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Reliability analysis of repairable systems with recurrent misuse-induced failures and normal-operation failures

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ABSTRACT

Failure of a repairable system may be attributed to operators' misuse or system deterioration. The misuse may further deteriorate the system under normal operating conditions. Motivated by a real-world data set that records the recurrence times of misuse-induced failures and the normal-operation failures, this study proposes a stochastic process model for recurrence data analysis, where one type of failures is affected by the other. A non-homogeneous Poisson process and a trend-renewal process are separately used as the baseline event process models for the misuse-induced failures and the normal-operation failures, respectively. These two models are then combined by treating the event count of misuse-induced failures as covariate of the event process of normal-operation failures. A Bayesian framework is developed for parameter estimation and dependence tests of the two failure modes. A simulation study and the recurrence data from a manufacturing system are used to demonstrate the proposed method.

1. Introduction

A repairable system is a system that can be restored to a satisfactory operation state through repair actions [1,2]. Most complex systems, such as aircrafts, automobiles, machine tools, etc., are repaired rather than replaced upon failures. When the repairable systems are fielded and in service, detailed information about the failures such as failure causes and maintenance records may be available due to the use of data management system [3–6]. Seeking for high availability under limited total-cost-of-ownership, it is generally of interest to investigate the failure patterns of repairable systems in field conditions based on their recurrent failure data [7–20]. The renewal process and the non-homogeneous Poisson process (NHPP) are two types of popular models for recurrent failure data analysis [17–20]. The renewal process assumes that a repair upon a failure returns the system to an as-same-as-new state (ASAN). By contrast, when the NHPP is adopted, the system is assumed to be restored to the state right before the failure, which is as-same-as-old (ASAO). Generalized models with Poisson process and renewal process as special cases have also been introduced [21–23]. Despite the wide application of these models, a repair in reality essentially restores the system to a state between ASAN and ASAO, which is known as the imperfect repair. Popular models dealing with the recurrence data with imperfect repairs includes the inhomogeneous gamma process [26], the modulated power law process [27], the geometric process [28], the generalized renewal process models [29], the reduction of failure hazard models [30], and their variants and extensions [31–36]. Recently, the trend-renewal process (TRP) introduced by Lindqvist et al. [23]. which includes both renewal process and NHPP as special cases, has attracted great attention [24,25]. However, among the models, the recurrence data have not been stratified as per failure modes. These models are mainly used for recurrence data with only one type of failures.

In practice, failures of repairable systems may result from various factors. These failures can be categorized into different types for failure pattern analysis, giving rise to repairable systems with multiple failure modes. Moreover, the failures belonging to one mode may impact the occurrences of other modes. The impact can be a one-way effect or a mutual effect among different failure modes, leading to recurrence data with complex failure patterns. Because the interaction effect among failure modes is hidden under the recurrence data, to implement an in-depth study of the recurrence data, it is then critical to analyze the recurrence data with various failure modes differentiated. Mun et al. [37] proposed a model for a repairable system with two failure modes. In the model, they lumped together these failure modes and introduced a superposed process model for the recurrence data. Because the failure modes are superposed, the recurrence data in their paper was fundamen-

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tally the occurrence times of one general failure mode, for which the two failure modes were lumped together without any differentiation. Yang et al. [38] studied relative failure frequency estimation among different failure modes for repairable systems, where the failure modes were assumed independent. The dependence among different failure modes is omitted in their study, which, however, is a critical aspect needed to be addressed in this paper. When the dependence exists between different failure modes, Somboonsavatdee and Sen [39] introduced a shared frailty structure to model the dependence among multiple dependent failure modes. The shared frailty structure is mainly for the situation where the failures are impacted by some common causes, or the interaction effect among failure modes is presented in a mutually equal way. Recently, Xu et al. [24] introduced a multi-level trend renewal model for recurrence data analysis of multi-level systems, where subsystem-level replacement events may affect the rate of occurrence of the component-level replacement events. Yang et al. [25] introduced a copula-based TRP for multi-component systems, where the mutual effect of multi-type failures among dependent components were characterized based on the TRP and a copula function. However, their model is not suitable for the situation where one failure mode may have a one-way effect on the event process of another failure mode. This one-way effect may be introduced by a common yet long-neglected failure mode, i.e., the failures caused by the system misuses. The papers reviewed above have all omitted this aspect, and it becomes the main research motivation of this paper.

This study is motivated by a real data set consisting failure time, failure causes, and detailed description of the failures for one type of machine tools. By pre-analyzing the failure causes with the help of machine tool expertise, the failures have been sorted to two failure modes, i.e., the failure induced from the misuse of operators and the failure due to the natural deterioration of the machine tools. In particular,

- The misuse-induced failure refers to the failure caused by system misuse, such as improper operation, system overload, inappropriate maintenance, etc.
- The normal-operation failure refers to the failure caused by system deterioration, component failure, damage of structure, etc.

According to the expert knowledge, it is strongly believed that the misuse may further deteriorate the system under normal operating conditions. On the other hand, the frequency of misuse-induced failures cannot be affected by the normal-operation failures. In light of this, the above reviewed models are not suitable for the recurrence data in this study. To investigate the pattern between the misuse-induced failure process and the normal-operation failure process, we propose a new model for the recurrent failure data analysis. An NHPP and a TRP are used as the baseline models for the misuse-induced failures and the normal-operation failures, respectively. The impact of the misuse-induced failures on normal-operation failures is studied by incorporating the event count of the NHPP as a dynamic covariate into the TRP. A Bayesian framework is developed for parameter estimations and dependence tests of the two failure modes. A method for event prediction, taking account of parameter estimation uncertainty, is developed for the proposed model. An illustrated example originated from recurrence data analysis of machine tools is used to demonstrate the proposed method.

The rest of the paper is organized as follows. Section 2 introduces the proposed model for repairable systems with misuse-induced failure and normal-operation failures. Section 3 develops a Bayesian parameter estimation method for the proposed model and two simulation procedures for event prediction. Section 4 presents a Bayesian hypothesis testing for model selection. Section 5 demonstrates the effectiveness of Bayesian parameter estimation through a simulation study. Section 6 illustrates the proposed methods through the recurrent failure data analysis of machine tools. Section 7 gives a conclusion of the paper with brief discussion of further research topics.

2. The proposed model

2.1. Notation

For a recurrent event process, let $0 \le T_1 < T_2 < \cdots$ be the arrival times of the events, and t_k is the observed value of T_k. Let $W_k = T_k - T_{k-1}$ be the inter-arrival time between the $(k-1)$ st and kth event, and $w_k = t_k - t_{k-1}$ is the observed value of W_k. The counting process $\{N(t), t \ge 0\}$ records the cumulative number of events, where $N(t)$ is the number of events over $[0, t]$. Further let $N(s,t) = N(t) - N(s)$ be the number of events over $(s, t]$, and $H(t) = \{N(s) : 0 \le s < t\}$ indicates the event history right prior to t. Let τ denote the end-of-follow-up time of the recurrent process. In addition, the t^+ and t^- are used to denote the times that are infinitesimally larger or smaller than t. We then have $\Delta N(t)$ and $N(t^-)$ separately denoting the number of events in the intervals $[t, t+\Delta t)$ and $[0, t)$.

To differentiate the notation for the misuse-induced failure process and the normal-operation failure process, the superscript (M) and (O) are separately attached to the notation presented above. For instance, $T_k^{(M)}$ and $T_k^{(O)}$ separately denote the arrival time of the kth misuse-induced failure, and the arrival time of the kth normal-operation failure.

2.2. Model for misuse-induced failures

Generally, the rate of occurrence of misuse-induced failures is negatively correlated to operators' knowledge about the system and their proficiency of operation. The rate of occurrence of the misuse decreases accordingly with the accumulation of the operators' operation experience. The misuse-induced failure is usually not severe, which is often minimally repaired. Out of this consideration, the following assumptions are made.

- A non-homogeneous Poisson process (NHPP) with decreasing intensity function is adopted to capture the dynamics of the misuse-induced failure process.
- The misuse-induced failure process is not affected by the normal-operating failures.

The intensity function of the misuse-induced failure process, which describes the intensity of misuse-induced failure occurring at the present moment, is given as follows.

$$\lambda^{(M)}\left(t|H^{(M)}(t)\right) = \lim_{\Delta t \to 0} \frac{\Pr\left\{\Delta N^{(M)}(t) = 1\right\}}{\Delta t} = \lambda^{(M)}(t), \tag{1}$$

where $\lambda^{(M)}(t)$ is a nonnegative integrable decreasing function. Common models of $\lambda^{(M)}(t)$ include the exponential model, $\lambda^{(M)}(t) = \exp(\alpha + \beta t)$, and the power law model, $\lambda^{(M)}(t) = (\beta/\eta)(t/\eta)^{\beta-1}$.

Based on the intensity function, the conditional survival function of $W_k^{(M)}$ is obtained as

$$\begin{aligned} S^{(M)}\left(w|t_{k-1}^{(M)}\right) &= \Pr\left\{W_k^{(M)} > w|T_{k-1}^{(M)} = t_{k-1}^{(M)}\right\} \\ &= \exp\left(-\int_{t_{k-1}^{(M)}}^{t_{k-1}^{(M)}+w} \lambda^{(M)}(u)du\right) \\ &= \exp\left(-\Lambda^{(M)}\left(t_{k-1}^{(M)}+w\right) + \Lambda^{(M)}\left(t_{k-1}^{(M)}\right)\right), \end{aligned} \tag{2}$$

where $\Lambda^{(M)}(t)$ is the cumulative intensity defined as $\Lambda^{(M)}(t) = \int_0^t \lambda^{(M)}(u)du$. According to the property of the NHPP [20], the variance and mean value of the number of misuse-induced failure, $\mathrm{var}\{N^{(M)}(t)\}$ and $E\{N^{(M)}(t)\}$, are equal, which can be numerically described by the cumulative intensity function $\Lambda^{(M)}(t)$.

By substituting $t_{k-1}^{(M)} + w$ with t in Eq. (2), the conditional survival function of $T_k^{(M)}$, defined as $\Pr\{T_k^{(M)} > t|T_{k-1}^{(M)} = t_{k-1}^{(M)}\}$, can be obtained. The conditional probability density function (PDF) of $T_k^{(M)}$ given $T_{k-1}^{(M)} = t_{k-1}^{(M)}$ is then given as

$$f^{(M)}\left(t|t_{k-1}^{(M)}\right) = \lambda^{(M)}(t)\exp\left(-\Lambda^{(M)}(t) + \Lambda^{(M)}\left(t_{k-1}^{(M)}\right)\right). \tag{3}$$