A Bayesian Model to Approximate ΔT for Semiconductor Cyclic Stress Testing

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Abstract

In this work a Bayesian model to approximate the temperature rise in a semiconductor device during cyclic stress testing is presented. A known relationship is extended to different DMOS areas and prior knowledge on the model parameters from literature, experts, known physical relations and already available data from previous technologies is included. The analysis of the sampled posterior distributions indicate good model quality and, compared to least squares parameter estimates, the posterior means are more reliable from a physical point of view.

Keywords: Bayesian ΔT model, semiconductor testing, reliability.

1 Introduction

Temperature is one of the driving forces that causes device failure at semiconductor cyclic stress testing. During a stress pulse the device heats up and cools down within milliseconds. Hence, beside the ambient temperature, the temperature rise within one stress pulse (ΔT) is of key interest for the generation of a reliable lifetime model. Devices with an integrated temperature sensor exist, but its construction implies a change in the structure and a dislocation of the hottest spot, therefore it is not possible to measure the maximum ΔT of the semiconductor device. Alternatively, electro-thermal Finite Element (FEM) simulations [1] are performed based on detailed device models. Since the time effort for these simulations is especially high for devices with big DMOS areas, we propose to use an approximation formula for ΔT.

2 Approximation for ΔT

Glavanovics and Zitta[2] showed that ΔT for a stress pulse can be approximated by the following formula

$$\Delta T = T_{dest} - T_{amb} = k_{th} \cdot P_{max} \cdot t_p^N, \tag{1}$$

where T_{amb} is the ambient temperature, P_{max} is the maximum power of the stress pulse and t_p is the pulse width. T_{dest} (destruction temperature), k_{th} and N are fitting parameters which can be estimated based on the results from Energy Ramp Up (ERU) tests. With Equation 1, the reached ΔTs for different stress pulses during cyclic stress testing can be calculated and used to predict the lifetime of the semiconductor device. In general, it is assumed that T_{dest} is the same for devices with the same metal structure and k_{th} scales with the DMOS area, but data analysis shows that also N depends on the DMOS area, hence Equation 1 is extended to

$$\Delta T = T_{dest} - T_{amb} = C \cdot A^{N_1} \cdot P_{max} \cdot t_p^{-N_2 \cdot A^{N_3}+1}, \tag{2}$$

Since measured temperatures of a stress pulse are not available but the energies via the power and pulse width ($E = 1/2 \cdot P_{max} \cdot t_p$), the energy is used as the output

$$E = \frac{1}{2} \cdot (T_{dest} - T_{amb}) \cdot C^{-1} \cdot A^{-N_1} \cdot P_{max} \cdot t_p^{N_2 \cdot A^{N_3}}. \tag{3}$$

This implies that posterior distributions for $\theta = (T_{dest}, C, N_1, N_2, N_3, \sigma^2)$ are of interest. Prior knowledge from literature, experts, known physical relationships and already available data from previous technologies is available for T_{dest}, C, N_1 and $N_2 \cdot A^{N_2} + 1$. This information is included via normal, uniform and inverse gamma prior distributions are used for T_{dest}, C, N_1, σ^2 and a hierarchical prior for $N_3|N_2$. The measured energies follow a normal distribution, since only white noise is assumed as a disturbing factor. Therefore the joint posterior distribution is defined as

$$p(\theta|E) \propto P(E|\theta) \cdot P(T_{dest}) \cdot P(C) \cdot P(N_1) \cdot P(N3|N2) \cdot P(N_2) \tag{4}$$

Equation 3 cannot be linearized by a logarithmic transformation and $P(N_2, N_3)$ is a hierarchical normal prior, therefore no analytical solution for the posterior distributions exists. We apply a slice sampling algorithm[3] to sample from the posterior distributions. The analysis of the results show that the Bayesian posterior distributions are more robust compared to a least squares point estimation. Additionally, from a physical point of view, the posterior means are the more reliable parameter estimates.

References

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