



Review

Machinery health prognostics: A systematic review from data acquisition to RUL prediction

Yaguo Lei^{*}, Naipeng Li, Liang Guo, Ningbo Li, Tao Yan, Jing Lin

State Key Laboratory for Manufacturing Systems Engineering, Xi'an Jiaotong University, Xi'an 710049, China

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ABSTRACT

Machinery prognostics is one of the major tasks in condition based maintenance (CBM), which aims to predict the remaining useful life (RUL) of machinery based on condition information. A machinery prognostic program generally consists of four technical processes, i.e., data acquisition, health indicator (HI) construction, health stage (HS) division, and RUL prediction. Over recent years, a significant amount of research work has been undertaken in each of the four processes. And much literature has made an excellent overview on the last process, i.e., RUL prediction. However, there has not been a systematic review that covers the four technical processes comprehensively. To fill this gap, this paper provides a review on machinery prognostics following its whole program, i.e., from data acquisition to RUL prediction. First, in data acquisition, several prognostic datasets widely used in academic literature are introduced systematically. Then, commonly used HI construction approaches and metrics are discussed. After that, the HS division process is summarized by introducing its major tasks and existing approaches. Afterwards, the advancements of RUL prediction are reviewed including the popular approaches and metrics. Finally, the paper provides discussions on current situation, upcoming challenges as well as possible future trends for researchers in this field.

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Abbreviations: CBM, condition based maintenance; RUL, remaining useful life; HI, health indicator; HS, health stage; AI, artificial intelligent; FT, failure threshold; PHM, prognostics and health management; NASA, National Aeronautics and Space Administration; RMS, root mean square; IMS, Intelligent Maintenance Systems; PHI, physics health indicator; VHI, virtual health indicator; AR, autoregressive; PCA, principal component analysis; SOM, self-organizing map; HMM, Hidden Markov model; PDF, probability density function; EoL, end-of-life; FPT, first predicting time; SVM, support vector machine; RVM, relevance vector machine; ANN, artificial neural network; KNN, K-nearest neighbor; NF, neural fuzzy; PE, Paris-Erdogan; KF, Kalman filtering; PF, particle filtering; IG, Inverse Gaussian; PH, proportional hazards; GPR, Gaussian process regression; FFNN, feed-forward neural network; RNN, recurrent neural network; SVR, support vector regression; RMSE, root mean square error; CI, confidence interval; RA, relative accuracy; CRA, cumulative relative accuracy; ETA, exponential transformed accuracy.

* Corresponding author.

E-mail address: yaguolei@mail.xjtu.edu.cn (Y. Lei).<https://doi.org/10.1016/j.ymssp.2017.11.016>

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1. Introduction

Condition based maintenance (CBM) is a maintenance strategy which monitors the health condition of machinery in real time and makes an optimal maintenance decision based on condition monitoring information [1,2]. This strategy is effective in reducing unnecessary maintenance operations and improving the reliability of machinery, thus becoming more and more popular in recent years. Health prognostics is one of the major tasks in CBM, which aims to predict the remaining useful life (RUL) of machinery based on the historical and on-going degradation trends observed from condition monitoring information [3–5]. As shown in Fig. 1, a machinery health prognostic program is generally composed of four technical processes [6], i.e., data acquisition, health indicator (HI) construction, health stage (HS) division and RUL prediction. At first, measured data, such as vibration signals, are acquired from sensors to monitor the health condition of machinery. Then, from the measured data, HIs are constructed using signal processing techniques, artificial intelligent (AI) techniques, etc., to represent the health condition of machinery. After that, according to the varying degradation trends of HIs, the whole lifetime of machinery is divided into two or more different HSs. Finally, in the HS which presents obvious degradation trend, the RUL is predicted with the analysis of the degradation trends and a pre-specified failure threshold (FT).

Machinery health prognostics has attracted more and more attention from academic researchers and industrial operators in recent years. Fig. 2 shows the variation of publication numbers over time on the topic of machinery prognostics in the past 20 years, which is counted based on the search result from the Web of Science. It is seen that the publication number pre-

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