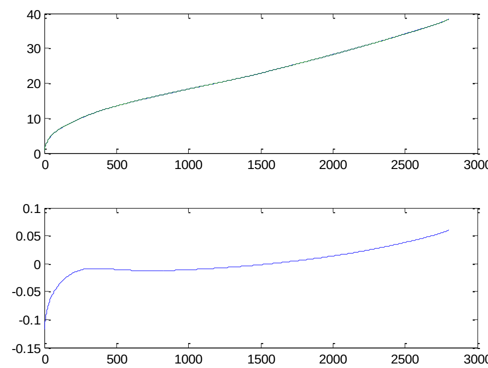

Fig. 6: Results of NFS evolution model.

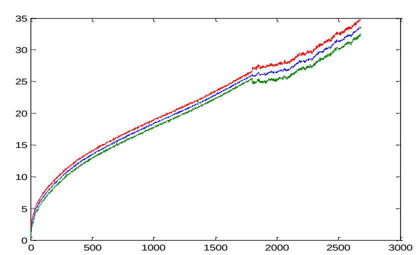

Fig. 7: Particle filter; learning and prediction phases.

Table V summarizes the results of the RUL percentiles prediction at different prediction times. 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. If the results are quite convincing, the uncertainty of the prediction remains very high.

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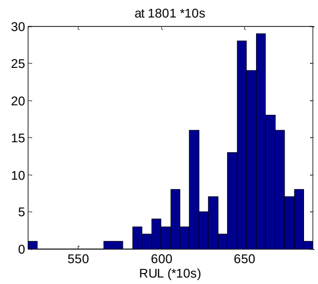

Fig. 8: PDF RUL prediction at 18010s

TABLE V: RESULTS OF PERCENTILES OF THE RUL AT DIFFERENT TIMES

Percentiles of predicted RUL at time - in (s)	5prct	median	95prct	True RUL
Ber_{1-3} - 18010	5975	6520	6780	5730
Ber_{1-5} - 23010	510	1210	2280	1610
Ber_{1-6} - 23010	145	1475	2415	1460

V. PRACTICAL ASPECT OF THE APPROACH

The flow chart of the Fig. 9 illustrate our approach to perform machine RUL prediction:

A number of vibration data samples are collected from sensors installed on the equipment. The data is then transferred in buffer to be processed by the prognostic software. The prognostic software (implemented as computer program or procedure written as source code in a conventional programming language and presented for execution by the CPU as object code for instance) processes the received data following the steps of the approach described above:

- A plurality of statistical features are extracted and transformed to its cumulative form to identify the advanced prognostic feature as health indicator.
- After the identification of the health status of the equipment, the RUL with its confidence bounds is then predicted by propagating the trend of the health indicator until it reached the pre-defined threshold using the PF assuming the fault growth follows the proposed NFS.

Finally, the prognostic software outputs prognostic information which can be further displayed on HMI.

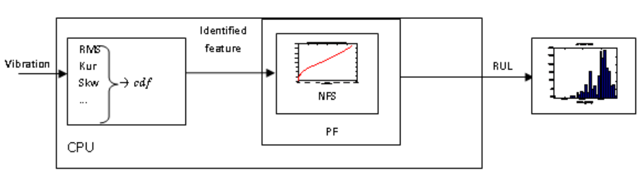

Fig. 9: Embodiment of the approach

VI. CONCLUSION

The prognostic feature which is used for the prediction of the remaining useful life (RUL) for the PHM case study is done by further pre-processing the extracted feature transforming it into its cumulative form. The identified feature exhibits a monotonic trend that clearly reflects the evolution of machine degradation.

We have adopted the particle filtering technique for the prediction of the RUL with an integrated NFS predictor to simulate the machine fault evolution model.

This approach was validated through a set of collected bearing run to failures data.

The results of the RUL predictions are very promising, and need to be further confirmed with data acquired on different stack technologies. The challenge remaining for the future work is to reduce the uncertainty of the RUL prediction.

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