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# Bayesian degradation modeling for reliability prediction of organic light-emitting diodes

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## ABSTRACT

Simpler degradation models are generally preferred to simplify analytical procedure of failure-time estimation which follows the degradation modeling. However, the luminosity degradation of organic light-emitting diode (OLED) tends to exhibit an initial unstable period followed by stable and more gradual degradation. The degradation mechanisms of OLED luminosity are illustrated via a stochastic two-compartment model. Conjoining the data with prior information accumulated from field testing, we propose two hierarchical Bayesian models to characterize the nonlinear degradation path of OLED: Bayesian change-point regression model and Bayesian bi-exponential model. The hierarchical Bayesian models effectively fit the nonlinear degradation paths of OLEDs. Analytical results of OLED degradation indicate that reliability estimation from the hierarchical Bayesian models can be substantially improved over the log-linear model which has been widely accepted as a degradation model of light displays.

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## 1. Introduction

New product testing presents a significant challenge to manufacturers of highly reliable products as competitive markets compel them to evaluate product reliability within shorter testing times and with limited resources. The most common approach for testing such products is to use accelerated life testing where a failure is hastened by loading higher stresses than normal use conditions. Additionally, in a testing environment where degradation measurements are available along with failure data, degradation analysis has been an alternative approach over standard failure-time analysis because it does not only lead to improved reliability inference, but because it can also provide additional information related to failure mechanisms [1].

In degradation analysis, the accuracy of failure-time estimation depends highly on the choice of model for observed degradation paths. Based mainly on longitudinal measurements of degradation, simpler degradation models are typically preferred to simplify analytical procedure of failure-time estimation which follows the degradation modeling. A failure-time distribution is estimated by extrapolating performance degradation from established

degradation model even if a failure, defined as the time at which the degradation path first reaches a critical threshold value, is not observed in degradation testing duration. Deviating from assuming degradation model, if experimental results can be represented in a more complicated form, resulting failure-time prediction will be highly biased. For instance, in the analysis of vacuum fluorescent displays (VFDs) showing non-monotonic degradation due to incomplete burn-in, Bae and Kvam [2,3] showed that a complicated mixture model that captures the burn-in effect is more efficient in the devices' reliability estimation than simple exponential decay model (that is, log-linear model).

This research is motivated by luminosity degradation testing data of organic light-emitting diodes (OLEDs). Luminosity degradation of OLEDs is one of the main issues to make this technology sufficiently promising in a number of commercial applications. Despite the importance of the issue, a limited number of studies have been done, especially on physical models based on degradation mechanisms. In this article, the degradation mechanisms of OLED luminosity are illustrated using a stochastic two-compartment model for the densities of host and guest triplet excitons inside OLED, and resulting degradation paths of OLED are of complex nonlinear form in terms of model parameters, often leading to computational difficulty. We represent the nonlinear degradation paths of OLED mainly in the Bayesian framework. The Bayesian approach has considerable advantage over existing frequentists' approaches in that inference can always be provided

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without the need for approximations by using modern computational methods, e.g., Markov chain Monte Carlo (MCMC) [4]. Furthermore, using prior information accumulated from field testing, we can improve the accuracy of modeling degradation paths and as a result, increase the possibility of a correct decision-making with respect to products reliability. Based on the fitted degradation model, we derive a failure-time distribution using the Gibbs sampling procedure [5].

The paper is organized as follows. Section 2 employs a stochastic two-compartment model to describe the degradation physics of OLED luminosity. Section 3 introduces hierarchical Bayesian degradation models. Section 4 derives the failure-time distribution using Gibbs sampling. In Section 5, the OLED degradation data are analyzed following the proposed Bayesian approaches. Some concluding remarks are presented in Section 6.

## 2. Degradation physics of OLED luminosity

OLED is a kind of LED whose emissive electroluminescent layer is comprised of a film of organic compounds. OLED has been vigorously developed as an alternative display for portable devices such as smart mobile phones because it possesses several advantages over other display devices such as liquid crystal displays (LCDs) and LEDs: self-emission, large intrinsic viewing angle, and fast switching speed. In light display devices, luminosity is the most important performance characteristic and industry standards define a failure at the time when a device luminosity falls below 50% of its initial value [6]. The operational stability of OLED device is mainly governed by electrical aging phenomena, which appear in the form of luminosity degradation as operational time has elapsed. The luminosity decrease has been illustrated through two independent degradation mechanisms: extrinsic degradation and intrinsic degradation [7]. Extrinsic degradation is associated primarily with use environment surrounding the device. Characterized by a decrease in the luminosity of OLED device, clear mechanisms of intrinsic degradation have not been fully understood. In this section, physical degradation mechanisms of OLED luminosity are investigated with a stochastic compartmental theory.

A compartment is taken to be a “black box” into which material or particle flows according to some specified stochastic kinetics. The basic elements of such models are the state variables associated with the compartments and the transfer rate constants associated with the exchange flow of materials of interest between the compartments. We take certain stochastic characteristics of both variables into account. A number of factors lead to uncertainties in the compartments and transfer rate constants of a certain compartment; inter-individual variability, environmental effects, measurement and sampling conditions and so on. This kind of approach has a precedence in bilirubin metabolism [9] and animal science [10]. The detailed kinetics of the stochastic two-compartment model are given in Appendix A. We will illustrate how the nonlinear model given by Eq. (18) is applied to degradation physics of OLED luminosity in the following.

In terms of the two-compartment system in Fig. 1 [8], denote  $\theta_1(t)$  and  $\theta_2(t)$  be the densities of host and guest triplet excitons at

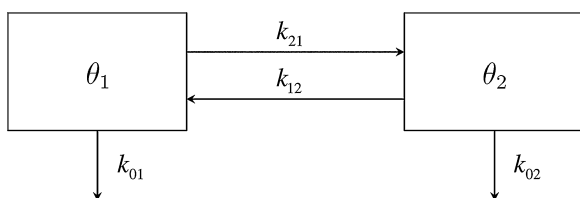


Fig. 1. Stochastic two-compartment model.

time  $t$ , respectively. The excitons are responsible for phosphorescence and fluorescence of OLED, that is, OLED luminosity. The rates of exciton relaxation on the host and guest are denoted by  $k_{01}$  and  $k_{02}$ , respectively, and the forward and reverse triplet transfer rates between host and guest are denoted by  $k_{21}$  and  $k_{12}$ , respectively. In the absence of exciton-formation processes, the rate equations are

$$\begin{aligned} \dot{\theta}_1(t) &= -k_{01}\theta_1(t) - k_{21}\theta_1(t) + k_{12}\theta_2(t), \quad \text{and} \\ \dot{\theta}_2(t) &= -k_{02}\theta_2(t) - k_{12}\theta_2(t) + k_{21}\theta_1(t). \end{aligned} \quad (1)$$

The degradation model of OLED luminosity over time is obtained by solving the linear equation (1) and the resulting model is a bi-exponential model as [11]

$$y(t) = \phi_1 e^{-\lambda_1 t} + \phi_2 e^{-\lambda_2 t}, \quad \lambda_1, \lambda_2 \geq 0, t \geq 0, \quad (2)$$

where  $y(t)$  denotes the OLED relative luminosity at time  $t$ ,  $\phi_1$  and  $\phi_2$  are constants determined by initial conditions of host and guest triplet excitons, satisfying  $\phi_1 + \phi_2 = 1$ , and  $\lambda_1$  and  $\lambda_2$  are, respectively

$$\lambda_1, \lambda_2 = \frac{1}{2} \left[ (k_{01} + k_{21} + k_{02} + k_{12}) \pm \sqrt{(k_{02} + k_{12}) - (k_{01} + k_{21})}^2 + 4k_{12}k_{21} \right].$$

The decay rate of the host is much higher than that of the guest, that is,  $\lambda_1 \gg \lambda_2$  [11]. The bi-exponential model, often called “two-compartment model,” was used in the accelerated degradation model of OLED [12] and also used to describe the degradation mechanics of plasma display panel (PDP) luminosity by incorporating nano-contamination effects during a series of manufacturing processes [13]. Their modeling approaches are mainly based on a nonlinear random-coefficients model which assumes that some parameters in the bi-exponential model are random to represent item-to-item variation.

In this paper, we propose hierarchical Bayesian modeling approaches to fit the nonlinear degradation paths of OLED: a Bayesian change-point regression model with one change-point and a Bayesian bi-exponential regression model. In existing literature, Bayesian methods have been used to analyze repeated-measurement data suitable for degradation data analysis in pharmacokinetics (e.g., Wakefield et al. [14] and Gelman et al. [15]). The bi-exponential model can be represented as the sum of linear terms instead of exponential terms for the purpose of modeling simplicity because original performance and its log-performance work equally well when the amount of degradation is relatively small [16]. Introducing a change-point regression model for the degradation paths of OLED luminosity in a Bayesian framework, we seek to estimate the unknown time change-point within a degradation paths which presents a transition from one regime (e.g., host triplet excitons) to the other regime (e.g., guest triplet excitons) through prior information about the change-point. A Bayesian change-point problem for regression model has been adopted by Chin Choy and Broemeling [17] without continuity constraint, and Smith and Cook [18] with continuity assumption at the change-point. Carlin et al. [19] presented hierarchical Bayesian change-point models and used a Gibbs sampler to obtain posterior inference. Recently, Chen and Tsui [20] proposed an empirical Bayes method for a two-phase degradation model with application to rotational bearings. They did not include continuous constraint on the two-phase degradation of bearings to consider abrupt jump at the change-point. Bae et al. [21] proposed a hierarchical Bayesian change-point regression model to fit the two-phase degradation patterns of PDPs. However, our proposed change-point regression model is different from existing Bayesian models in that we take distinct change-point regression formula in which all of degradation measurements for individuals are incorporated in estimating the parameters of the change-point regression model. The incorporation

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