General linearized model use for High Power Reliability Assessment test results: Conditions, procedure and case study

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ABSTRACT

In semiconductor manufacturing for automotive, AECQ_100 standard requires test of load drivers in continuous short circuit conditions: this test is called High Power Reliability Assessment (HPRA). It is about a robustness test in which a sample of parts is led to breakages on a cycled overload or short circuit current. The test is stopped when a sufficient number of parts to conduct a statistical analysis failed. The expected result from this statistical analysis is failure cycle modeling according to the test temperature. But this is a complex modeling that has to be proceeded in several steps, the final step being use of a general linearized model. This paper presents the main features of modeling, but it shows their implementation on a real HPRA test in Load Short Circuit (LSC) condition. Modeling allows result prediction at a temperature for which a test has not been performed, but it allows also a full explanation of the phenomena: for example, it enables to estimate activation energy of acceleration factor in the test, but also the failure mechanisms at the breakage origin. This paper highlights the necessary conditions for the tests so that interpretation may be complete and significant.

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1. Introduction

The AECQ-100 standard for automotive requires electronic component manufacturers to perform a High Power Reliability Assessment (HPRA) on the protection drivers. HPRA takes on the form of accelerated stress tests: components operate in a continuous short circuit condition, in an oven at monitored temperature. The overload or short-circuit current is seen continuously switched on–off. Several parts are used for a test, and the result is the number of on–off cycles that each of the parts can endure before to fail.

This paper deals with modeling of these HPRA test results when the temperature is modified from one test to the other one [1,2]. But this modeling is complex since it is about to mix several modeling conditions: in a first time, modeling focuses on modeling at one temperature, before addressing modeling the result curve on all the different temperature set-up.

There are two final purposes of this HPRA test result modeling:
- the first one is to predict HPRA result at a temperature at which the test was not already led;
- the second one is to explain the failure mechanisms that caused each of the failures: that explanation purpose is going to bring about the question of the temperature as the factor of the failure mechanism type.

Far to be only a theoretical paper, this work describes the different modeling steps in a real case study. It gives some practical recommendations to model HPRA test results, but in extension any accelerated stress test results.

2. HPRA test description

The AECQ_100 standard defines the precise requirements for the HPRA test conditions.

Devices that have the function to power supply to an external load, usually provide embedded protections against system malfunction due to short circuit of that load. The HPRA addresses these protections, testing their robustness on an on-off-cycled short-circuit or overload current. Schematic depends on the type of parts (low side or high side devices), and a specific resistance and inductance simulate the cable length between the device and the short-circuit.

The AECQ_100 describes two types of HPRA tests: it speaks about a Terminal Short Circuit (TSC) when the short-circuit occurs close to the device, and about a Load Short Circuit (LSC) when it occurs at the end of the cable. The values of the cable length simulation components depend on the device specifications.

An HPRA test is constituted by a minimum of 10 DUT, taken from 3 different lots. During the cycling, each DUT is monitored and the number of cycles that it went through before failing is recorded: the statistical analysis and modeling use this data. The final result for the component is given by a grade level, defined by the number of cycles until the first observed failing DUT, or by the total number of tested cycles, if no failure occurs with a sample during the duration of the test.
3. Regression and modeling methodology

Let a couple of random numerical variables \( (X, Y) \). If \( Y \) and \( Y \) are not independent, knowledge of the value taken by \( X \) changes uncertainty about the realization of \( Y \). \( X \) is called explaining variable or predictor, and \( Y \) is the explained variable or criteria.

Typically, this uncertainty decreases since conditional distribution of \( Y \), according to a value \( x \) of \( X \) \( (X = x) \), \( E(Y/X) \), has a variance inferior in mean to the variance of \( Y \) distribution. If the random phenomena of \( X \) is assumed to be able to predict the random phenomena of \( Y \), a prediction formula of \( Y \) by \( X \) is searched as well as prediction error estimation, measured by variance of:

\[
\varepsilon = Y - \text{(prediction of } Y) \text{.} \tag{1}
\]

This variance \( \text{Var}(\varepsilon) \) is wanted the smallest possible.

If \( X \) and \( Y \) follow a normal distribution, conditional distribution of \( Y \), according to \( X \), can be described by:

\[
E(Y/X) = A + BX. \tag{2}
\]

Therefore:

\[
Y = A + BX + \varepsilon. \tag{3}
\]

This last formula defines what is called linear regression.

We have now \( n \) couples \( (x_i, y_i) \), from \( i = 1 \) to \( n \) that constitute an \( n \)-sample of independent observations of \( (Y, X) \). In that case, we have only to assume that for each observation, we have:

\[
y_i = A + Bx_i + \varepsilon_i \tag{4}
\]

where \( \varepsilon_i \) are independent realizations of a variable \( \varepsilon \); \( \varepsilon \) has a null expected value and a constant variance \( \sigma^2 \), whatever \( x \). Then, we speak about linear model rather than linear regression.

To estimate \( A \), \( B \) and \( \sigma^2 \), least square mean method uses the fact that \( E(Y/X) = A + BX \) (2) is the best estimation of \( Y \) by \( Y \) in quadratic mean.

We look for a straight line with the equation:

\[
\text{(Predicted } y) = a + bx \tag{5}
\]

such as \( \Sigma(y_i - \text{predicted } y_i)^2 \) is minimal.

We speak about the general linearized model when:

- probability distribution for \( Y \) is no longer normal: it can be a Poisson distribution, an exponential or gamma one, and so on...
- the link function \( g \) between \( E(Y/X) \) and \( X \) is not as simple as a linear form, but it is expressed by a matrix \( X' \):

\[
g(E(Y/X)) = X'B \tag{5}
\]

- the least square mean method has to be replaced by the maximum likelihood estimation (MLE).

4. HPRA test modeling

In HPRA tests, such as defined and led following the AECQ_100 requirements, temperature can be the explaining variable or predictor, and the failure cycle is the explained variable or criteria.

4.1. HPRA test modeling steps

To model HPRA test results, the first step is to model failure cycle distribution per temperature: this knowledge determines if modeling by a linear model is possible or not, as the least mean square method use.
Another HPRA test led on 20 parts with another test equipment configuration highlighted a Lognormal model (see Fig. 2) [3].

AECQ_100 standard recommends modeling by a Weibull or lognormal model. The choice between the two ones is based on the Akaïke or Bayesian information criterions (AIC, BIC): these criterions are calculated in order to determine the most appropriate model, balancing a relevant explanation (lower AIC) and an accuracy prediction (lower BIC):

\[
\text{Bayesian information criterion (BIC)} = -2\log\text{likelihood} + k \ln(n) \quad (7)
\]

\[
\text{Akaïke information criterion (AICc)} = -2\log\text{likelihood} + \frac{2k}{n-k-1} \quad (8)
\]

\[
\text{AICc} = AIC + \frac{2(k+1)}{(n-k-1)} \quad (9)
\]

where \(k\) is the number of estimated parameters in the model, and \(n\), the number of observations in the set of data.

Typically, the model with the lower AIC criterion will be chosen.

### 4.3. Failure cycle distribution comparison

Seven LSC HPRA tests are performed at six different temperatures (20, 60, 70, 80, 85 and 90 °C). A Weibull model is chosen for each of the distributions: modeling uses the maximum likelihood method as confidence interval estimation method. The question is to study if the distributions are different according to the temperature.

The statistical Wilcoxon Group Homogeneity test, based on a ChiSquare statistics, allows study the similarity of the distributions. In that case, the low p-value at an alpha-risk of 5% shows that there is a difference between the distributions (ChiSquare = 105.4576, Degree of Freedom = 5, p-value < 0.0001).

A Weibull model is defined by two parameters:

- \(\alpha\) is the scale parameter, and \(\beta\), the shape parameter.
- The probability distribution has the following equation:

\[
F(t) = 1 - e^{-\left(\frac{\text{temperature}}{\alpha}\right)^\beta} \quad (10)
\]

The six failure cycle distributions can be different by one parameter among the two ones, or by all the two parameters. We are led to model the different possibilities and to compare them with the same AIC and BIC criteria. The models where scale and shape are all different are chosen (see Table 1).

Finally, study of the Cox–Snell residuals allow conclude about the failure cycle distribution comparison: on their plot, data points do not drift too much from the diagonal, proving that the choice for Weibull models with different scales and shapes is relevant (See Figs. 3 and 4.).

### 4.4. Activation energy estimation

Activation energy estimation results from the estimation of the parameters \(\alpha\) and \(\beta\) for each of Weibull modeling and from the slope coefficient of the regression line of \(\ln(\alpha)\) function of \((1/\text{temperature in Kelvin})\) (see Table 2, and Fig. 5). From this activation energy, acceleration factor (AF) from one temperature to the other one, can be obtained by the following equation [4]:

\[
\text{AF} = \exp\left[\frac{\text{Ea}}{K} \times \left(\frac{1}{T_j-0} - \frac{1}{T_j-t}\right)\right] \quad (11)
\]

where:

- \(\text{Ea}\) = activation energy

### Table 1

<table>
<thead>
<tr>
<th>Model</th>
<th>(-2 \log \text{likelihood})</th>
<th>AICc</th>
<th>BIC</th>
<th>Number of parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>No effect</td>
<td>1505.752</td>
<td>1509.987</td>
<td>1513.73</td>
<td>2</td>
</tr>
<tr>
<td>Regression</td>
<td>1351.475</td>
<td>1357.955</td>
<td>1363.442</td>
<td>3</td>
</tr>
<tr>
<td>Separate location</td>
<td>1304.788</td>
<td>1321.223</td>
<td>1332.711</td>
<td>7</td>
</tr>
<tr>
<td>Separate location and scale</td>
<td>1283.511</td>
<td>1315.121</td>
<td>1331.379</td>
<td>12</td>
</tr>
</tbody>
</table>

### Table 2

Examples of energy activation and acceleration estimation from the curve in Fig. 5.

<table>
<thead>
<tr>
<th>Regression line: (\ln(\alpha) = (\text{Ea}/K)/\text{Temp in Kelvin})</th>
<th>(\ln(\alpha) = 6324.8/\text{Temp in Kelvin} - 5.974)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(\text{Ea}/K)</td>
<td>6324.8</td>
</tr>
<tr>
<td>(K = \text{Boltzman constant})</td>
<td>8.65E-05</td>
</tr>
<tr>
<td>(\text{Ea})</td>
<td>0.547</td>
</tr>
<tr>
<td>(\text{AF}) between 20 °C and 90 °C</td>
<td>64</td>
</tr>
</tbody>
</table>

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4.5. HPRA modeling by a general linearized model

At that step, we concluded that the failure cycle distributions for a set temperature are not normal, but fit with a Weibull or Lognormal model. So, the only one possible modeling method is to use a general linearized model with a maximum likelihood algorithm to estimate the confidence interval [5].

In the last step, it is about to model the failure cycle according to the test temperature. In that modeling, the failure cycle fits with the maximal probability in the distribution for a set temperature. The best model to use in that modeling is the gamma or zero inflated gamma distribution. The gamma distribution covers a lot of distribution types, for example the Weibull distribution.

Always for the same six LSC HPRA tests at six different temperatures, modeling with a general linearized model and a zero inflated gamma distribution allowed find the equation linking the cycle failure to the temperature:

\[
\text{Cycles} = \exp(17.055 - 0.065 \times \text{temperature}) \tag{12}
\]

Prediction of the failure cycles becomes possible for any temperature in the range of the observations (see Fig. 6.). Modeling validation can be performed on one hand by plotting the predicted values by the observed ones and on the other hand by plotting the residuals: this last graph does not have to show any trend (see Fig. 7. and 8.).

5. Discrimination of the failure mechanism types in HPRA tests

All the parts that fail in HPRA tests are analyzed in a failure analysis laboratory. Comparison between the analysis results on failed parts for different temperatures allows understand if there are several types of failure mechanisms dependent on the temperature value.

Another study may be a statistical analysis on the plot of the failure cycle function of the temperature, assuming that existence of two or more mechanism types is seen on the plot through a curve slope or shape different per mechanism.

From the result of the HPRA test described previously, a study to bring out different failure mechanisms is performed. An assumption can be the existence of two mechanisms: one below a temperature of 60 °C and another one from 60 °C and beyond, since the whole curve of the failure cycle function of the temperature seems to show a slope change at 60 °C. A modeling is performed from only the results beyond 60 °C and compared with the whole curve. The model found from only the points beyond 60 °C is different from the model on all the points, which is in favor of the existence of two failure mechanisms or at least two behaviors. But, observation of the confidence intervals for the two models brings out a larger uncertainty on the full model below 60 °C because of the lack of data [6] (see Fig. 9). No conclusion is really possible, without performing other HPRA tests from 20 °C to 60 °C.

K Boltzman constant
Tj-o operating life junction temperature (K)
Tj-t accelerated test junction temperature (K).

Fig. 5. Regression line of Ln(α) function of 1/temperature: slope is equal to Ea/K.

Fig. 6. Prediction curve and individual confidence intervals at 95%.

Fig. 7. Plot of the observed failure cycle values by the predicted ones.

Fig. 8. Plot of the modeling residuals by the predicted values.
6. Conclusion

For HPRA tests, failure cycle modeling according to the test temperature is complex because above all, it is about modeling of not-normal distributions. The only one model that can be implemented is the general linearized model, after a sound characterization of the failure cycle distributions per test temperature.

This process can be applied generally to all the robustness tests where the devices under test are led to breakage. Variability of the behavior of the DUT for a specific stress condition causes these abnormal distributions.

Furthermore, it becomes important to lead to a lot of tests and to have many data, if a change in the slope that may highlight a change in the part behavior according to the stress temperature, or different failure mechanisms, may be observed. For this case study of HPRA tests led in LSC configurations, more tests will have to be performed at lower temperature.

References