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Application of multi-output Gaussian process regression for remaining useful life prediction of light emitting diodes

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ABSTRACT

Light-emitting diodes (LEDs) are the preferred technology today when it comes to lighting both for indoor and outdoor applications, predominantly due to their high efficiency, environmental resilience and prolonged lifetime. Given their widespread use, there is a need to quickly qualify them and accurately predict the reliability of these devices. Due to their inherently long operational life, most LED reliability studies involve the use of degradation tests and application of filter-based prognostic techniques for dynamic update of degradation model parameters and estimation of the remaining useful life (RUL). Although they are in general very effective, the main drawback is the need for a specific state-space model that describes the degradation. In many cases, LED degradation trends are affected by a multitude of unknown factors such as unidentified failure modes, varying operational conditions, process and measurement variance, and environmental fluctuations. These variable factors that are hard to control tend to complicate the selection of a suitable state-space model and in some cases; there may not be a single model that could be used for the entire lifespan of the device. If the degradation patterns of LEDs under test deviate from the state space models, the resulting predictions will be inaccurate. This paper introduces a prognostics-based qualification method using a multi-output Gaussian process regression (MO-GPR) and applies it to RUL prediction of high-power LED devices. The main idea here is to use MO-GPR to learn the correlation between similar degradation patterns from multiple similar components under test and thereby, bypass the need for a specific state space model using available data of past units tested to failure.

1. Introduction

Light emitting diodes (LEDs) are increasingly used nowadays for general indoor and outdoor lighting, advertisement displays, medical devices etc. [1–3]. A common failure mode in LED devices is lumen degradation, which involves degradation of the light output (brightness) to about 70% of its initial value (standard criterion for LED failure) [4, 5]. With lifetimes varying widely from 2000 to 70,000 h [6], the prolonged lifetime of LED devices make conventional reliability prediction through accelerated life test and failure data analysis on large sample size lots unfeasible. Therefore, we are in need of other methodologies to quickly qualify LEDs. A variety of degradation models such as the exponential model [7, 8], bi-exponential model [9] and the rate kinetics-based physical model [10] have all been used for estimating the lifetime of LED devices in the past. Although the above-mentioned methods are generally effective, the use of a specific "analytical" degradation model is the main common drawback in them. If the degradation pattern deviates from the model due to external perturbations or unanticipated new failure mechanisms in the product under test, the results of the prognosis may be rendered useless as the predictions are likely to deviate far from the true value.

In this study, we propose the use of a prognostic method based on multi-output Gaussian process regression (MO-GPR). Gaussian process regressions are Bayesian non-parametric modeling techniques. It is logical to expect that the light output degradation trends from different LED devices fabricated using the same process flow should show similar time-based evolution patterns under the same operational condition, fabrication process and test setup environment. The key idea of MO-GPR framework is that it exploits the "output correlation" between multiple degradation traces such that the output can leverage information from one another and provide more accurate prediction in comparison to modeling them individually [11]. In the past, MO-GPR has been used for compiler performance analysis [12], physiological time series analysis [13], financial time series prediction [14], and prognosis of the remaining useful life (RUL) for lithium-ion batteries [15]. To the authors' knowledge, there is no report on MO-GPR for RUL

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prediction of light emitting diodes. With batteries degrading quite "consistently" either in a concave or convex manner and given the general validity of the exponential model for battery charge capacity degradation, the need for MO-GPR is less important in the case of batteries, than it is for LEDs, where much of the physics governing degradation is yet to be understood and wherein degradation patterns are quite complex with multiple distinguishable phases [16, 17].

This paper is organized as follows. Section II discusses the basics governing the standard Gaussian process regression and multi-output Gaussian process regression (MO-GPR). Section III presents the results of the prognosis of MO-GPR by analyzing three different data sets for efficiency and accuracy: one data set with synthesized data for demonstration of the drawback of model-based methods and other two data sets, which have been extracted from the test data presented by Chang et al. [16]. Finally, Section IV presents a conclusion of the study highlighting the pros and cons of the MO-GPR approach.

2. Single output/multi-output Gaussian process regression

2.1. Single-output Gaussian process regression (SO-GPR)

Let us consider a scalar input involving the prediction of the light output ($f(t)$) versus time. It is assumed that n noisy data points of the light output of a LED can be described by:

$$\{t_i, y(t_i) = f(t_i) + \varepsilon_i\},\ i = 1,\ ...,n \tag{1}$$

where t is the time variable, $\varepsilon_i \sim \mathcal{N}(0, \sigma_s^2)$ is the measurement noise (with σ_s being the standard deviation) and is assumed to be known. Gaussian process regression assumes a Gaussian probability distribution over the functions $f(t)$:

$$f(t) \sim \mathcal{N}(m(t), \kappa(t,t')) \tag{2}$$

where $m(t)$, $\kappa(t,t')$ are the mean and covariance functions. The mean $m(t)$ is normally taken as zero, without loss of generality. The covariance function is used to encode the coupling between f values in accordance with the distance in the t values. There are many covariance functions that can be used [18]. Two popular choices are the squared exponential (SE) and Matern covariance functions:

$$\kappa_{SE}(t,t') = \theta_f \exp\left(-\frac{(t-t')^2}{2\theta_l}\right) \tag{3}$$

$$\kappa_{Ma}(r) = \theta_f \frac{2^{1-\nu}}{\Gamma(\nu)}\left(\frac{\sqrt{2\nu}\,r}{\theta_l}\right)^{\nu} \mathrm{B}_{\nu}\left(\frac{\sqrt{2\nu}\,r}{\theta_l}\right)$$
$$r = \|t - t'\|_2 \tag{4}$$

where r is the Euclidean norm between times, θ_f, θ_l are hyper-parameters controlling the scaling of $f(t)$ and t respectively, ν is a non-negative parameter of the covariance and B_ν is the modified Bessel function.

The Gaussian process assumes that any finite subset of outputs, $f(t)$, follows a joint Gaussian distribution. The joint prior distribution of n training points (observations), $T = \{t_1, \ldots, t_n\}$; $\mathbf{y} = \{y_1, \ldots, y_n\}$, with a new test point t^* is:

$$\begin{bmatrix} \mathbf{y} \\ f^* \end{bmatrix} = \mathcal{N}\left(\begin{bmatrix} \mathbf{0} \\ 0 \end{bmatrix}, \begin{bmatrix} \mathrm{K}(T,T) + \sigma_s^2 I & \mathbf{k}(T,t^*) \\ \mathbf{k}(t^*,T) & \kappa(t^*,t^*) \end{bmatrix}\right) \tag{5}$$

where $K(T,T) \in R_{n\times n}$ is the symmetric positive semidefinite covariance matrix with its elements representing the covariance between the training points. The posterior distribution conditioned on data $\mathbf{y}$ is:

$$f^*|T, \boldsymbol{y}, t^* \sim \mathcal{N}(\hat{f}(t^*), \ddot{\mathrm{I}}f^2(t^*)) \tag{6}$$

The posterior prediction mean and variance are then given by:

$$\hat{f}(t^*) = \mathbf{k}^{\mathscr{T}}(T,t^*)[K(T,T) + \sigma_s^2 I]^{-1}\mathbf{y} \tag{7}$$

$$\sigma^2(t^*) = \kappa(t^*,t^*) - \mathbf{k}^{\mathscr{T}}(T,t^*)[K(T,T) + \sigma_s^2 I]^{-1}\mathbf{k}(T,t^*) \tag{8}$$

Before using (7) and (8) to make a prediction, the hyper-parameters θ_f, θ_l and the noise variance, σ_s, are learned from the training data by minimizing the negative log-likelihood function (NLK):

$$\Theta_t = \{\theta_f^{opt}, \theta_l^{opt}, \sigma_s^{opt}\} = \underset{\theta_f,\theta_l,\sigma_s}{\arg\min}\ NLK \tag{9}$$

where

$$NLK = 0.5\mathbf{y}^{\mathscr{T}}[K(T,T) + I\sigma_s^2]^{-1}\mathbf{y} + 0.5\log|K(T,T) + I\sigma_s^2| + \log(2\pi)n/2 \tag{10}$$

2.2. Multi-output Gaussian process (MO-GPR)

As mentioned earlier, it is normal to expect that the degradation of light output for different LEDs under similar conditions have similar patterns. The MO-GPR can be used to approximate l light output degradation trends of different LEDs simultaneously by considering the correlations between them. This is achieved by considering the degradation trends of the different LEDs as a single time series and an addition label input l and forming a new covariance function:

$$\kappa_{MO-GPR} = \kappa_c(l,l,\Theta_c) \times \kappa_{yy}(t,t',\Theta_t) \tag{11}$$

where the term, $\kappa_c(l,l,\boldsymbol{\theta}_c)$, encodes the correlation between the degradation trends of different LEDs and $\kappa_{yy}(t,t',\theta_t)$ captures the covariance between the different cycles of data for the same test unit. Assume that $\mathrm{n}^{(j)}$ measurements are available for the j^{th} LED. The covariance matrix for L LEDs can be written as:

$$K_{MO-GPR} = K_c(l,\Theta_c) \otimes K_t(t,\Theta_t) \tag{12}$$

The hyperparameters for MO-GPR may be optimized by maximizing the log-likelihood. The main technical issue here is how to construct a covariance matrix that is positive semi-definite and can capture the correlation between the degradation trends. Free-form parameterization [18] is a general method for parameterization. It uses Cholesky decomposition and parameterizes the correlation covariance matrix using the elements of the lower triangular matrix:

$$K_c = \mathbb{L}\mathbb{L}^T = \begin{bmatrix} \theta_{c,1} & 0 & \ldots & 0 \\ \theta_{c,2} & \theta_{c,3} & & 0 \\ \vdots & & \ddots & 0 \\ \theta_{c,k-L+1} & \theta_{c,k-L+2} & \ldots & \theta_{c,k} \end{bmatrix} \tag{13}$$

Thus, there are a total of $k = L(L+1)/2$ hyper-parameters for encoding the correlation between the l degradation trends. The diagonal elements of the matrix represent the correlation of degradation trends of LEDs with themselves. The non-diagonal elements are used to capture the correlation in the degradation between multiple LED units. The MATLAB® implementation of MO-GPR is available in Ref. [13]. The application of the proposed method here to different sets of LED test data is illustrated in detail in the following section.

3. Results and discussions

3.1. Data Set A – Synthesized Data Set

In this subsection, we generated three sets of data and used them for demonstrating the drawback of using fixed specific state space model in RUL prognosis. The data is generated using the switch exponential degradation model as follows:

$$y_i(t) = \begin{cases} B_{i_1}\exp(-\alpha_{i_1}t) & t \le t_i \\ B_{i_2}\exp(-\alpha_{i_2}t) & t > t_i \end{cases};\quad i = \{1,\ 2,\ 3\}$$
$$B_{i1,i2} \in [90\ 102];\quad \alpha_{i_1},\ \alpha_{i_2} \in [0.0002\ \ 0.003] \tag{14}$$

where t_i (hrs) is the time when the change in the degradation model