Case Studies in Engineering Failure Analysis 7 (2016) 65–70

Contents lists available at ScienceDirect

Case Studies in Engineering Failure Analysis

journal homepage: www.elsevier.com/locate/csefa

Bayesian analysis of low-cycle fatigue failure in printed wiring boards

Rong Pan[a,*], Xinyue Xu[a], Joseph Juarez[b]

[a] Arizona State University, United States
[b] Honeywell Inc., United States

ARTICLE INFO

Article history:
Received 28 July 2016
Received in revised form 28 October 2016
Accepted 7 November 2016
Available online 12 November 2016

Keywords:
Reliability
Circuit board
Thermal cycling test
Weibull regression
Bayesian analysis

ABSTRACT

In this study, a low-cycle fatigue experiment was conducted on printed wiring boards (PWB). The Weibull regression model and computational Bayesian analysis method were applied to analyze failure time data and to identify important factors that influence the PWB lifetime. The analysis shows that both shape parameter and scale parameter of Weibull distribution are affected by the supplier factor and preconditioning methods Based on the energy equivalence approach, a 6-cycle reflow precondition can be replaced by a 5-cycle IST precondition, thus the total testing time can be greatly reduced. This conclusion was validated by the likelihood ratio test of two datasets collected under two different preconditioning methods Therefore, the Weibull regression modeling approach is an effective approach for accounting for the variation of experimental setting in the PWB lifetime prediction.

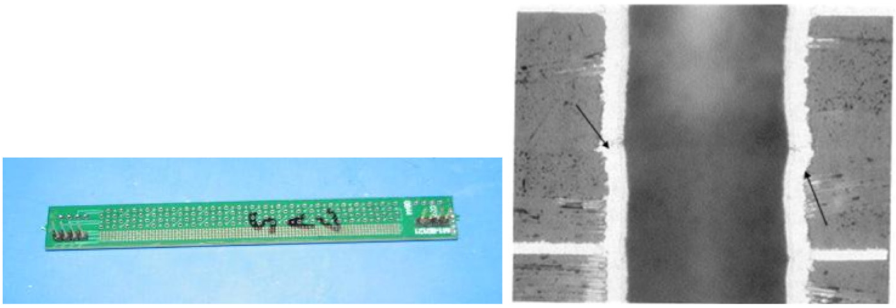
1. Background

Accelerated life testing (ALT) of printed wiring boards (PWB) is an essential tool for predicting circuit board lifetime in the electronic industry. A standard practice of using ALTs is to simulate thermally induced failure or low-cycle fatigue by subjecting a circuit board coupon to a prescribed number of specific thermal cycles that represents in-service use of the product [1]. For example, the standard practice in the avionic industry employs interconnect stress test (IST) per IPC-TM-650 [2] with all coupons in a lot passing 350 thermal cycles as the acceptance test criteria. In our experiment, the test coupons were driven beyond the normal test limits of 350 cycles as suggested in [3,4] to precipitate failures and to study differences in preconditioning processes. The goal of this study is tri-folded: First, we develop an energy-equivalent model for establishing the IST setup. Second, we compare the results from coupons fabricated by four suppliers. Lastly, this case study demonstrates the effectiveness of using Weibull regression and computational Bayesian analysis techniques for electronic component failure analysis.

The IST coupons are manufactured along the side of a circuit board prototype and multiple via barrels are produced on it (see Fig. 1(a)). The failure mode of the data presented in this paper is thermally induced fatigue due to the expansion and contraction of via barrels (a via is the mechanism by which different circuit layers are connected). These low cycle fatigues on interconnects have drawn a lot of attentions from academic researchers and industrial practitioners [5–7]; however, most of them discussed the fatigues on lead or lead-free solders, not on via barrels. Fig. 2(b) illustrates the fractures in a via barrel.

* Corresponding author.
E-mail address: rong.pan@asu.edu (R. Pan).

http://dx.doi.org/10.1016/j.csefa.2016.11.001
2213-2902/



(a) (b)

Fig. 1. (a) A typical PWB coupon used in this study; (b) Failure mode is a cracked via barrel at arrow points due to thermal induced fatigue.

Failure is determined when coupon resistance is at greater than 10% resistance change from the original resistance at the initial cycle at the highest point of the test temperature after preconditioning. The resistance increases because when a crack forms less material is left to conduct current.

A preconditioning thermal cycle step is required before the designed thermal cycling test that simulates the life experience of circuit board. This preconditioning step is to account for the thermal stress during the circuit board's soldering process. Two modes of heat transfer can be used to reproduce the production thermal stress – the resistive heat transfer as used by IST or the convection heat transfer by reflow oven. Although the latter one can more realistically represent the manufacturing process, it demands invaluable manufacturing resource (reflow oven) and is costly and time consuming. In contrast, IST can heat the internal environment of tested coupons by resistive heat transfer in a very short time. Therefore, it is important to know what IST settings can be used to replace the reflow preconditioning.

2. Experiment

PWB coupons of size 5" × 0.7 × 0.1" were used in this experiment. Each coupon was made of 14 layers of circuitry with an electrical circuit daisy chain. These coupons came from four different suppliers and a batch of six coupons was tested together at one time. There were a total of 134 coupons being tested. The failure times (number of thermal cycles) of these test coupons are given in Appendix A. If a coupon did not fail, its survival time is marked with "+".

A test coupon may experience 5 or 6 IST preconditioning cycles (IST5 or IST6) or 6 reflow preconditioning cycles (RFO6). The experimental settings of these preconditioning methods are described below:

- Use IST to heat test coupons for three minutes until it reaches the maximum temperature of 230 °C, and then cool the coupon in the room temperature (25 °C) environment for two minutes. This makes one cycle time for the IST test to be five minutes. However, this experimental setting was modified for the coupons from one supplier, in which the maximum temperature was increased to 240 °C and 245 °C.

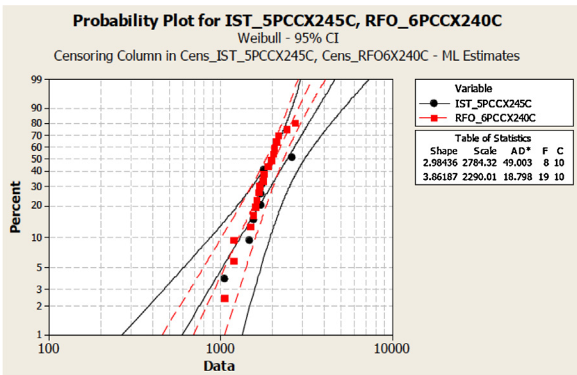


Fig. 2. Weibull plots for the 5-cycle IST (245 °C) data and the 6-cycle RFO data.

- Pass test coupons through the reflow oven for 12 min under the temperature of 250 °C. This way, coupons are heated directly via convection heat transfer. The test coupon then stays in the room temperature environment for 8 min to cool down. Thus, one cycle time for the reflow system is 20 minutes.

3. Engineering analysis

Prior to the selection of the Weibull distribution as the appropriate lifetime distribution for the data, all the data sets were fitted by Weibull, normal, logistic, lognormal and loglogistic distributions. We ranked these distributions by their Anderson-Darling statistics. It was found that both Weibull and lognormal distributions have the best goodness-of-fit; however, the Weibull distribution was chosen, because at the highest cycles-to-failure the Weibull distribution tended to have a better fit when we examined the individual probability plot of each data set.

3.1. Weibull regression model

Weibull distribution has two parameters – the shape parameter $v > 0$and the scale parameter (the characteristic life) $\eta > 0$, and its probability density function is given by

$$f(t) = \frac{v}{\eta}\left(\frac{x}{\eta}\right)^{v-1} e^{-(t/\eta)^v} for t > 0 \tag{1}$$

Accordingly, its cumulative failure distribution function is given by

$$F(x) = 1 - e^{-(t/\eta)^v} \tag{2}$$

and the reliability function

$$R(x) = e^{-(t/\eta)^v} \tag{3}$$

The shape parameter v is often influenced by the supplier factor and the preconditioning method, because they have an impact on the material being tested. Thus, we model the shape parameter by the following linear function:

$$v = \alpha_0 + \alpha_1 s_1 + \alpha_2 s_2 + \alpha_3 s_3 + \alpha_4 r \tag{4}$$

where s_1, s_2 ands_3 are indicator variables for identifying suppliers and r represents the preconditioning method. When $s_1 = 1$ and $s_2 = s_3 = 0$, the first supplier's coupon is in use. Similarly, the second and third suppliers are identified by $s_2 = 1$ and $s_3 = 1$, respectively, and the last supplier is identified by $s_1 = s_2 = s_3 = 0$. The reflow and IST preconditioning methods are indicated by $r = 1$ and $r = 0$, respectively. Using this regression model, we can pool all available data for model parameter estimation.

For the scale parameter, our previous study suggests that it can be influenced by the energy absorbed by the coupon during the preconditioning step [8]. As each preconditioning method has different targeted temperature, ramping time and cycle time, we calculate their joule equivalent energy using the following equation:

$$Energy = PCC * \Delta T * \frac{RT}{CT} \tag{5}$$

where PCC represents the number of preconditioning cycles, ΔT represents the temperature gap between ramping temperature and cooling down temperature, RT is the ramping time, and $CT$is the total cycle time. According to [9], coupons reach steady state temperatures so fast that it is reasonable to assume that these coupons are always at the readout temperature. Based on the inverse power law, a log-linear model for the Weibull characteristic life is given by

$$\log\eta = \beta_0 + \beta_1 s_1 + \beta_2 s_2 + \beta_3 s_3 + \beta_4 \log e + \beta_5 r \tag{6}$$

where variable e denotes the energy absorbed by coupon.

3.2. Bayesian inference

In order to integrate prior knowledge of Weibull parameters into our data analysis, we chose the Bayesian inference method. A Weibull regression analysis was conducted in WinBUGS environment [10] using the following model:

$$t[i] \sim weibull(v[i], \lambda[i])$$

$$v[i] = \alpha_0 + \alpha_1 s_1[i] + \alpha_2 s_2[i] + \alpha_3 s_3[i] + \alpha_4 r[i]$$

Table 1
Posterior estimation of Weibull regression parameters.

node	mean	s.d.	p-value	2.5%	median	97.5%
alpha0	3.353	0.3618	<0.0001	2.668	3.342	4.076
alpha1	0.3456	0.5693	0.6636	−0.7581	0.3476	1.488
alpha2	−2.039	0.4438	<0.0001	−2.884	−2.045	−1.147
alpha3	0.3183	0.5573	0.6778	−0.7455	0.3054	1.44
alpha4	0.9209	0.4466	0.0952	0.06004	0.9201	1.806
beta0	19.12	0.9538	<0.0001	17.25	19.07	21.1
beta1	−1.104	0.06232	<0.0001	−1.225	−1.104	−0.9813
beta2	−2.906	0.1896	<0.0001	−3.27	−2.912	−2.513
beta3	−0.6304	0.05737	<0.0001	−0.7407	−0.6305	−0.5184
beta4	−1.755	0.1462	<0.0001	−2.06	−1.748	−1.467
beta5	0.2382	0.05425	<0.0001	0.1332	0.2379	0.3475

$$\lambda[i] = \eta[i]^{-v[i]}$$

$$\log\eta[i] = \beta_0 + \beta_1 s_1[i] + \beta_2 s_2[i] + \beta_3 s_3[i] + \beta_4 \log e[i] + \beta_5 r[i]$$

where i represents ith test data, $i \in N$, $N$is the total number of test data.

Our prior knowledge about these parameters was derived from a similar test conducted in [4]. In their test, there were 54 coupons under the IST preconditioning process for six cycles that has the joule equivalent energy of 738, and another 58 coupons under reflow preconditioning process for six cycles with the joule equivalent energy of 615. Fitting their data resulted in the equation, $\log\eta = 26 - 3\log e$. Therefore, we set the prior distribution, $\beta_4 \sim N(-3, 1)$. Other prior distributions are specified as $\beta_0 \sim N(20, 1)$,$\beta_i \sim N(0, 1)$, $i = 1, 2, 3, 5$. In addition, the prior distributions for $\alpha's$ are set as $\alpha_0 \sim N(2.5, 1)$, $\alpha_i \sim N(0, 1)$, $i = 1, 2, 3$.

Markov chain Monte Carlo (MCMC) method was implemented by the Gibbs sampler, which iteratively drew samples of a parameter from its corresponding conditional distribution model (see [11] for the details of Gibbs sampler).

4. Numerical analysis

Two Markov chains with different initial values were run, with 100,000 iterations and 10,000 burn-in iterations for each chain. To validate the model and parameter settings, the Gelman-Rubin convergence diagnosis was performed. We had found the high autocorrelations among $\beta_0$and β_4 samples. The reason of high autocorrelations in these parameters can be explained by the low variety of equivalent energy values. Therefore, we conducted sample thinning with 20 thinning interval being set for each parameter.

Table 1 gives the posterior estimations of model parameters. Using the estimated value of each parameter and its corresponding standard deviation value, we can perform a t test to show whether or not the parameter is statistically significant. The p-values of these tests are listed in the table. We notice that, for the Weibull shape parameter, only supplier 2 has a significant effect, while the effects from other suppliers are not statistically different. For the scale parameter (characteristic life), all suppliers are significant. In addition, the large magnitude of β_4 (the coefficient of the equivalent energy factor) indicates that the energy equivalence variable can explain a large portion of variability in the Weibull distribution's characteristic life. Meanwhile, the negative value of β_4 indicates that the lifetime of PWB coupon is inversely proportion to the energy it absorbed. The method of preconditioning has an impact on the lifetime of PWB coupon only through the Weibull characteristic life, not through its shape parameter, as the coefficient α_4 is not statistically significant.

Using the regression model for the Weibull characteristic life, we may consider replacing the traditional reflow precondition by a proper IST precondition. As stated in [8], a 6-cycle reflow precondition with the temperature range from 25 °C to 250 °C, 12 min ramp time and 20 min cycle times can produce 782 joule equivalent energy, thus the last two terms of the right hand side of Eq. (6) is calculated as $-1.755 \times \log 782 + 0.2382 = -4.84$. By using an IST precondition with the temperature range from 25 °C to 245 °C, 3 min ramp time and 5 min cycle time, a 5-cycle IST has 660 joule equivalent energy and the last two terms of Eq. (6) is $-1.755 \times \log 660 = -4.94$, which is close to the previous reflow calculation. Thus, this IST preconditioning method can be used to replace the traditional reflow preconditioning method so as to avoid the use of reflow oven in the test and to reduce the total testing time. Furthermore, we performed a likelihood ratio test on the 5-cycle IST data (245 °C) and the 6-cycle RFO data from Supplier 4 and concluded that their failure time distributions are not statistically different. This conclusion is also confirmed by Fig. 2, where the fitted Weibull distributions for these two datasets overlap each other.

5. Conclusion

The low-cycle fatigue tests were conducted on the PWB coupons from four different suppliers. In this paper we demonstrate the use of Weibull regression model and computational Bayesian analysis method for identifying important factors on PWB lifetime. Our result shows that as the lifetimes of coupons from four suppliers are different in general, coupons from supplier 2 possess significantly lower life characteristic than others. Furthermore, we demonstrate that the energy equivalence approach is an effective approach for accounting for the variation in lifetime estimation due to different preconditioning methods and for setting IST parameters. Based on this approach, a 6-cycle reflow precondition can be replaced by a 5-cycle IST precondition, thus the total testing time can be greatly reduced.

Acknowledgements

We thank the anonymous referee for his/her constructive comments and suggestions. This work was partially supported by the NSF Grant CMMI 1301075.

Appendix A. Thermal cycle test dataset

Thermal cycle test dataset

Supplier 1			Supplier 2		Supplier 3		Supplier 4		
IST5 (230C)	IST6 (230C)	RFO6	IST5 (230C)	RFO6	IST5 (230C)	IST6 (230C)	RFO6	IST6 (240C)	IST5 (245C)
483	754	764	75	81	607	556	1055	1179	1056
340	520	637	11	84	608	556	1195	1512	1473
387	578	668	23	86	649	662	1196	1880	1567
539	851+	798	121	92	803	805	1491	1903	1713
321	491	616	8	103	827	851	1559	1934	1728
449	578	747	73	190	1065	933	1616	2149	1744
611					1500+	945	1622	2185	1809
618					1500+	956	1674	2424	2610
623					1500+	990	1706	2464	1800+
665					1500+	1048	1765	1800+	1800+
769					1500+	1108	1802		1800+
819					1500+	1151+	1889		1800+
869					1500+	1500+	1971		1800+
918					1500+	1500+	2045		1800+
1000+					1500+	1500+	2076		2821+
1000+					1500+	1500+	2120		2821+
1000+					1500+	1500+	2176		2821+
					1500+	1500+	2437		2821+
							2733		
							1800+		
							1800+		
							1800+		
							1800+		
							1800+		
							1800+		
							1800+		
							2800+		
							2800+		
							2800+		

References

[1] Dieter GE. Mechanical metallurgy. 2nd ed. New York, NY: McGraw-Hill; 1976.
[2] IPC-TM-650 Test methods: manual, Test Methods Subcommittee (7–11). (2001, May). DC current induced thermal cycling test (Number 2.6.26). Northbrook, IL: Association Connecting Electronics Industries (IPC), http://www.IPC.org.
[3] K.D. Cluff, M. Osterman, Defining accelerated test requirements for PWBs: A physics-based approach, presented at Association Connecting Electronics Industries (IPC) Printed Circuits Exposition, Long Beach, CA, March, 2002.
[4] B. Slough, *IST correlation study between Multek Asia, PWB Interconnect Solutions, and Multek Germany* (Report number MET161404, Tracking #1614). Jingan Town, Doumen, Zhuhai, Guangdong, PRC: Multek Asia Analytical & Materials Development Lab., 2005.
[5] Pang JHL, Xiong BS, Low TH. Low cycle fatigue models for lead-free solders. Thin Solid Films 2004;462–463:408–12.
[6] Jing HY, Zhang YY, Xu LY, Zhang GS, Han YD, Wei J. Low cycle fatigue behavior of a eutectic 80Au/20Sn solder alloy. Int. J. Fatigue 2015;75:100–7.
[7] Zhu Y, Li X, Gao R, Wang C. Low-cycle fatigue failure behavior and life evaluation of lead-free solder joint under high temperature. Microelectr. Reliabil. 2014;54:2922–8.
[8] Juarez J. Accelerated life testing of electronic circuit boards with applications in lead-free design. Ph.D Dissertation. Arizona State University; 2011.

[9] Blattau MD. Evaluation of IST test technology for plated through hole reliability. Master Thesis. College Park: University of Maryland; 1999.
[10] Lunn DJ, Thomas A, Best N, Spiegelhalter D. WinBUGS – a Bayesian modelling framework: concepts, structure, and extensibility. Stat. Comput. 2000;10:325–37.
[11] Gelman A, Carlin JB, Stern HS, Dunson DB, Vehtari A, Rubin DB. Bayesian Data Analysis. 3rd Edition Boca Raton, FL: CRC Press; 2014.