Machine health prognosis based on multi-regime condition monitoring signals

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Abstract. This paper presents a proposal for machine health prognosis based on multi regime condition monitoring (CM) signals. The basis idea is performing deeply analysis of CM signals that possibly includes steady state signals – that is normal condition, and developing transient signal that represents some faults exist in the machine. Trigonometric features is extracted from such signals and some energy vectors was used to calculate the health index of machine. Prognosis is then performed on the machine which has the lowest health index, that means the worst condition of the machine. RUL prediction is addressed to estimate the remaining life of the machine up to breakdown. The proposed method gives relatively promising results of RUL prediction that possibility give some times for maintenance actions before catastrophic failure occurs.

1 Introduction

Machine condition monitoring (MCM) cannot be bargained of its implementation in industry due to the widely benefits taken from safety aspect to business profits. The consequence of loss of profits due to unplanned downtime of industrial critical assets have forced the engineers to change their traditional maintenance strategy to be condition-based and more intelligent. Through the intelligent maintenance, the industries hope to optimize the operational life span – that is, the remaining useful life (RUL) – as well as quality, security and environmental standards.   It also optimizes the availability of the assets, thus avoiding high downtime costs [1].

In recent years, a significant amount of research work has been undertaken to develop models that can be used to estimate RUL in industrial machineries to support the intelligent maintenance system. Selecting the appropriate techniques of prognosis for a particular application is critical to obtain the ultimate success of prognosis implementation. For example, the articles reported research work of prognosis system is listed in Refs. [2-11] and many more have already been reported in the literatures. Even so the such works obtained high appreciation in the state of the art in a fields, it do little to help operators in typical industry selecting the appropriate method for their specific needs. The reported

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works tend to focus on the technical (or theoritical) merits and demerits of each approach rather than the practical implementation issue.

Therefore, this paper contributes the strategy of prognosis system to estimate the RUL in such of simple way and applicable. The proposed method consists of recognition of regime signal acquired by condition monitoring device, data preprocessing, feature extraction, health assessment and prognosis strategy.

2 Method and Materials

The method employed in this paper includes signal processing and feature extraction of vibration signals. Some of signal processing techniques thru fast-fourier transform (FFT), discrete wavelet transform (DWT) and emperical mode decomposition (EMD) were used for data preparation which is valuable for health assessment process as well as feature extraction.

2.1 Signal Processing and Feature Extraction

FFT is a common tool for spectrum analysis to obtain dominant frequency components present in time domain signals and to assign them of various physical phenomena. The signal transformation is formulated in the simple form as follows:

$$X(k) = \sum_{n=0}^{N-1} x(n) e^{-\frac{i2\pi kn}{N}} \tag{1}$$

Basically, it tranforms the signals from time domain into frequency domain which is capable for digitization signals analysis.

DWT transforms the signal from time domain into a different form, that is, a series of wavelet approximation and details in time-scale domain as follows

$$dwt(j,k) = \frac{1}{\sqrt{2^j}} \int x(t) \psi^* \left(\frac{t - k 2^j}{2^j} \right) dt \tag{2}$$

where $\psi^*(t)$ denotes conjugate wavelet function, j is number of level.

EMD method introduced by Huang et al [12] is a relatively new approach to signal analysis. It was developed from assumptions of: (i) the signal is an integration of intrinsic components of oscillations, (ii) every linear and non-linear mode has at least one maximum and one minimum, (iii) the signal is characterized by a time series between successive extrema. Each signal is decomposed into a finite number of intrinsic mode function (IMF) through a shifting process and then examined using some conditions as described in [12].

Feature extraction was conducted on decomposed signals by DWT at defined level, i.e., level 4, using classical statistical and trigonometric method. The aim of feature extraction is to obtain the salient features that clearly reflect failure progression in meaningful way. Trigonometric feature is calculated using standard deviation of inverse hyperbolic sinus and inverse tangent as follows

$$F_{t1} = \sigma \left(\log \left[x_j + (x_j^2 + 1)^{1/2} \right] \right) \tag{3}$$

$$F_{t2} = \sigma \left(\frac{i}{2} \log \left(\frac{i + x_j}{i - x_j} \right) \right) \tag{4}$$

The mentioned data processing method were employed to signal reconstruction which is assumed there is no information lost from the signal. Furthermore, an energy index model was calculated from the reconstructed signal for generating health assessment through correlation analysis (CA). CA is modeled as cosines distance of two vectors that related to the energy of the reconstructed signals.

$$CA = \frac{\boldsymbol{\varepsilon}_1 \cdot \boldsymbol{\varepsilon}_n}{|\boldsymbol{\varepsilon}_1||\boldsymbol{\varepsilon}_n|} \tag{5}$$

where $\boldsymbol{\varepsilon}_1$ and $\boldsymbol{\varepsilon}_n$ are vectors of energy index model calculated from signal regime normal (steady state) and faulty state, respectively. The values of CA ranges between zero and one, higher CA means a higher correlation between evaluated signals.

Furthermore, the prediction of RUL is approached by a non-linear state space models as a finite-dimensional system as follows [12]

$$x(t+1) = f(t, x(t), u(t), w(t); \theta)$$
$$y(t) = h(t, x(t), u(t), v(t); \theta) \tag{6}$$

where $y(t)$, $u(t)$ are output predictors and input, $w(t)$, $v(t)$ and θ are sequences of independent random varaibles and a vectors of unknown parameters, respectively. The predictor is then constructed from [13]

$$\hat{y}(t|\theta) = g(t, Z^{t-1}; \theta)$$
$$Z^t = (y^t, u^t) = (y(1), u(1), ..., y(t), u(t)) \tag{7}$$

The method of machine health prognosis based on multi-regime condition monitoring signals is summarized in Fig. 1. This method includes system capability of selecting regime based on a certain health status and a specific operating conditions. Some procedures involved in this method such as regime clustering, feature extraction, information reconstruction, health index determination, health and risk status, diagnosis and prognosis of RUL.

Moreover, the procedure of information reconstruction from the MCM signals is depicted in Fig 2. The previous method were employed to obtain the information from the regimed signals for machine health prognosis.
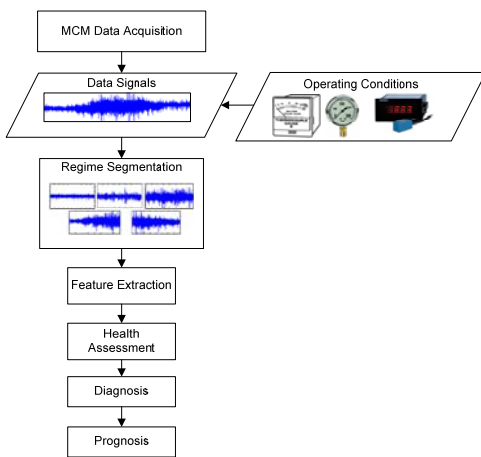
Fig. 1 Multi-regime machine health prognosis.
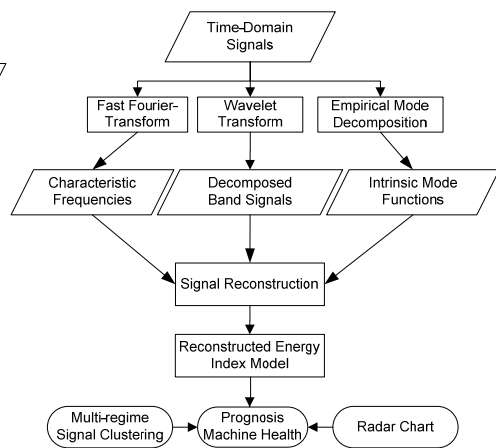
Fig. 2 Information reconstruction of signals.

Condition monitoring signal collected from data acquisiton devices is segmented into several regimes which is defined by user. Feature extraction is performed using

trigonometric features as formulated in equations (3) and (4). Machine health state index is calculated based on energy of the regimed signals after signal reconstruction as shown in Fig. 2.

The acquired time-domain signal is processed using FFT, wavelet transform and EMD to obtain characteristic frequencies, decomposed signals and IMF, respectively. Reconstruction information is conducted based on processed signal which is free from background noise. Energy index model is then generated for machine health state index according to equation (5). This index is presented in radar chart for machine condition monitoring purpose. Finally, prognosis machine is performed using data from machine health state and regimed-signal.

2.2 Data

The data used in this research is originally developed by PRONOSTIA, an experimental platform from FEMTO-ST Institute, France. This test-bed is dedicated to test and validate fault detection, diagnosis and prognosis of rolling element bearing [14,15]. This platform allows to perform accelerated degradations (run-to-failure) of bearing at constant and/or variable bearing conditions, while gathering on-line condition monitoring data. The tested bearings could have various type of faults such as inner race, outer race, cage and rolling element.

The conditions of the measurement data are summarized in Table 1. Vibration signals were acquired from data acquisition card using sampling frequency 25.6 kHz with recording samples of 2560 samples in time duration 10 second.

Table 1. Datasets of vibration measurement using PRONOSTIA.

| Datasets	Condition#1 (1800rpm, 4000N)	Condition#2 (1650rpm, 4200N)	Condition#3 (1500rpm, 5000N)
Learning set	Bearing1_1 Bearing1_2	Bearing2_1, Bearing2_2	Bearing3_1 Bearing3_2

3 Results and Discussion

Vibration signal presented in Fig. 3 is assumed coming from MCM device that has been installed in the system. At early stage, the signal represents normal condition recorded from rolling element bearing housing, but grows suddenly become transient till the end of the life. The recorded signal is then devided into several regimes from normal to transient regime that shows some degradations have experienced in the machine. For example, seven regimes of signal have been simulated and preprocessed using previous methods including FFT, DWT and EMD. Each regime gives three energy models extracted from FFT, DWT and EMD, so therefore there are 21 energy model vectors from which health assessment can be derived.

Applying equation (5), the calculation of CA represents health index of the machine presented in radar chart. Higher CA means machine in normal condition, otherwise the machine in abnormal (degradation) condition that needs maintenance actions. Fig.4 shows the lowest health index comes from bearing data C5, this means the abnormality has been detected. Further analysis should be attempted for such signals to estimate how much time left till the end life of this bearing. This process actually known as prognosis of RUL.

(a)   (b)
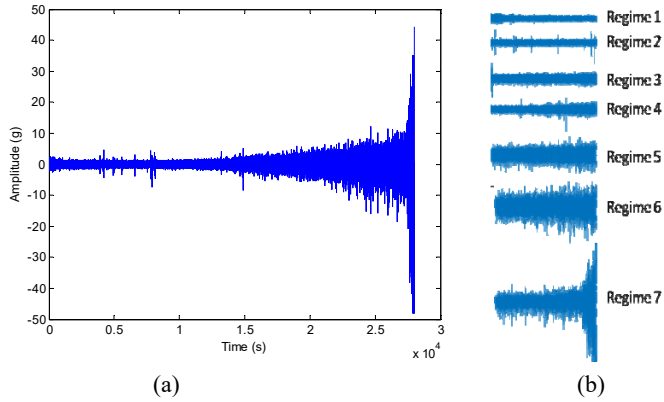
Fig. 3 Vibraton signal acquired from bearing1_1: (a) run-to-failure signal; (b) regimed signal.
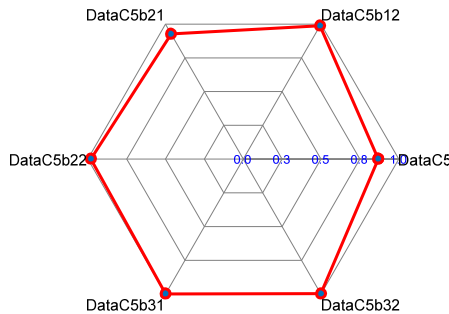
Fig. 4 Radar chart of health index.
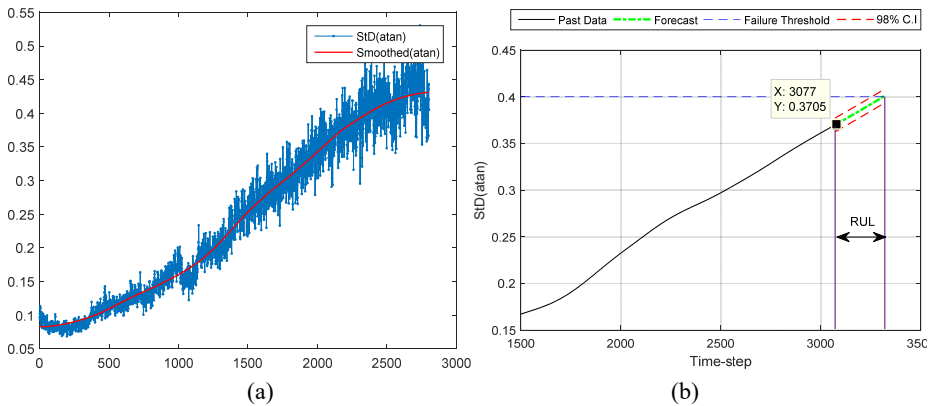
(a)   (b)
Fig. 5 (a) Feature of $\sigma(atan)$; (b RUL prediction $\sigma(atan)$.

Trigonometric features are then extracted from the abnormal signals using equations (3) and (4) and yield standard deviation of inverse hyperbolic sinus and inverse tangent. Fig. 5a shows, for example, feature of standard deviation of inverse tangent. Prognosis of machine is conducted based on these features by means of time series prediction using non-linear state-space models in equations (6) and (7).

Prognosis model was trained by using 1000 past time data points for building a dynamic forecast model. The threshold of failure is assumed and set up 0.6 and 0.4 for $\sigma(asinh)$ and $\sigma(atan)$ features, respectively. The predictors learned the past time data dan predict the future data points based on determined model. Fig. 5b shows the result of RUL prediction of $\sigma(atan)$ features using 250 step-ahead horizon presented by the estimated time of predictors when hits the determined threshold. As results, feature of $\sigma(asinh)$ and $\sigma(atan)$ gives 246 and 243 time-steps of RUL prediction, respectively. In real application, the predicted RUL allows the actions of maintenance before the system reachs catastrophic failures.

4 Conclusion

This paper deals with prediction of RUL based on multi-regime condition monitoring signals. The acquired signals was partitioned to separate the steady-state or normal condition and the transient mode that represents of faults exist in the machine. Feature extraction has been performed on regimed signal to generate health index through CA calculation. The lowest index shows the worst condition of machine, therefore, prognosis is employed to predict RUL of machine. The proposed method gives relatively promising results of RUL prediction that possibility give some times for maintenance actions before catastrophic failure occurs.

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