A Method of Operational Reliability Assessment for Equipment Based on Dynamic Degradation Signal

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Abstract—The traditional approaches to reliability estimation are based on probability statistics depending on large sample failure lifetime data. Such approaches yield statistical results that reflect average characteristics of the same kind of systems, under the same condition. They can not gain a particular individuals reliability ability. Dynamic monitoring data based on condition can provide with useful information about the reliability assessment for the equipment. By using reliability modeling techniques with equipment condition feature and information measures, a new methodology of reliability assessment based on equipment dynamic vibration signal feature extraction using proportional hazards model is proposed. The proposed approach can establish a linkage between equipment condition monitoring information and reliability statistics. It is suitable for providing effective individuals reliability assessment by equipment vibration-based degradation signal. The reliably operational ability of equipment is enhanced. This can afford equipment technical support for the preventive maintenance of reliability-centered based on equipment condition. Finally, a practice example of key component, namely rolling bearing is given to demonstrate that the method is valid and reasonable.

Keywords—reliability; monitoring information; proportional hazards models; vibration signal

I. INTRODUCTION

Reliability plays a significant role in the overall performance of equipments. Today’s complex and advanced equipments demand high reliability and safety. Operational reliability, safety, maintenance cost effectiveness and asset availability have a direct impact on the competitiveness of organizations and nations. Monitoring of dynamic degradation signal and predicting its progression using periodic inspection data are important to ensure safety and reliability of mechanical equipment. The traditional approaches to reliability estimation are based on probability statistics depending on large sample failure lifetime data. Such approaches can not reflect reliability ability of a particular individual. Dynamic monitoring data based on condition can provide with useful information about the reliability assessment for the individual equipment. Condition-based dynamic monitoring data are commonly available and Vlok [1] found that its use on enhancing the accuracy of the assessment. In applications with few or no failures, degradation data can provide more information than traditional censored failure-time data. Degradation data modeling and analysis are very important in reliability practice. It has been a new research direction in reliability engineering, as in Refs.[2-5]. Generally, system degradation data and lifetime data is lacking comparing to component information by reason of system relevance, measurement complexity, technological difficulty, limitation of lead time and the like. So fully use sub-system, packing unit and component degradation information or lifetime data is profitable. Gebraeel [6] focused on the development of a neural network-based degradation model that utilizes condition-based sensory signals to compute and continuously update residual life distributions of partially degraded rolling contact thrust bearings. Chinnam [7] proposed general polynomial regression models for modeling degradation signals and estimating individual component reliability, and the method is used to monitor high-speed steel drilling holes in stainless-steel metal plates. Applications of condition monitoring techniques improve the traditional statistical techniques have shown a remarkable improvement in reliability assessment in the recent years. The integration of condition monitoring information with reliability analysis has not been well explored. From the point of equipment condition monitoring information, this paper study reliability assessment based on equipment dynamic degradation signal. A linkage between equipment condition monitoring information and reliability statistics can be established by using proportional hazards model. Affectice individual reliability assessment is realized by equipment vibration-based degradation signal.

In this paper, proposed model attempts to use condition monitoring information for reliability estimation. The proposed novel approach is described in detail. The remainder of the paper is organized as follows. Reliability modeling based on dynamic degradation signal is built in Section II. In Section III, experimental methodology of reliability assessment is illustrated and discussed with a case study of rolling bearing used in manufacturing equipment. Finally, Section IV concludes the overall paper.
II. RELIABILITY MODELING BASED ON DYNAMIC DEGRADATION SIGNAL

Performance of degradation failure equipment needs a characteristic measure to express. It changes slowly along with working time or storage time. And it is usually monotonic increasing or descending function. If there are equipments (subsystem or components) characteristics whose degradation over time can be related to reliability, then collecting ‘degradation data’ can provide information about the equipments reliability as it degrades with time. This is very meaningful for reliability assessment based on conditions [8].

In production systems, physical performance characteristics, such as force, torque, vibration, and acoustic-emission signatures, temperature, etc., can be measured to evaluate the degree of performance of critical units such as bearings, spindles, and cutting tools. Off-line performance degradation study may model time-to-failure distribution which reflects population characteristics, and on-line performance monitoring can be directly used for system performance reliability assessment which reflects characteristics of a particular component. The key of studying is how to build linkages between operational condition of dynamic degradation and reliability model.

A. Weibull Proportional Hazards Model

The proportional hazards model developed by Cox [9] is a widely accepted semi-parametric model for analysis of failures with covariates. It has been successfully used for survival analyses in medical and economics areas. It is most used in reliability engineering recently [10-11]. For the complexity of equipment and randomness of developing fault, reliability model based on dynamic degradation signal can obtain hazards, and operational reliability in some condition is achieved in the end too.

In the case of the proportional hazards model, the assumption is made that the intensity function is the product of a baseline hazards and a positive functional term as follows

$$ h(t;Z) = h_0(t) \exp(\gamma \cdot Z) $$

(1)

where $h(t;Z)$ is hazard, and $h_0(t)$ represents the baseline intensity and $\exp(\gamma \cdot Z)$ is a positive functional term as a function of a vector of regression coefficients $\gamma$ and a vector of covariates $Z(t)$, which in itself may depend on time as well. The proportional hazard model is so called because the intensity of any two units with the same age but different covariate values are proportional to each other.

In this study, we use a parametric baseline, merely for convenience of computation in the posterior optimization process. A very flexible parametric baseline intensity that has been successfully applied in many case studies is the Weibull or Power-law process, defined as

$$ h(t) = \frac{\beta}{\eta} \left( \frac{t}{\eta} \right)^{\beta-1} \exp\left(\frac{-t}{\eta}\right) $$

(2)

where $\beta$ is the shape-parameter, and $\eta$ the scale parameter. In case $\beta = 1$, the baseline intensity is an exponential distribution and does not depend on time at all.

Eq. 2 is substituted in Eq. 1, the proportional hazards model can therefore be written as

$$ h(t;Z) = \frac{\beta}{\eta} \left( \frac{t}{\eta} \right)^{\beta-1} \exp(\gamma \cdot Z) $$

(3)

Accumulative proportional hazards $H(t;Z)$ is derived as following

$$ H(t;Z) = \int_0^t h(t,Z)dt $$

(4)

The relation between hazards function and reliability function is

$$ R(t) = \exp(-H(t;Z)) = \exp\left(-\int_0^t h(t,Z)dt\right) $$

(5)

Here, $f(t)$ is probability density function of failure. Reliability function is derived as

$$ R(t) = \exp\left(-\int_0^t h(t)dt\right) $$

(6)

So, Weibull proportional reliability function $R(t;Z)$ is

$$ R(t;Z) = \exp\left(-\int_0^t h(t,Z)dt\right) $$

(7)

B. Maximum Likelihood Estimate for Reliability Parameter

In order to estimate the parameters $\beta$, $\eta$ and $\gamma$ in the Weibull proportional hazard model, maximum likelihood estimates (MLE) is used. MLE is very powerful and practical method in parameter estimates as in [12-13]. Maximum likelihood estimation is used to provide a one-step method to estimate the model’s parameters. A closed form expression of the likelihood function is derived for a two-parameter truncated Weibull distribution with time-independent shape parameter [14].

Assumed data $(t_1, t_2, \cdots, t_i)$ , estimated parameter is defined as $\theta$, $n_i$ is failure data in $n$ samples. Likelihood function can be written as

$$ L(\theta) = \prod_{i \in F} f(t_i, \theta) \prod_{i \in C} R(t_i, \theta) $$

(8)
Where, \( f(t, \theta) \) is probability density function of failure, \( R(t, \theta) \) is reliability function, and \( F, C \) is failure data set and censored data set respectively.

Parameter estimate \( \theta \) can be obtained by solving equation as following

\[
\frac{\partial}{\partial \theta} L(\theta) = 0
\]

or

\[
\frac{\partial}{\partial \theta} \ln[L(\theta)] = 0
\]

Two parameter Weibull proportional hazards probability density function and reliability function are substituted into Eq. 8, so Weibull likelihood function is written as

\[
L(\theta) = \prod_{i \in C} \left[ \left( \frac{\beta}{\eta} \right)^{\beta} \exp\left( \frac{t_i}{\eta} \right) \exp\left( \gamma \cdot Z(t_i) \right) \right] \prod_{i \in I} \left[ \exp\left( - \left( \frac{t_i}{\eta} \right)^{\beta} \exp(\gamma \cdot Z(t_i)) \right) \right]
\]

Logarithm of Eq. 9 is written as

\[
\ln[L(\theta)] = n_f \ln \left( \frac{\beta}{\eta} \right) + \sum_i \ln \left( \frac{t_i}{\eta} \right)^{\beta-1} + \sum_i \gamma \cdot Z(t_i) - \sum_i \left[ \left( \frac{t_i}{\eta} \right)^{\beta} \exp(\gamma \cdot Z(t_i)) \right]
\]

Using maximum likelihood estimation, quasi-differential coefficient \( \ln[L(\theta)] \) for estimate parameter \( \beta, \eta \) and \( \gamma \) respectively, three non-linear equations can be obtained. According to the Nelder-Mead’s algorithm [15-16], which is an iterated optimization method that no derivation. By means of fminsearch optimization function in the toolbox of Matlab software, then, parameter \( \beta, \eta \) and \( \gamma \) can be obtained.

Once the values of model parameters are obtained, hazards can be calculated according to work time \( t \) and covariate \( Z \). Consequently, the reliability indexes, such as \( R(t) \), \( f(t) \) may be calculated respectively.

### III. RELIABILITY ASSESSMENT EXAMPLE

Bearings are among the most widely used mechanical elements in equipments. It is significant studying reliability and life assessment of bearings. Bearing condition monitoring using vibration signals is the commonly used method for assessing the condition of a bearing. In this application study, statistical indices such as the kurtosis factor and root mean square(RMS) value of the vibration are introduced to Weibull proportional hazards model. Focus on tracing the bearing reliability assessment.

The vibration signal measured by accelerometer from bearing was collected under the sampling rate of 12.8 kHz. Two indices-kurtosis factor and RMS value which are closely related to bearings degradation are obtained. Using covariate \( Z_1(\text{kurtosis}) \), \( Z_2(\text{RMS}) \), which reflect operational condition of equipment, Eq. 3 as weibull proportional hazards model is expressed as

\[
h(t; \tau) = \frac{\beta}{\eta} \left( \frac{t}{\eta} \right)^{\beta-1} \exp(\gamma_1 Z_1(\text{kurtosis}) + \gamma_2 Z_2(\text{RMS}))
\]

Using maximum likelihood estimate method of proportional hazards model according to Section II, which is an iterated optimization method no derivation. By means of fminsearch function in the toolbox of Matlab software, initial value of fminsearch function is assigned depending on bearing in different operational condition. Finally, results of parameters estimate in condition 1 and 2 are obtained as table 1.

Figures 1 and 2 show the time domain waves in the two different states from bearing in the running. Figures 3 and 4 show the degradation features of Kurtosis and RMS from bearing in the two different states in the running. Intercepted degradation time is 100 times sample time, that is 100×0.64 = 64s.

Figures 5 and 6 show the reliability estimates by the proportional hazards model using the observed degradation features from bearing in the two different states running. The two curves are discrete reliability and least square fitting reliability. The curves reflect magnitude and trend of reliability from bearing in the two different states running. Reliability is 0.8 or so in state 1, and descends slowly. Reliability is 0.6 or so in state 2, and descends fast. Descending trend of reliability is proximately stationary in two states. This is because undergoing time is short. If monitoring degradation data from short time to long time can be obtained, descending trend of reliability is obvious. These receive much attention to reliability assessment in certain life cycle of equipment.

<table>
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<th>Table 1: Results of Parameter Estimates at State 1 and 2</th>
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<td>state</td>
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Figure 1. The waves of time domain in state 1
Aiming at equipment characteristics of fluctuant operating condition and lacking failure sample, a new methodology of reliability assessment based on equipment dynamic vibration signal feature extraction using proportional hazards model is proposed. The method is developed from the point of equipment condition monitoring information by considering degradation signal based vibration condition. A practical example of rolling bearing degradation monitoring data is given to demonstrate that the approach is valid. The approach estimates on-line reliability of equipment current condition based on real time monitoring and feature extracting, and accommodates novel assessment approach for equipment reliability of lacking failure data. It is provided with active role on safeguarding equipment reliability and safety by deducing reliability mobility, implementing sound maintain decision.

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