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An intelligent approach to machine component health prognostics by utilizing only truncated histories

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ABSTRACT

Numerous techniques and methods have been proposed to reduce the production downtime, spare-part inventory, maintenance cost, and safety hazards of machineries and equipment. Prognostics are regarded as a significant and promising tool for achieving these benefits for machine maintenance. However, prognostic models, particularly probabilistic-based methods, require a large number of failure instances. In practice, engineering assets are rarely being permitted to run to failure. Many studies have reported valuable models and methods that engage in maximizing both truncated and failure data. However, limited studies have focused on cases where only truncated data are available, which is common in machine condition monitoring. Therefore, this study develops an intelligent machine component prognostics system by utilizing only truncated histories. First, the truncated Minimum Quantization Error (MQE) histories were obtained by Self-organizing Map network after feature extraction. The chaos-based parallel multilayer perceptron network and polynomial fitting for residual errors were adopted to generate the predicted MQEs and failure times following the truncation times. The feed-forward neural network (FFNN) was trained with inputs both from the truncated MQE histories and from the predicted MQEs. The target vectors of survival probabilities were estimated by intelligent product limit estimator using the truncation times and generated failure times. After validation, the FFNN was applied to predict the machine component health of individual units. To validate the proposed method, two cases were considered by using the degradation data generated by bearing testing rig. Results demonstrate that the proposed method is a promising intelligent prognostics approach for machine component health.

1. Introduction

Condition-based maintenance recommends maintenance actions on the basis of the information collected through condition monitoring, thus reducing significantly the production downtime, spare-part inventory, maintenance cost, and safety hazards [1]. Prognostics is regarded a significant and promising tool for achieving these benefits for machine maintenance. A large number of prognostic models, specifically data-driven models, require abundant historical event data, such as failure times. However, in practice, industrial and military communities would rarely allow their assets to run to failure. Once a defect is detected in a unit, the unit is often replaced or overhauled before it fails. The unit is known to survive up to the time of replacement or repair. However, no information is available whether the unit would fail if left undisturbed. As defined by A. Heng, et al., data of this

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kind are called "truncated data", "truncated histories" or "suspended data". Publications related to the modeling of suspended condition monitoring (CM) data in existing prognostic models are limited [2].

In conventional reliability analysis, only failure and suspension times are utilized to construct the likelihood function for estimating the lifetime distribution of the probability density function. The Weibull distribution is typically used in reliability analysis and in predicting future reliability and expected time to failure [3–5]. Lu and Meeker [6] developed a two-stage statistical method for estimating the fix-effect and random-effect parameters by using the remaining life distribution model using degradation data from both failure and suspension histories. The proportional hazard model can also incorporate both failure and suspension history data in estimating the model parameters [7].

Recently, Heng et al. [8] demonstrated an approach including both the suspended CM and event data in training an intelligent prognostics model, in which the outputs are the reliability values or the probability of survival at future time horizons [2]. An intelligent machine prognostics system [9] was developed based on survival analysis and support vector machine by utilizing the truncated and un-truncated data collected from the CM routine. The survival probability of the failure time of machine components was then estimated. Tian et al. [7] trained a special artificial neural network (ANN) by utilizing the failure histories and suspension histories with the obtained optimal predicted life values, which were determined by minimizing the validation mean square error in the training process of ANNs. The trained ANN can be used for predicting the remaining useful life of equipment.

The ideas of the aforementioned conventional reliability methods and current machine component prognostics approaches can be summarized as: these models are established based both on failure and on truncated histories. However, in real world, there are many cases with only truncated histories available (without failure histories), for which the current approaches would not be able to obtain accurate prognostics models. Moreover, machine component prognostics using only truncated histories has rarely attracted more attention in the past decades. Therefore, this problem inspires the authors to carry out the related works, and to propose an approach to machine component health prognostics by utilizing only truncated histories.

This study develops an intelligent machine component prognostics approach by utilizing the chaos-based parallel multilayer perceptron (CPMLP) network and a polynomial to fit residuals of minimum quantization errors (MQEs) and to generate extra-MQEs and failure times following the truncation times. The feed-forward neural network (FFNN) was trained by data inputs from the MQE series that correspond to the target vectors of the survival probability, which were estimated by using the intelligent product limit estimator (iPLE) method using the existing truncation times and the generated failure times. After validation, the FFNN was applied to predict the machine component health of individual units. Two cases were considered by using the degradation data generated by a bearing test rig to validate the proposed method. Results demonstrate that the proposed method is a promising intelligent prognostics approach for machine component health.

The following sections of this paper are organized to describe clearly the modeling and validation process.

2. Related models

2.1. Self-organizing map network

The self-organizing map (SOM) network proposed by Kohonen [10] is one of the ANN suitable for data clustering and is psychologically plausible. The SOM network comprises an input layer of nodes, in which the inputs to the ANN are applied, and an output layer of neurons called competitive layer, where the categorizations (groupings) of the inputs are formed [11,12], as shown in Fig. 1. Unlike networks based on supervised learning, which require that target values corresponding to input vectors are known, SOM can be used to cluster data without knowing the class membership of the input data [13]. With proper visualization methods [14], SOM is a powerful tool for discovering and visualizing the general structures of the state space. Moreover, SOM is an efficient tool for visualizing the system behavior and for condition monitoring and system degradation detection [15]. In this study, SOM is employed to calculate the truncated MQEs, which are the inputs of the FFNN prognostic model.

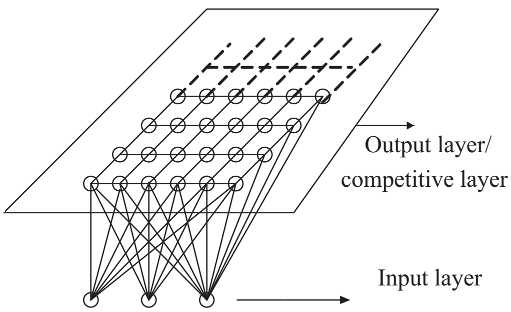

Fig. 1. Structure of an SOM network.