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A Bayesian approach to degradation-based burn-in optimization for display products exhibiting two-phase degradation patterns

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ABSTRACT

Motivated by the two-phase degradation phenomena observed in light displays (e.g., plasma display panels (PDPs), organic light emitting diodes (OLEDs)), this study proposes a new degradation-based burn-in testing plan for display products exhibiting two-phase degradation patterns. The primary focus of the burn-in test in this study is to eliminate the initial rapid degradation phase, while the major purpose of traditional burn-in tests is to detect and eliminate early failures from weak units. A hierarchical Bayesian bi-exponential model is used to capture two-phase degradation patterns of the burn-in population. Mission reliability and total cost are introduced as planning criteria. The proposed burn-in approach accounts for unit-to-unit variability within the burn-in population, and uncertainty concerning the model parameters, mainly in the hierarchical Bayesian framework. Available pre-burn-in data is conveniently incorporated into the burn-in decision-making procedure. A practical example of PDP degradation data is used to illustrate the proposed methodology. The proposed method is compared to other approaches such as the maximum likelihood method or the change-point regression.

1. Introduction

Burn-in is an important screening method to weed out weak or defective products before shipping to customers [1]. It is generally conducted by running products for a pre-determined amount of time under designed or accelerated stress conditions [2,3]. Conventional burn-in tests identify defective or weak products by inducing their failures over the testing periods (referred to as *failure-based* burn-in tests hereafter). Various aspects of failure-based burn-in tests, including test durations, stress types and levels, and residual-life distributions after burn-in, have been investigated by numerous researchers over the past four decades (e.g., [4–8]). Most research centers on how long and under what conditions the burn-in process should be conducted to maximize cost efficiency and field reliability. Comprehensive reviews of failure-based burn-in test design have been conducted by Kuo et al. [1] and Liu and Mazzuchi [9].

For highly reliable products, traditional failure-based burn-in tests may be ineffective because long burn-in duration may be required to observe failures [10]. Now, along with degradation data for performance measures related to product failures, *degradation-based* burn-in tests are being considered as a promising alternative to failure-based burn-in tests [11]. Previous studies on degradation have focused on developing degradation models to estimate failure-time distributions [12–19], predicting remaining useful life distribution for a unit being monitored [20–23], and exploring preventive maintenance policies for continuous monitoring of degrading products [24–26]. Some recent studies considered degradation-based burn-in models and methods. Tseng and Tang [27] proposed a cost-optimal burn-in policy via a Wiener process degradation model. Under the assumption that there exists some proportion of weak products in the population, they proposed a total cost function consisting of burn-in operation cost, measurement cost, and misclassification cost. The burn-in decision variables they used were burn-in duration and the cutoff point. At the end of burn-in, if a unit's degradation level exceeded the cutoff point, it was classified as a weak unit. Tseng and Peng [28], Tseng et al. [11], and Tsai et al. [29] later explored this degradation-based burn-in approach to create several burn-in testing protocol. Tseng and Peng [28] introduced an integrated Wiener process to describe cumulative degradation, then derived an optimal burn-in policy based on the cumulative degradation model. Tseng et al. [11] proposed a burn-in procedure with multiple cutoff points. Tsai et al. [29] assumed that the underlying degradation pattern followed a gamma process instead of the Wiener process. Xiang et al. [30], Ye et al. [31], Peng et al. [32], and Feng et al. [33]

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considered simultaneous optimization of burn-in and preventive maintenance with the decision variables corresponding to burn-in duration, cutoff point, and replacement interval. Ye et al. [10] planned burn-in tests considering two competing failure modes: soft (degradation-threshold) failure and catastrophic failure. Zhai et al. [34] considered measurement errors in degradation based burn-in. They used Wiener process to model the underlying degradation and considered Gaussian measurement errors in the observations.

All of the aforementioned studies on the degradation-based burn-in tests assumed that the burn-in population consists of weak and normal units, and that the main purpose of burn-in is to identify the weak ones based on the degradation data collected in the burn-in tests. The heterogeneity of the burn-in population is usually modeled by a mixture degradation model (e.g., the mixed Wiener process, the mixed gamma process) [11,27–31] or a random-effect degradation model [10,32,33]. However, motivated by the two-phase degradation phenomenon observed in light displays, this study considers a different type of burn-in planning problem for products exhibiting two-phase degradation patterns.

An industrial collaborator conducted a degradation test on six plasma display panels (PDPs) to assess their reliability at a constant stress level. The six individual PDP degradation paths, which were analyzed by Bae et al. [16], consist of relative luminosity measurements inspected regularly. As shown in Fig. 1, after a rapid decrease in brightness at the initial stage of the degradation testing, the decrease in paths slowed. Bae et al. [16] explained the degradation physics concerning this two-phase degradation phenomenon for PDPs. During the PDP manufacturing process, impurities remain inside the PDPs, and due to a temporary "poisoning effect" of the impurities, the light display will initially experience a rapid decrease in light intensity until the impurities are completely burned out, at which time the light degradation will continue at a slower, more stable rate [16]. PDP manufacturers execute a burn-in procedure (called "aging" in the industry) to burn off the impurities. The major purpose of this burn-in procedure is to eliminate the initial rapid degradation phase before shipping to customers. Infant mortality (i.e., early failures of weak products) is not a major concern in terms of luminosity degradation. Many other products such as organic light-emitting diodes (OLEDs) [35], lithium-ion batteries [36], and direct methanol fuel cells [37] have similar two-phase degradation patterns. Therefore, the proposed burn-in methods described in this study have potential application for those products as well.

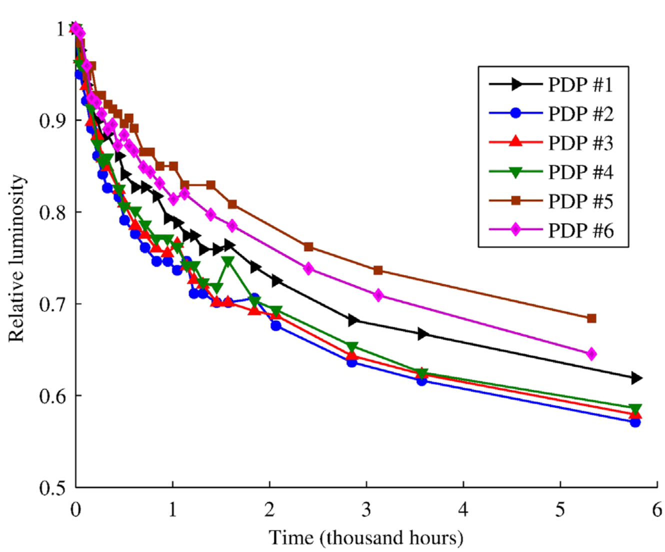

Fig. 1. Observed degradation paths of six PDPs: relative luminosity vs. measurement time.

This study used the Bayesian approach to plan degradation-based burn-in tests. Traditional maximum likelihood based burn-in planning methods usually assume that the model parameters are known before planning and conducting the burn-in test. However, in actual situations, uncertainties in the model parameters dominate the burn-in test environments [9]. In such cases, Bayesian methods are more appropriate and have been proven to be effective in planning failure-based burn-in tests [7,8]. This study adopts the Bayesian framework in degradation-based burn-in test planning methodology.

The remainder of this paper is organized as follows. The proposed methodology is presented in Section 2. Both reliability and cost criteria are considered, and the associated Bayesian computational methods are developed. The PDP example used by Bae et al. [16] is revisited to illustrate the proposed methodology in Section 3. Finally, this study is concluded and future research directions are outlined in Section 4.

2. Methodology

This section presents the proposed burn-in methodology using PDPs as an illustrative example. The actual degradation path of a unit is a monotonic decreasing function of the deterioration of a quality or performance characteristic over time. In degradation analysis, a "soft" failure is usually defined in terms of the amount of degradation to a critical threshold level. In display industry, when manufacturers ship the display products like PDPs and OLEDs to customers, they set initial display brightness to the level which is requested by the customers, and a display unit is considered to have failed when its luminosity falls below 50% of its initial value [16]. Therefore, the relative luminosity, instead of the luminosity, is selected as the performance characteristic.

2.1. Degradation modeling

A degradation model adequately describing the two-phase degradation path is essential for planning burn-in tests. Two different modeling approaches have been proposed in the literature. Bae and Kvam [38] developed a change-point regression model to describe the two-phase degradation patterns of PDPs. Bae et al. [16] employed a bi-exponential model for the PDP degradation paths. The bi-exponential model was also applied to describe the two-phase degradation of direct methanol fuel cells [37]. This study adopts the bi-exponential degradation model because it provides a better fit for the PDP degradation data than the change-point regression model [39].

The expected degradation path of a unit randomly selected from the burn-in population is described by the following nonlinear function [16]

$$\eta(t;\gamma_1,\gamma_2,\varphi)=\varphi\exp(-\gamma_1 t)+(1-\varphi)\exp(-\gamma_2 t), \tag{1}$$

where $\eta(\cdot)$ represents the expected degradation path of the relative luminosity, $\varphi\in(0,1)$ denotes the initial proportion of impurities, and $\gamma_1>0$ and $\gamma_2>0$ represent the impurities' degradation rate and the inherent degradation rate of plasma phosphors, respectively. Because the impurities' degradation rate, γ_1, is expected to be greater than the inherent degradation rate, γ_2, we reparameterize the bi-exponential model (1) as

$$\eta(t;\boldsymbol{\theta})=\varphi\exp(-(\gamma+\Delta\gamma)t)+(1-\varphi)\exp(-\gamma t), \tag{2}$$

where $\gamma>0$ represents the inherent degradation rate of plasma phosphors, and $(\gamma+\Delta\gamma)$ denotes the impurities' degradation rate. Letting $\Delta\gamma>0$ can yield the desired two-phase degradation