Application of a Gaussian Process Prior to Predict Smart Power Semiconductor Lifetime Data

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Abstract

In this paper different Gaussian process priors are investigated to predict complex semiconductor lifetime data. The data of interest is a mixture of two log-normal distributed heteroscedastic components where data can be right censored. Due to censored observations MCMC simulations are necessary to determine the posterior density distribution. For this purpose the statistical toolbox *GPstuff* for MATLAB® has been extended. For the model selection and evaluation goodness of fit criteria such as ARD, Bayes factors, predictive density distributions and sums of squared errors are used.

The results indicate that the application of a Gaussian process prior serves as a reliable alternative to currently applied methods.

Keywords: semiconductor reliability; Bayesian inference.

1 Introduction

In automotive industry end-of-life tests are necessary to verify that semiconductor products operate reliably. Since it is not possible to test a sufficient amount of devices at real stress conditions, accelerated stress tests in combination with statistical models are commonly applied to achieve reliable forecasts for the lifetime of the devices under tests (DUTs). Due to the fact that data is highly complex, frequently used acceleration models like

Arrhenius and Coffin-Manson lack accuracy.

Previous investigations [1, 6] have shown that the currently applied Bayesian Mixtures-of-Experts Norris-Landzberg (MoE) and a Bayesian network model (BN) interpolate well, but both lack accuracy in case of extrapolation. It is assumed that, in general, ordinary linear based regression models cannot capture the complex behavior of the observed data. To increase modeling flexibility the application of a Gaussian process prior is proposed.

2 Data Characteristics

For this investigation lifetime data from five similar device types obtained under 65 different electrical and thermal stress conditions from a cycle stress test system [2] is investigated. The lifetime data follows a mixture distribution with two log-normal components representing two different failure mechanisms [1]. Both components include censored data.

The stress test conditions are defined by the induced current, pulse length, repetition time, and the device-specific voltage. Based on these electrical parameters, the DUT heats up and cools down within one stress cycle. This temperature rise causes mechanical stress due to mismatching thermal expansion coefficients of the different layers in the device. Therefore, electro-thermal and thermo-mechanical effects are the main reasons for devices failure. To capture all these effects, electrical parameters, analytically derived as well as simulated thermal and mechanical stress parameters, respectively, are investigated.

3 Model Development & Evaluation Results

To model the lifetime data, different Gaussian process priors (GP) [7] are investigated. Since the Norris-Landzberg model [6] turned out to give the best fit for the data of interest, the following three models are investigated:

- Norris-Landzberg model based on nominal values (GP_n),
- Norris- Landzberg model based on measured values (GP_m), and
- model based on a complete 150μs sequence of the DUT specific energy measurements ($\mathrm{GP}_{150\mu s}$).

Bayesian parameter learning is performed in the MATLAB® toolbox *GPstuff* [8] using a combination of surrogate slice [4] and elliptical slice [5] sampler. To provide a direct comparison between the investigated models, firstly, the two mixture components are modeled independently from each other, next, they are mixed by estimated mixture weights, that are modeled by a cumulative Beta distribution function [6].

The results show that the sum of a linear and a constant covariance function gives the best fit for all investigated models. For the evaluation of the model quality, the Bayesian Information Criterion (BIC) [3] is determined, see Table 1. The results indicate that the models using a Gaussian process prior give a better fit than MoE or BN for both mixture components.

model	*MoE*	*BN*	GP_n	GP_m	$GP_{150\mu s}$
BIC_1	179.02	181.12	177.7	142.9	129.8
BIC_2	360.62	358.32	355.9	339.4	241.0

Table 1: BIC_1 and BIC_2 denote the BIC value corresponding to the first and second mixture component, respectively.

For the evaluation of the goodness of prediction, posterior predictive distributions are evaluated and sum of squared errors of predictions (SSEPs) are analyzed, see Table 2. Thereby, especially the predictive power of the GPs based on measured values is hardly worth mentioning, whereas the results gained by GP_n are comparable with the MoE and BN models.

model	*Dev. A*	*Dev. B*	*Dev. C*	*Dev. D*	*Dev. E*
MoE	1.84	4.19	0.89	2.47	0.50
BN	1.93	4.47	0.89	5.26	0.22
GP_n	1.93	4.93	0.99	5.36	0.48
GP_m	8.35	0.89	0.89	5.25	1.75
$GP_{150\mu s}$	7.35	3.80	0.28	4.20	2.31

Table 2: Means of SSEP for device types A, B, C, D, and E based on the five investigated models.

4 Summary

In this paper different GPs have been investigated to model highly complex smart power semiconductor lifetime data. The results have been evaluated and compared with currently applied methods.

Based on the selected GP prior, the posterior distributions of the model parameters and the posterior predictive distributions were determined. The results show that the application of a GP prior to smart power semiconductor lifetime data represents a reliable alternative to currently applied methods.

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