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Parameter estimation and remaining useful life prediction of lubricating oil with HMM

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ABSTRACT

Lubricating oil plays a vital role in the full life-span performance of the machine. Lubricating oil deterioration, which leads to the attenuation of oil performance and severe wear afterwards, is a slow degrading process, which can be observed by condition monitoring, but the actual degree of the oil degradation is often very difficult to examine. The main purpose of lubricating oil degradation prediction is to estimate the failure time when the oil no longer fulfills its functions. We suppose that the state process evolution of lubricating oil degradation can be modeled using a hidden Markov model (HMM) with three states: healthy state, unhealthy state, and failure state. Only the failure state is observable. While the lubricating oil is in service, vector data that are stochastically related to the deterioration state are obtained through on-line condition monitoring by an OLVF (On-line Visual Ferrograph) sensor at regular sampling epochs. A method of Time Series Analysis (TSA) is applied to the healthy portions of the oil data histories to get the residuals as the observable process containing partial information to fit the hidden Markov model. The unknown parameters of the fitted hidden Markov model are estimated by the Expectation-Maximization (EM) algorithm. The remaining useful life (RUL) of lubricating oil can be evaluated through explicit formulas of the characteristics such as the conditional reliability function (CRF) and mean residual life (MRL) function in terms of the posterior probability.

1. Introduction

Lubricating oil is used to reduce wear and friction from the mobile components, eliminate contamination, remove heat from friction surfaces, and avoid machine failure and reduce the cost for unscheduled maintenance afterwards. Therefore, lubricating oil condition should be monitored and the oil should be replaced regularly to extend the period when the machine is in good state [1]. Recently, condition monitoring (CM) of lubricating oil has attracted a considerably attention in research and it plays a vital role in industries [2]. The oil data obtained from CM have been used to assess the actual condition of the operating machine in [3], but to our knowledge, HM models for lubricating oil deterioration and replacement when the machine is in the healthy state have not been developed in the literature. Taking into account that the time period when a machine is in the healthy state is usually considerably longer than the length of time between oil replacements, it is assumed in this paper that the machine condition is stable and will not affect considerably the speed of oil deterioration.

Wear debris level in lubricating oil has been proved to be one of the most common degradation features to evaluate lubricating oil degradation [2]. Relative wear debris concentration has been obtained from an image captured by an on-line sensor (OLVF) at a sampling epoch [4]. By this, the wear debris presenting in a lubricating oil sample can be categorized as a large and small group according to their sizes by controlling the oil flow rate and magnet field intensity [4]. When the machine is in operation, wear debris accumulate in the lubricating oil and the concentration increases, which leads to the lubricating oil degradation [5].

Although analysis on wear debris in lubricating oil has been utilized in practice for many years to estimate machine condition, little work has been done using statistical approaches to model and analyze oil data for the purpose of assessing the lubricating oil degradation and predicting its remaining useful life. The prediction with the CM data can be obtained by the conditional reliability function (CRF) and mean residual life (MRL) function [3], which indicates the failure time when the oil cannot fulfill its functions anymore, and should be changed. In condition monitoring area, RUL prediction was applied for particle contaminated lubricating oil by applying physical models using a particle filtering technique [5], as well as the application on rotational bearings with two-phase threshold model using Bayesian methods [6].

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To our knowledge, no statistical models have been developed in the literature which could be applied to the RUL prediction of lubricating oil.

In this paper, we present a statistical approach to predict the RUL of lubricating oil subject to deterioration using oil data obtained by an OLVF sensor. Statistical methods of deteriorating systems, which are utilized in industry to model the degradation process for early fault detection using CM information, are categorized into one of three main approaches: the proportional hazard modeling (PHM) [7], stochastic recursive filtering [8], and hidden Markov modeling (HMM) [9]. HMM, which has been proved to be efficient in gradual degradation system modeling [10,11] and the RUL prediction [11], and applied in many areas such as speech recognition, econometrics and condition-based maintenance [12], is employed in this paper with two types of stochastic processes, namely hidden state process and observation vector process in order to model the degradation process and predict the RUL of lubricating oil. The state and observation parameter estimations of the fitted HMM under partial observations of lubricating oil deterioration can be obtained by the Expectation-Maximization (EM) algorithm [11].

The residuals are obtained using a vector autoregressive (VAR) model as the observation process in the hidden Markov framework. Once the parameters of the HMM are estimated, we use the explicit formulas for the conditional reliability function (CRF) and the mean residual life (MRL) function in terms of the posterior probability [13], which can be used for RUL prediction of lubricating oil. The CRF indicates the probability that the oil can survive during a period of time and has not failed yet, and the MRL can be calculated by using the posterior probability [14]. It is very new in the Tribology area to apply the EM algorithm and HMM to model the degradation process and estimate the RUL of lubricating oil focusing on the lubricating oil condition.

The HMM-based procedure is shown in Fig. 1. The rest of the paper is organized as follows. In Section 2, a VAR model is fitted to the real 2-dimensional oil data from an OLVF sensor collected at regular time epochs, and the residuals for both the healthy and unhealthy portions of the oil data histories are obtained. In Section 3, the state and residual process are modeled as an HMM, and the estimation procedure of the unknown parameters is developed using the EM algorithm. In Section 4, the formulas for the conditional RF and MRL have been applied, which can be used to predict the RUL of lubricating oil. Finally, the conclusions and future research are summarized in Section 5.

2. Vector autoregressive modeling and computation of residuals

The real condition monitoring data were obtained for the detection of lubricating oil deterioration from a four-ball test rig [15] in order to predict the RUL of the lubricating oil afterwards. During the operational life of the tribo-pairs, oil data were collected every $\Delta = 4$ minutes by an OLVF sensor, which is an on-line ferrographic sensor based on Image Technology, and it provided wear debris concentrations that came from the direct wear during these 4 minutes. The total number of data histories recorded is 27, which consist of $N=11$ failure histories and $M=16$ suspension histories. The failure history is defined as the history that ends with observable failure, which indicates that the lubricating oil is out of use at that moment, and the suspension history is defined as the history that ends when the lubricating oil is still in operation and has not lost its functions.

To avoid over-parameterization, we use the 2-dimensional monitoring data consisting of small wear particles and large wear particles obtained from the OLVF sensor for analysis. A typical data history is given in Fig. 2, and the working conditions are listed in Table 1. IPCA shows three stages including run-in, normal, and severe stages, which agrees with the typical "Bathtub Curve".

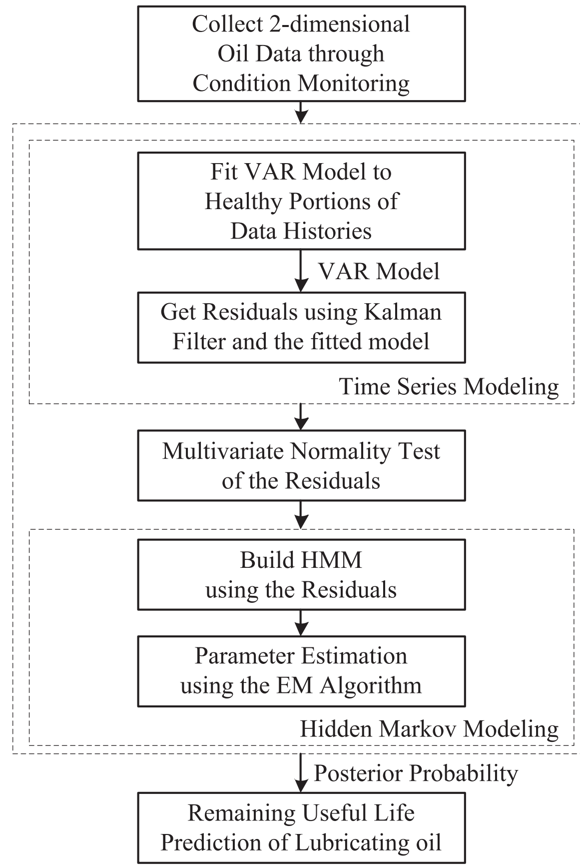

Fig. 1. HMM-based procedure for RUL prediction.

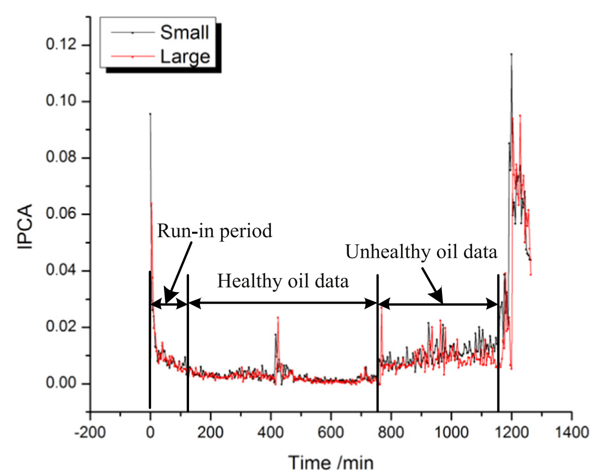

Fig. 2. Wear debris concentration of small and large particles.

Table 1
Working conditions for the test.

Test no.	Load/N	Rotated rate/rpm	Time/min	Downtime duration/min
1	1500	1000	360	0
2	1500	1000	360	240
3	2000	1000	210	720
4	2000	1000	240	60
5	2000	2000	60	480