Reliability Engineering and System Safety xxx (xxxx) xxx–xxx

Contents lists available at ScienceDirect

Reliability Engineering and System Safety

journal homepage: www.elsevier.com/locate/ress

Condition-based maintenance for systems with aging and cumulative damage based on proportional hazards model

Bin Liu[a,*], Zhenglin Liang[b], Ajith Kumar Parlikad[b], Min Xie[a,c], Way Kuo[a]

[a] *Department of Systems Engineering and Engineering Management, City University of Hong Kong, Kowloon, Hong Kong*
[b] *Institute for Manufacturing, Department of Engineering, University of Cambridge, CB3 0FS, UK*
[c] *City University of Hong Kong Shenzhen Research Institute, Shenzhen, China*

ARTICLE INFO

Keywords:
Condition-based maintenance
Aging and degradation
Proportional hazards model
Unknown distribution parameters
Cumulative damage

ABSTRACT

This paper develops a condition-based maintenance (CBM) policy for systems subject to aging and cumulative damage. The cumulative damage is modeled by a continuous degradation process. Different from previous studies which assume that the system fails when the degradation level exceeds a specific threshold, this paper argues that the degradation itself does not directly lead to system failure, but increases the failure risk of the system. Proportional hazards model (PHM) is employed to characterize the joint effect of aging and cumulative damage. CBM models are developed for two cases: one assumes that the distribution parameters of the degradation process are known in advance, while the other assumes that the parameters are unknown and need to be estimated during system operation. In the first case, an optimal maintenance policy is obtained by minimizing the long-run cost rate. For the case with unknown parameters, periodic inspection is adopted to monitor the degradation level of the system and update the distribution parameters. A case study of Asphalt Plug Joint in UK bridge system is employed to illustrate the maintenance policy.

1. Introduction

With the development of sensor technologies, system condition can be monitored at a much lower expense, which prompts the application of condition-based maintenance (CBM). CBM takes advantage of the online monitoring information to make maintenance decisions. For a system subject to CBM, based on the collected condition information, maintenance actions are carried out only when "necessary" [18,19]. Compared with the traditional time-based maintenance, CBM has shown its priority in preventing unexpected failure and reducing economic losses [29,34].

CBM is conducted based on the observation that systems usually suffer a degradation process before failure, and the degradation process can be observed by degradation indicators such as temperature, voltage and vibration. In literature, many researchers used multi-state deteriorating models to describe the degradation process and formulated the maintenance strategy as a Markov or semi-Markov decision process [21,26]. Although Markov model is widely used in degradation modeling, one disadvantage is that the classification of system state is very arbitrary [14,15,4].

Recently, more emphasis is paid to continuous degradation processes. In the framework of continuous degradation, the degradation process is usually described by a general path model or a stochastic-process-based model such as Wiener process, Gamma process and inverse Gaussian process [17,32,33]. Caballé et al. [3] proposed a CBM for systems with continuous degradation and external shocks. Peng and van Houtum [23] developed a joint CBM and lot sizing policy for systems subject to continuous degradation.

An implicit assumption of the previous research is that a system fails when its degradation level exceeds a pre-specified failure threshold. However, in reality, the failure threshold is difficult to determine and usually it is a random variable depending on the environment condition and the product's characteristics. In this paper, the cumulative damage is modeled as a continuous degradation process. We argue that degradation process does not necessarily lead to system failure, but increases the likelihood of failure. Both internal aging and cumulative damage contribute to system failure. Examples of the joint effect of aging and cumulative damage on system failure can be found in systems such as high-voltage power transformers and bridge systems [22,28,31]. For a new transformer, its insulation strength can withstand severe events such as transient overvoltage and lightning strikes. When a transformer ages, its internal condition degrades, which makes it more vulnerable to fluctuating environment condition and increases the risk of failure. For a bridge system, failures are usually triggered by

* Corresponding author.
E-mail address: binliu9-c@my.cityu.edu.hk (B. Liu).

http://dx.doi.org/10.1016/j.ress.2017.04.010

external events such as hurricane, flood and overload. If a bridge system undergoes severe deterioration, it may hit the point where tiny external influences can lead to system failure. The degradation itself does not directly lead to system failure, but it increases the probability of failure when exposed to external events.

A convenient and prevalent way to integrate the aging and degradation effect into system failure is by a proportional hazards model (PHM) [16]. PHM incorporates a baseline hazard function which accounts for the aging effect with a link function that takes the inspection information into account to improve the prediction of failure [24]. Applications of PHM can be found in various fields such as finance, manufacturing system and energy generators [11].

In literature, several studies have been conducted on maintenance policy in the PHM framework. Banjevic et al. [1] developed a control-limit maintenance policy for systems subject to periodic inspection. Ghasemi et al. [8] proposed a CBM policy for systems with imperfect information, where the condition the system cannot be directly monitored. Wu and Ryan [30] investigated the value of condition monitoring in the PHM setting, where a continuous-time Markov chain was used to describe the system condition. Wu and Ryan [31] further extended the model by considering Semi-Markov covariate process and continuous monitoring. Tian and Liao [27] proposed a CBM policy for multi-component systems using PHM. Lam and Banjevic [12] investigated the issue of inspection scheduling for CBM. In all of these previous studies, the degradation process is characterized via Markov or semi-Markov model. In addition, the distribution parameters in the PHM are assumed as known in advance.

This paper aims to develop CBM policies for systems subject to aging and cumulative damage. The system is subject to aging and extremely frequent cumulative damage (e.g., traffic load to a bridge), where the extremely frequent cumulative damage is approached by a continuous degradation process. PHM is used to model the joint effect of aging and cumulative in the framework of failure rate. The effect of cumulative damage is modeled as the stochastic covariate in the PHM framework. The system is subject to periodic inspection, which is assumed to be perfect. At inspection, maintenance actions are carried out based on the observed condition information. Optimal maintenance policies are obtained by minimizing the long-run cost rate. Specifically, two CBM models are developed by assuming respectively known distribution parameters and unknown distribution parameters. In the case where the distribution parameters are unknown, the parameters have to be estimated and updated at each inspection, and maintenance decisions are made subsequently.

This paper differs from the existing works in that: (a) It incorporates the influence of both aging and cumulative damage in modeling the failure rate. (b) It argues that degradation itself does not directly result in system failure, but increases the risk of failure. (c) It utilizes the observed condition information to update distribution parameters for making appropriate maintenance decisions.

The remainder of this paper is organized as follows. Section 2 presents the degradation-integrated failure model, where PHM is used to describe the impact of aging and cumulative damage. Section 3 formulates two maintenance models. One assumes known distribution parameters while the other assumes unknown distribution parameters. Application of the maintenance models to Asphalt Plug Joints in UK bridge system is presented in Section 4. Finally, concluding remarks and future research suggestions are given in Section 5.

2. Degradation-integrated failure model

This paper considers a single-unit system subject to aging and cumulative damage. The cumulative damage is modeled as a continuous degradation process. For systems such as bridges, which are subject to traffic load hours by hours, a continuous degradation process is reasonable to characterize the cumulative damage over time. In this paper, we use “cumulative damage” and “degradation process” interchangeably. In the present paper, the degradation process derives from cumulative shocks, which is an external factor. Besides the external factor, the system also suffers from internal aging factors. That is to say, the aging and the degradation are two processes. Therefore, we model the system subject to both aging and degradation process. Different from previous studies which assume that soft failure occurs when the degradation level hits a pre-specified threshold, we here consider sudden failure, which depends on both the aging and cumulative damage. For most infrastructure systems, failures usually happen due to external shocks or serious events, and degradation makes it more vulnerable when exposed to shocks. As previously described, the degradation process itself does not directly lead to system failure, but it increases the failure rate of the system. PHM is used to characterize the influences of degradation level on system failure rate. The degradation level of the system is represented as the value of covariate in the PHM framework [13]. Based on PHM, the failure rate at time t is given by

$$h(t;X_t)=h_0(t)\varphi(X_t) \quad (1)$$

where $h_0(t)$ is the baseline failure rate at time t, which is a non-decreasing function of t. X_t is the degradation level at time t, and $\varphi(\bullet)$ is a positive function projecting the degradation level to the failure rate function. Let $X=\{X_t, t\geq 0\}$ be a continuous stochastic process that depicts the degradation process. Various stochastic processes can be used to describe the degradation process, among which a wide used candidate is the general path model [20]. Assume that $X_t=g(t;\theta,\alpha,\varepsilon(t))$, where $g(\bullet)$ is a parametric function that characterizes the evolution of the degradation process, θ is a random variable that accounts for unit-to-unit variability, α is a random parameter that captures the initial degradation level among the components' population, $\varepsilon(t)$ is an independent and identically distributed (iid) random error term [6]. The selection of $g(\bullet)$ depends on system characteristics and can take a variety of forms such as linear, exponential or logarithmic. In this paper, for simplicity, we assume that $g(\bullet)$ is a linear function. The degradation process can be denoted as $X_t=\alpha+\theta t+\varepsilon(t)$ [7,9], where the error term $\varepsilon(t)$ follows a Gaussian distribution with mean zero and variance σ^2, α and θ follow Gaussian distributions, with mean $\mu_0'=\mu_0-\sigma^2/2$ and variance σ_0^2, and mean μ_1 and variance σ_1^2. Since $\varepsilon(t)$ is independent of time t, we may suppress the notation of t and denote $\varepsilon(t)$ as ε. In Eq. (1), the baseline failure rate function, $h_0(t)$, accounts for the aging effect, which can be explained as the normal failure rate when no cumulative damage is imposed. The influence of cumulative damage is incorporated in the degradation level X_t. Obviously X_t follows a Gaussian distribution,

$$X_t \sim N(\mu_0+\mu_1 t-\sigma^2/2,\ \sigma_0^2+\sigma_1^2t^2+\sigma^2) \quad (2)$$

It is assumed that $\mu_0+\mu_1 t-\sigma^2/2 \gg \sigma_0^2+\sigma_1^2t^2+\sigma^2$, such that the probability of X_t being negative can be neglected and X_t stochastically increases with t almost surely. Given the degradation process x, the conditional reliability can be obtained as

$$R(t;x)=P(T>t|x_s,0\leq s\leq t)=\exp\left(-\int_0^t h_0(s)\varphi(x_s)ds\right) \quad (3)$$

where T is the time to failure and x_s is the realization of X_s at time s. The probability density function (pdf) is given as

$$f_T(t;x)=\lim_{\Delta t\to 0^+}\frac{P(t\leq T<t+\Delta t|T>t)}{\Delta t}=\frac{h_0(t)\varphi(x_t)}{\exp\left(\int_0^t h_0(s)\varphi(x_s)ds\right)} \quad (4)$$

The expected lifetime of the system can be obtained as

$$E[T]=E[E_{|X_s,0<s<T}[T]]=\int_0^\infty\int_0^\infty t\bullet f_T(t|x_s)f_{X_s}(x_s)dx_s dt \quad (5)$$

where f_{X_s} is the pdf of degradation level by time s. If the projecting function $\varphi(\bullet)$ is exponential, $h(t;X_t)=h_0(t)\exp(\beta X_t)$, where β is the