Bayesian Prediction of SMART Power Semiconductor Lifetime with Bayesian Networks

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Abstract

In this paper Bayesian networks are used to predict complex semiconductor lifetime data. The data of interest is a mixture of two log-normal distributed heteroscedastic components where data is right censored.

To understand the complex behavior of data corresponding to each mixture component, interactions between geometric designs, material properties and physical parameters of the semiconductor device under test are modeled by a Bayesian network. For the network's structure and parameter learning the statistical toolboxes *BNT* and *bayesf Version 2.0* for MATLAB have been extended. Due to censored observations MCMC simulations are necessary to determine the posterior density distribution and evaluate the network's structure.

For the model selection and evaluation goodness of fit criteria such as marginal likelihoods, Bayes factors, predictive density distributions and sums of squared errors are used.

The results indicate that the application of Bayesian networks to semiconductor data provides useful information about the behavior of devices as well as a reliable alternative to currently applied methods.

Keywords: Semiconductor Reliability; Lifetime Prediction; Bayesian Networks; Bayesian Inference.

1 Introduction

In automotive industry, end-of-life tests are necessary to verify that semiconductor products operate reliable. To save resources, accelerated stress tests [6] in combination with statistical models are commonly applied to predict the lifetime measured in cycles to failure (CTF). Previous investigations [1], [10] have shown that the currently applied Bayesian Mixtures-of-Experts extended Coffin-Manson (MoE) model is sufficient for interpolation. In case of extrapolation, it cannot describe the complex behavior of the data and lead to inaccurate results. It is assumed that this lack of accuracy may be based on the fact that the model does not include physical parameters reflecting interactions between different geometric designs or material properties of the device under test (DUT) [10]. Hence, a Bayesian network including these factors is proposed.

2 Data Characteristics & Available Information

For this paper lifetime data obtained under different electrical and thermal stress conditions from a cycle stress test system [6] is investigated.

The stress test conditions are thereby defined by current (I), pulse length (t_p), repetition time (t_{rep}) and the device-specific voltage (V). Additionally, parameters considering the geometric design of the device, e.g. current density (J), are available. The main reasons for the failing of the devices are electro-thermal and thermo-mechanical effects caused by repetitive stress. To capture these effects, temperature simulations as well as thermal and mechanical stress parameters [3], [13] are included. Altogether 18 covariates for the Bayesian network are available.

Since lifetime data is a mixture of two log-normal distributed components representing two different failure mechanisms [2], the dataset is divided into two subsets. For the model 169 and 867 datapoints for the first and second component, respectively, tested under 65 different stress conditions are used. Both components include censored data.

3 Model Development & Evaluation Results

For modeling lifetime data, Bayesian networks (BN) [7], [8], [12] are used. The nodes were assigned to be either discrete or continuous. To define the conditional probability distributions (CPDs), root and gaussian nodes are applied [9].

Different approaches using the automatic relevance determination (ARD) algorithm [11], see Figure 1, and priors on edges are investigated, because it is assumed that the number of data is too small for such a large network. The

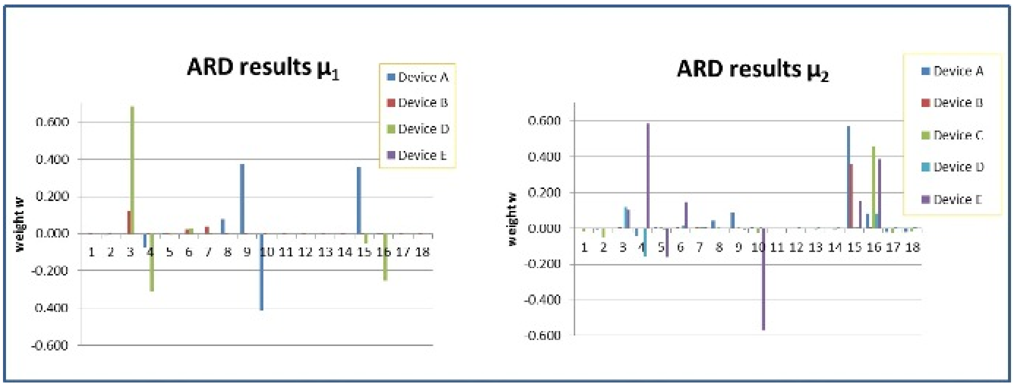

Figure 1: ARD selected covariates for each component. The application of different covariates for different components is proposed.

marginal likelihood is approximated with the method proposed by Draper [4]. The largest marginal likelihood value indicates the best BN for the first and second component, which is then used for lifetime modeling.

Bayesian structure and parameter learning is performed in MATLAB using an enhance version of the BNT [9] and extended MoE toolbox [1], [5] with MCMC methods. For the simulation of the posterior density distribution of the parameters normal and inverse-Gamma priors are applied.

For an evaluation, cross-validation using posterior predictive distributions and sum of squared errors of predictions (SSEPs) are compared. Furthermore, predicted outcomes are compared with the results gained by the currently applied MoE model. Since the MoE model was developed based on a subset of data, the same subset is used to learn the BNs and thus, to provide a direct comparison between the predictive power of the two different approaches. Predicting the lifetime with BNs, the posterior predictive distribution for each component is sampled independently and mixed by estimated mixture weights. It was shown [10] that the mixture weights can be modeled by a cumulative Beta distribution function.

Since it is infeasible to determine SSEPs for tests with no fails, they are neglected for this evaluation. Thus, the number of tests is reduced to 51. Table 1 shows the meanSSEP for the five evaluated device types. Overall, the MoE model achieves a meanSSEP of 2.76, whereas the BN model gives a meanSSEP of 2.88. The MoE model is slightly more accurate for two device types (B and C) and significantly more accurate for device type D. The BN gives significantly better results for device types A and E. Overall, the results of the MoE and BN model are comparable.

model	*Device A*	*Device B*	*Device C*	*Device D*	*Device E*
# tests	33	3	5	4	6
MoE	6.08	3.88	0.89	2.44	0.52
BN	3.83	4.12	0.96	5.26	0.22

Table 1: meanSSEP.

4 Summary

In this paper different BN have been proposed to model mixture distributed semiconductor lifetime data and to provide a reliable alternative to currently applied methods.

For the model 18 covariates were available and the network's structure was supposed to be too complex for the amount of data. Therefore, the model complexity had to be reduced. This was achieved by the ARD algorithm, which provided plausible results. Furthermore, prior knowledge for edges was available which was additionally used for the structure learning.

Based on the selected network, the posterior distributions of the model parameters were simulated. The posterior densities of the model parameters show small variations and indicate therefore a good fit.

Since the aim of this work was to provide reliable predictions, cross-validation using posterior predictive distributions has been performed and evaluated. The results show that the application of a BN represents a reliable alternative to currently applied methods.

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