Applied Meta-Analysis

of Lead-Free Solder Reliability

by

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ABSTRACT

This thesis presents a meta-analysis of lead-free solder reliability. The qualitative analyses of the failure modes of lead- free solder under different stress tests including drop test, bend test, thermal test and vibration test are discussed. The main cause of failure of lead- free solder is fatigue crack, and the speed of propagation of the initial crack could differ from different test conditions and different solder materials. A quantitative analysis about the fatigue behavior of SAC lead-free solder under thermal preconditioning process is conducted. This thesis presents a method of making prediction of failure life of solder alloy by building a Weibull regression model. The failure life of solder on circuit board is assumed Weibull distributed. Different materials and test conditions could affect the distribution by changing the shape and scale parameters of Weibull distribution. The method is to model the regression of parameters with different test conditions as predictors based on Bayesian inference concepts. In the process of building regression models, prior distributions are generated according to the previous studies, and Markov Chain Monte Carlo (MCMC) is used under WinBUGS environment.

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TABLE OF CONTENTS

CHAPTER Page

LIST OF TABLES

LIST OF FIGURES

Figure Page

1 INTRODUCTION

The lead free solder technique attracts lots of attention lately. It has been applied to so many industries ranging from daily electronic appliance to aerospace equipment. The gradually transition of traditional lead-based solder alloy to lead-free solder alloy makes it even more import ant to study the reliability of lead-free solder.

1.1 Reason of Using Lead-free Materials

1.1.1 Pollution Problem

Lead is a very common metallic element which is naturally from earth crust. Because it can be easily found by mining, lead becomes one of the most inexpensive metallic elements. Lead compounds can release lead to the air under some circumstances. Lead itself is very steady, so it will stay in the air and fall with rain to the soil and water. It can be easily get into what humans breath, eat, and drink from. The toxicity of lead for human being could cause cancer, affects the normal function of almost every organ in the human body. Since lead can't break down, it is very difficult to be eliminated out of the body. So lead can cause a big pollution problem for air, soil, water, and eventually effect on human health.

The traditional lead-based solder alloy was widely used for soldering manufactory. But it is difficult to recycle the entire component since almost every electronic equipment needs solder. There are tons of lead are buried or just threw away improperly, which is a big threat to environment.

1.1.2 Legislation or Potential Legislation of Forbidden Using Lead

Since the lead material can cause a lot of pollution problems to both human health and earth natural environment, some associations advocate the legislation of using lead.

On February 13th, 2003, European Union first announced the Restriction of Hazardous Substances (RoHS) which is also known as Directive 2002/95/EC. The RoHS directive restricts the use of six hazardous materials in the electronic and electrical industry filed. The six forbidden materials are lead (Pb), mercury (Hg), cadmium (Cd), Hexavalent chromium (Cr^{6+}), polybrominated biphenyls (PBB) and polybrominated diphenyl ether (PBDE). It took effect on 1th July 2006 and every European Union member must adopt its own enforcement by following the RoHS as a guide by the effective date. The RoHS is not just a directive for European Union. It also places an important role for the entire electronic and electrical industry for the whole world. Since European Union contains 28 member states in Europe, it has big influence for the whole world. Furthermore, for the global economic era now, one product could be made and assembled by any country. For example, there is a smart phone sold in Italy while its primary board could be designed by a company in United States, manufactured in Mexico, assembled in China. If Italy follows the RoHS, it means the whole production line must follow the RoHS, and this could involve many countries from all five continents. Therefore, all of these factories in other country have to avoid using lead materials.

1.1.3 Trade Barriers between Countries With Legislation or Not

As mentioned above, the global economy has connected factories from all over the world together. If a company or a factory wants export their products to another country, it must follow the rules in its client's country, if the use of lead is strictly regulated in that country. So to avoid the trade barriers, lots of company would rather choose to do business with lead-free manufactories.

Because more and more electronic and electrical manufactories become lead-free manufactories, it becomes a trend of electronic and electrical industry of not using lead materials.

1.2 Importance of Studying the Reliability of Lead-free Solder

Since lead-free solder alloys is widely used in the electronic and electrical industry, it's important to know their performance under different use conditions. For example, the circuit board of the central computer of a Boeing 747 aircraft is under continuous and different frequency vibrations when the aircraft is working. If lead-free solder alloy is used on the circuit board, will it fail under such vibration? Or how long will the board life time be? No one wants to risk a control system stop working during the flight. A reliability study of lead-free solder under vibration would give us a good prediction of the failure life of lead-free solder under such vibration. As another example, for the smartphone that you carry with you every day, the risk of dropping and bending will also affect the failure time of lead-free solder in it. A reliability study would simulate the failure situation so that further research could be conducted to prevent of failures based on the reliability study.

1.3 Meta-analysis

Meta-analysis is a popular method when it comes to combine the previous studies. It aims at utilizing the former studies about the same topic to generate an optimal conclusion by combining the historical knowledge of a specific topic with the current study of the same topic. Meta-analysis usually includes both qualitative and quantitative analysis. In my study, to obtain a better understanding of lead-free solder reliability, the idea of meta-analysis is applied. Chapter 2 demonstrates the quantitative analysis of properties and failure mechanisms of lead-free solder joint. Chapter 3 exhibits the data analysis of failure life time of lead-free solder joint under thermal test utilizing the prior knowledge from previous research.

2 BACKGROUND OF LEAD-FREE SOLDER ALLOY

2.1 Most common Lead-free Solder Alloy

2.1.1 SAC (105,305,405…) Family

SAC alloys have been very popular in industry recently. SAC is the short term of the alloys which contain Sn, Ag and Cu. With the different proportions of Sn, Ag and Cu, SAC family has lots of members for different usage. Table 2.1 lists some of the most popular SAC alloy used in industry, along with their properties. The solidus melting points are around 217℃ while the liquidus melting points are about 220℃ to 230℃. The densities of them are around 7.4 g/cm³.

Table 2.1 Mechanical Properties of SAC Alloy

Lead free Alloy	Components	Solidus melting ℃	Liquidus melting ℃	Density (g/cm³)	Electrical Resistivity (μΩ·m)	Tensile Strength At Break, (kgf/cm²)
SAC 0107	Sn99.2Ag0.1Cu0.7	217	228	7.32		
SAC 0307	Sn99Ag0.3Cu0.7	217	228	7.33		300
SAC 0807	Sn98.5Ag0.8Cu0.7	216	225	7.33	0.140	310
SAC 105	Sn98.5Ag1.0Cu0.5	215	227	7.32	0.133	400
SAC 263	Sn97.1Ag2.6Cu0.3	217	224	7.36	0.132	
SAC 305	Sn96.5Ag3.0Cu0.5	217	220	7.38	0.132	500
SAC 405	Sn95.5Ag4.0Cu0.5	217	220	7.44	0.132	530
SAC 387	Sn95.5Ag3.8Cu0.7	217	220	7.44	0.132	600
SAC 396	Sn95.5Ag3.9Cu0.6	217				

Out of all the SAC alloys, SAC305 is the most widely used SAC materials for waving soldering with good wetting behavior and superior joint strength.

2.1.2 SCN

SCN is the short terms of Sn99.3Cu0.7Ni0.05, which have been popular used for wave solder applications. The melting point of SCN is around 227℃, which is slightly higher than SAC 305 (217℃). Drop test and thermal cycling test [1] show that SNC performance similarly to SAC 305, however, SCN is less reliable comparing to Ag added SAC305. But cost of SCN is less than SAC, it is still a good choice to use SCN for industry based on its performance.

2.1.3 Sn-Ag Alloy

Sn-Ag alloy is also an alternative as lead-free solder material. Typically, Sn-Ag alloys contain 3% to 5% Ag. Sn- Ag is a good choice for high temperature solder. Sn96.5Ag3.5 is a widely used Sn-Ag alloy with melting point 221°C. Because of the high proportion of Ag, Sn96.5Ag3.5 maintains higher reliability for high temperature interconnect requirement. So Sn-Ag alloy are used for central heat and hot water pipes since the high temperature resistance as well as die attachments and electronic assemblies.

2.2 Effect of Ag in Lead-free Solder Joint Material

Ag has been used for solder alloy for years, in both tin-lead solder materials and lead-free materials. It plays a really important role in solder joint materials. Ag contributes some great properties for a solder alloy. The advantages of adding Ag into solder alloy materials are as follows.

2.2.1 Ag Lower the Melting Temperature

Lots of studies have been conducted for the solidus and liquidus melting point for Ag alloy. It indicates that the increase of Ag weight percentage in the alloy will result in the decrease of eutectic point within a certain rage. As it shows in Figure 2.1[2], considering the weight percentage of Ag fewer than 3.5% out of the total alloy weight, the liquidus melting temperature of alloy decreases as Ag content increases. Also in Figure 2.2, with 0.7% Cu in the alloy, when Ag weight percentage is below 1.5%, the increasing of Ag weight will dramatically decrease the alloy melting point. When Ag weight percentage is larger than 0.3%, the melting point of alloy is between 217℃ and 227℃, which meets the requirements of reflow soldering and lead-free wave soldering.

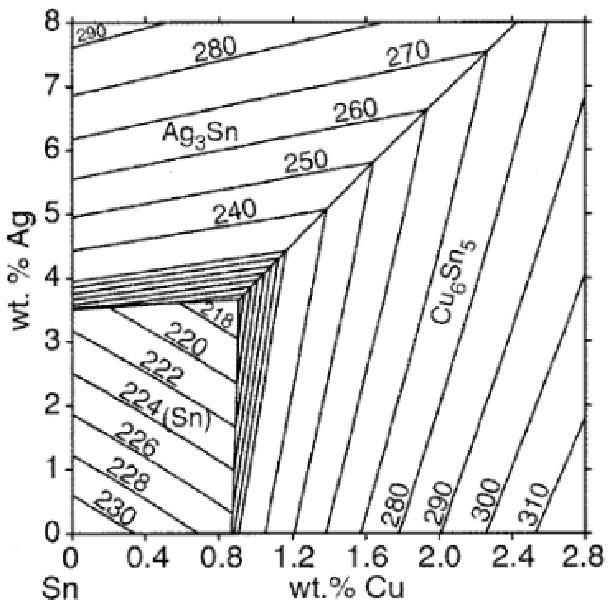


Figure 2.1 Liquidus Melting Temperature of SAC Alloy[2]

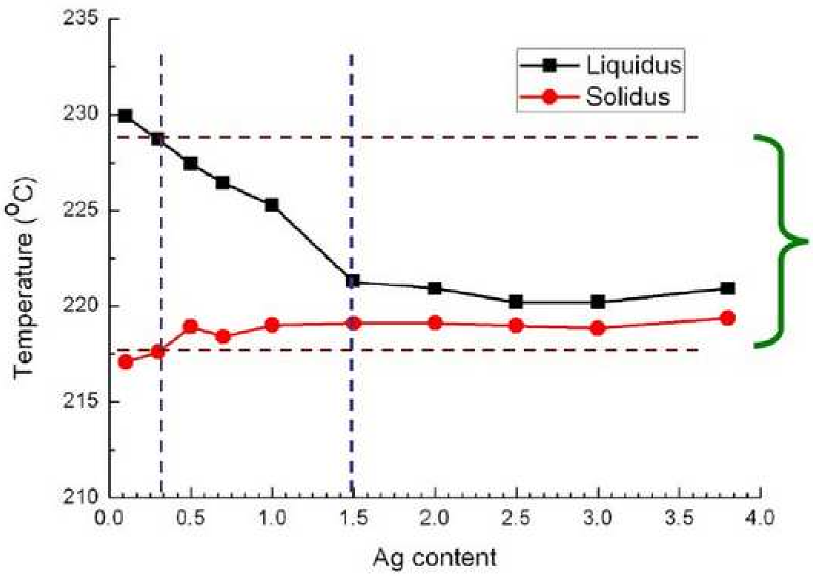


Figure 2.2 Liquidus Melting Points of Sn-xAg-0.7 Cu

2.2.2 Ag Improve Tensile Strength

Table 2.1 shows the mechanical properties of SAC alloy. In the seventh column of Table 2.1, there is an increase trend of tensile strength of alloy when the content of Ag increases. Ag content affects the Ag_3Sn intermetallic. Fine intermetallic compound (IMC) dispersion and Sn grain size was discovered by F.X. Che et al [3]. The dispersion of Ag_3Sn intermetallic and fine Sn grain size results in high tensile stress. [3]

2.2.3 Ag Improve the Wetting Behavior of Alloy

Intrinsic wetting ability is the ability of a liquid material which can still contact with solid material to maintain the intermolecular interactions between the liquid and solid materials when putting them together. And the wetting ability is a very important property of solder alloy since the function of solder alloy is to get the best connection with solid surfaces. SAC307 and Sn0.7Cu were tested for a wetting balance test. The result shows Ag added SAC alloys have lower surface tension which results in better wetting performance comparing with Ag free alloy.

2.3 Failure Modes of Lead-free Solder Under Different Tests

2.3.1 Drop Test

During the last two decades, portable electronic products have been very popular for the electronics manufacturing industry. People carry smart phones, digital cameras, and tablets with them all day long for working and entertaining. The high frequency of using increases the risk of accidently dropping the devices. And those portable devices can contain tons of solder joints on their main chips, which make it very important to study the reliability of lead-free solder joint under drop test.

a. Failure Mode

According to the drop tests conducted by Jin-Wook Jang et al [4], he tested two types of solder joints which are eutectic Sn37Pb and Sn3.8Ag0.7Cu (SAC387). Solder balls were all 200μm in diameter and sold on a 10mm*10mm BGA package. The drop height was 70 cm. After five drop tests for each assembly samples, scanning electron microscopy (SEM) was used for investigating the failure mode of drop tests.

For both lead-free for lead-based solder, failure occurred at interface of device side which was higher stressed.

For Sn3.8Ag0.7Cu lead-free solder, all failures were brittle interfacial cracking. The crack occurred in IMC layer and propagates through it. For Sn37Pb lead-based solder, most failures were bulk solder deformation; the crack propagated within the solder joint. The strain rate sensitivity of SAC solder alloy is much higher than lead-base solder alloy which is due to the crystal structure and Ag_3Sn intermetallic. The low stain rate results in solder deformation. While with the high stain rate intermetallic prevent the deformation of solder joint and crack will occur within the intermetallic layer instead of the bulk. However, the deformation of the solder alloy can absorb some of the strain and results in a longer failure life. In other words, SnPb performs better than lead-free alloy SAC387 in a drop test.

b. Low Ag Content in Lead- free Alloy Results in Better Performance

According to the drop test conducted by Kim, Hyunchul, et al [5], SAC105 and SAC405 were tested by dropping a 14 mm x 14 mm x 1 mm test vehicle with 15 printed circuit board soldered on. The free-fall test was designed with sine distributed acceleration. Peak acceleration was 1500g with 0.5 millisecond duration.

There were two types of failure modes. Crack propagated through IMC layer only and crack propagates through the bulk of solder joint. The propagate speed within IMC layer was higher than within the bulk of solder joint since IMC layer is way more brittle. In other words, solder joints with cracks within the bulk of solder joints have longer failure life than cracks through IMC layer. For SAC405, about 90% of the failure modes were cracks through IMC layers while 10% of them propagate through the bulk. However, the ratio of two types of failure modes in SAC105 was about 1:1. So the low Ag content lead-free alloy SAC105 performs better than high Ag content SAC alloy SAC405. It is due to the higher compliance and higher plastic energy dissipation ability of low Ag content alloy. [6]

2.3.2 Bend Test

Smart phones are getting slimmer and slimmer these days. The thinnest smart phone is only 5.55mm thick. The famous iPhone 6 is 6.9mm with 4.7” screen. But because the smart phones are too thin while the screens are too big at the same time, they can easily get bend by accident. iPhone 6 recently got lots of costumer reviews saying it can bend even when people sitting with the iPhone in the pocket. However, even if phones are bent, they might still work full functionally which means all the solder joints are in good shape and perfectly working. Some bend tests are necessary to evaluate the reliability of lead-free solder joints when bending, twisting or under pressure.

Ilho Kim and Soon-Bok Lee developed a cyclic bending test [7]. A PBGA test sample with 256 solder joints with diameter of 760 μm was used for this bending test. The test started with using 1Hz sinusoidal wave with different amplitudes as 25, 30, 40, 50 and 60 N. For each amplitudes load, there were five duplicate tests to reduce the random error. Sn37Pb and SAC405 were used as solder alloy to study the deference between lead-free and lead-base alloy under bending condition.

Result indicates the most severe failure occurred at both sides of the package, which is easy to explain since they were under the maximum pressure. For the solder balls, the failure crack length was in proportion to the distance from the center. Figure 2.3 [7] shows the difference of failure life time between Sn37Pb and SAC405. Both plots of Sn37Pb and SAC405 are showing large stress contributes to lower the failure life. When applied load is below 37N, SAC405shows longer failure time, while when applied load is larger than 37N, Sn37Pb shows better reliability than lead-free alloy.

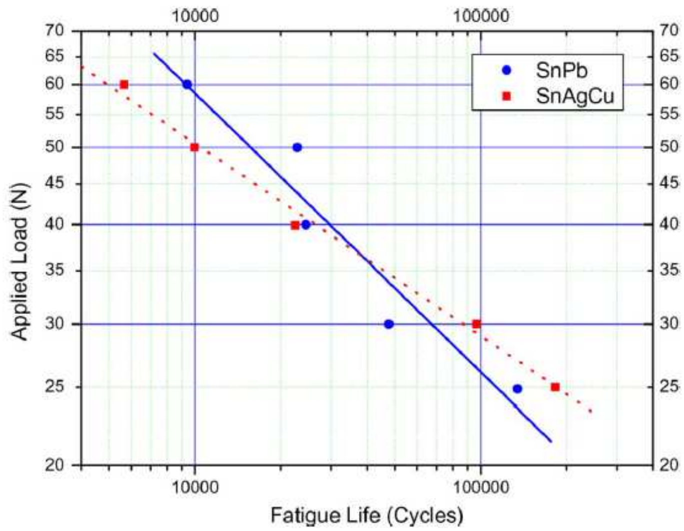


Figure 2.3 Failure Life Time in Bend Test[7]

A finite element analysis was also used to investigate the stress and strain induced in solder balls. As expected, the maximum stress and inelastic deformation occurred at the edge of the package and on the device side. The crack initially happened within the solder balls at the very edge of the board, and propagated towards the center of the package. Also, inelastic energy dissipation contributed a shorter failure life time of solder joints.

2.3.3 Thermal Cycling Test

a. SAC Alloy Has Higher Life Than Lead-based Solder Alloy

Finite element modeling is a good method to simulate the stress and strain distribution over the solder joints. Amir M. Lajimi et al. [9] simulated a 2-dimentional finite element model to replace an actual thermal cycling test for SAC and tin-lead solder joints at a lower cost. The thermal cycle temperature range was -55 °C to +75°C and a sin function was used to simulate the changing temperature with 20 minutes duration for each cycle. Results show that both SAC alloy and tin-lead alloy are at high reliability under thermal cycling test with at least 2000 cycles failure life time. However, SAC alloy performs better with a higher life time.

b. Failure Modes

According to thermal cycle test conducted by Suhling, Jeffrey C., et al [8], the key reason of the failure of lead-free solder joint under thermal cycle test is the crack across the joint until components are detached from the package. Initial cracks occur under the component, and propagate along the components edge until across the entire solder joint with a final failure.

c. Wider Range of Thermal Cycle Temperature Increases the Risk of Failure

In the test conducted by Hongtao Ma, et al [10], both SAC305 and Sn3.5Ag alloy showed the similar result that wider range of thermal cycle temperature accelerate the failure of solder joint. For narrow thermal cycle temperature range like 0–100 °C and −40–125 °C, cracks were easily found near the PCB side, the package side and within the bulk solder. But for wider thermal cycle range like −55–125 °C and −60–150 °C, samples indicated a mixture of failure mode and severer than narrow thermal range. Cracks occurred at both PCB and package sides of the samples. A large number of pad cratering failures were found in tested samples while there were no pad cratering failures in narrow thermal cycle condition. Studies showed that lead-free solder joints were stiffer at low temperature condition. So under extreme low temperature like −55 °C, solder joints absorb less energy causes cracks occur in laminate form the pad cratering failure which increases the risk of failure.

d. High Ag Content and Higher Bond Line Thickness Result in Better Fatigue Performance During Thermal tests.

Comparing SAC 105, SAC 305 and SAC 405, SAC 405 has the longest failure life while SAC 105 has the shortest under different bond line thickness. Also for each kind of those lead-free alloys, failure life increases as bond line thickness increases [11].

2.3.4 Vibration Test

a. Fixed Vibration Force

According to the vibration test conducted by Song, Jenn-Ming, et al [12], Sn37Pb, Sn0.7Cu, Sn3.5Ag were used for this experiments, samples were 20 mm*100 mm*4 mm rectangular with two V notches at the top and bottom sides of it which are clamped on the vibration device to form a simple cantilever-beam vibration system. A fixed harmonic vibration force 3.5 g was used to conduct the test.

Results showed that Sn37Pb, Sn0.7Cu and Sn3.5Ag all had similar failure life time under the vibration, Sn37Pb had the highest average failure life time which was around 23000 cycles, followed by Sn0.7Cu for 22000 and Sn3.5Ag which was around 21000 cycles. Although the failure life times were similar, the failure modes were quite different between lead-free and lead-based alloy. For lead-free alloys, there were proeutectic Sn dendrites within Sn-Ag and Sn-Cu while Sb-Pb did not contain that kind of microstructure. Those proeutectic Sn dendrites contributed to striated deformation pattern which resulted in high damping capacity. Along with the deformation pattern, the initial crack propagated tortuously through the samples instead of a straight crack as shown in SnPb alloy. The good damping capacity of lead-free alloy benefited them with the longer failure life time behavior under high level vibration test. Comparing to Sn-Pb alloy, both striated deformation of proeutectic Sn and interphase failure occurred under vibration. The initial crack propagated along Sn/Pb interphase and Sn/Sn grain boundaries, and striated deformation can absorb part of the energy.

b. Random Vibration

SAC solder alloy were used for vibration tests for different acceleration PSD (power spectral density) amplitudes [13]. The PSD amplitudes were 60 $(m/s^2)^2/Hz$, 80 $(m/s^2)^2/Hz$, 120 $(m/s^2)^2/Hz$ and 160 $(m/s^2)^2/Hz$. As a result, larger the PSD amplitudes ended up in the lower the failure life time of the lead-free solders. And it's easy to understand since the amplitude is proportional to the energy. Compare between different energy level, the same solder would have lower fatigue life when absorbing large energy. Furthermore, when PSD amplitudes increased, the failure mode of solder changed. The location of crack changed from within the bulk of solder ball close to PCB side to within the IMC interface close to BGA side. For the solder balls under 60 $(m/s^2)^2/Hz$ amplitude, cracks were within the bulk of solder ball close to PCB side and propagated almost randomly though the bulk until the failure occurs. There were cracks along the BGA side as well, but the speed of propagating was lower than the crack at PCB side. For the solder balls under 80 $(m/s^2)^2/Hz$ amplitude, only cracks at BGA side were observed and still randomly crossed the solder ball. For the solder balls under 120 $(m/s^2)^2/Hz$ amplitude, the crack initially occurred within the IMC layer and propagate along within IMC layer, at the end of crack, it went slightly into the bulk of solder ball and finally causes the failure. For the solder balls under 120 $(m/s^2)^2/Hz$ amplitude, crack initially happened at IMC layer and propagated straight along the IMC layer until the failure occurs. Also, cracks within IMC layer were considered as brittle failure while cracks within bulk are ductile failure.

c. High Frequency Vibration

SnPb alloys show better performance under high frequency vibration test comparing to lead-free alloy. SAC alloys show early failures at a lower number of vibration cycles which might due to a mixture of different failure modes. Observed failure modes are cracks through intermetallic layer and cracks through the solder but very close to the intermetallic layer. Comparing two high frequency vibration test conditions with 400Hz and 800Hz, both SnPb and SAC alloy show better fatigue life under 400Hz other than 800Hz. The result also shows the content of Ag is proportional to the fatigue cycle time.

3 WEIBULL REGRESSION ANAYSIS OF THERMAL CYCLE RELIABILITY OF LEAD-FREE SOLDER ALLOY

3.1 Description of Collected Data

To further study the fatigue life of lead-free solder alloy under thermal cycle, a data set from Joseph Juarez [14] has been used. Joseph Juarez designed a thermal test to investigate the influence of interconnect stress test (IST) and reflow thermal preconditioning processing on the failure cycle time of lead-free solder. The preconditioning process simulates the assembly process in the real production system. IST heats the internal environment of tested coupons by the interconnect circuit via resistive heat transfer in a very short time. In reaction the temperature of the coupon increases as the amount of current passed through the coupon increases. For this test, 5 inch*7 inch *1 inch coupons were used. Each coupon was made of 14 layers of circuitry with an electrical circuit daisy chain. SAC was tested as a representative of lead-free solder alloy in this test.

Each cycle was performed as follows: use IST to heat the coupon for three minutes until reaching the ramping temperature of 230°C, and then cool the coupon at a room temperature of 25°C for two minutes, making the cycle time for the IST test a total of five minutes. Other than IST, reflow was also considered as an alternative for the thermal process method. Different from IST, reflow system is more traditional as a thermal method with an oven involved. Each tested coupon passed through the reflow oven for 12minutes under the temperature 250°C. This way, coupons were heated directly via convection heat transfer. After 12 minutes in an oven, coupons stayed in room temperature environment for eight minutes cooling down. Thus, the total thermal cycle for reflow system was 20 minutes. After five or six preconditioning cycles, the same thermal condition method repeated to heat the coupons until failure occurred.

Other than thermal test methods, different suppliers for the components were considered as a factor of failure life behavior for lead-free solder. In this test, 3 suppliers were chosen and coded as supplier 1, 2 and 3. However, some of the data were missing the information of the supplier, in this case, coded it as supplier 4. A batch of six coupons was tested each time.

For supplier 1, three batches were tested under the IST environment for five preconditioning process cycles, one batch was tested using IST for six preconditioning process cycles, and one batch of coupons was tested using reflow for six preconditioning process cycles. Cycles to failure data were collected for each coupon which censored at 1000+ cycles. During the test for supplier 2, one batch was tested for IST method for five preconditioning process cycles while another one batch of coupons was tested using reflow for 6 preconditioning process cycles. Finally for supplier 3, only IST was used for thermal cycling condition, three batches were preconditioned for five cycles and another three batches were preconditioned for six cycles.

For the data without supplier information, three sets of data were collected under different thermal conditions. Ten coupons were tested under IST conditioning for six cycles with ramping temperature 240 °C and ratio of ramp time to cycle time is 0.6. Thirty coupons were tested under reflow conditioning for six cycles with ramping temperature 240 °C and ratio of ramp time to cycle time is 0.606. Eighteen coupons were tested under IST conditioning for five cycles with ramping temperature 245 °C and ratio of ramp time to cycle time was 0.6. Table 3.1 summarizes the collected test data.

Table 3.1 Thermal Cycle Test Data Set From Juarez's Tests

Supplier 1			Supplier 2		Supplier 3		Unknown Supplier		
IST 5	IST 6	RFO 6	IST 5	RFO 6	IST 5	IST 6	IST 6	RFO 6	IST 6
539	578	616	8	103	1500	556	1934	1971	1800
449	491	798	23	84	1500	1108	1880	1491	1567
918	754	668	75	86	1500	990	2424	1559	1744
321	520	764	121	190	1500	956	2464	1622	1800
819	578	637	11	81	1500	1151	1179	2437	1728
1000	851	747	73	92	1500	805	1512	1889	1713
483					607	662	1800	2045	1800
769					608	945	2149	1802	1800
1000					649	933	1903	1765	1800
623					827	1048	2185	1800	1800
611					1065	851		1800	2821
387					803	1500		1800	2821
618					1500	1500		1800	2821
340					1500	1500		1706	2610
869					1500	1500		1616	2821
1000					1500	1500		1196	1056
665					1500	1500		1800	1473
					1500	556		1800	1809
								2733	
								2176	
								2800	
								2800	
								1674	
								2120	
								2076	
								2800	
								1195	
								1055	
								1800	

3.2 Methodology

3.2.1 Weibull Regression

Weibull distribution is a very flexible continuous probability distribution with two parameters and it is widely used for reliability analysis. It has two parameters which are shape parameter $\upsilon > 0$ and scale parameter $\eta > 0$ with the probability density function as:

$$f(x) = \begin{cases} \frac{\upsilon}{\eta}\left(\frac{x}{\eta}\right)^{\upsilon-1} e^{-(x/\eta)^{\upsilon}} & x \geq 0 \\ 0 & x \leq 0 \end{cases}$$

Cumulative distribution function is

$$F(x) = \begin{cases} 1 - e^{-(x/\eta)^{\upsilon}} & x \geq 0 \\ 0 & x \leq 0 \end{cases}$$

The hazard rate function is

$$h(x) = \frac{\upsilon}{\eta}(\frac{x}{\eta})^{\upsilon-1}$$

And the reliability function is

$$R(x) = e^{-[(\frac{x}{\eta})]^{\upsilon}}$$

With shape parameter $0 < \beta < 1$, the Weibull distribution has a decreasing hazard function; when $\beta > 1$, the Weibull distribution has an increasing hazard function. Because of the flexibility given by shape parameter, Weibull distribution can be used to model failure time data with decreasing or increasing hazard function. When hazard function of the data is unknown, Weibull distribution is a good choice to adjust different types of failure data. [15]

3.2.2 Bayesian Inference

According to Bayes' Theorem, the probability of event A happens under the condition of event B happens is related to the probability of event B happens under the condition of event A happens:

$$\mathrm{P(A|B)} = \frac{P(B|A) \cdot P(A)}{P(B)}$$

Based on Bayes' Theorem, with a set of observed data y and unknown parameters θ, the Bayesian inference is to get a posterior based on the knowledge of prior of parameters θ and new data:

$$P(\theta \mid y) \propto P(y \mid \theta)P(\theta)$$

where $P(\theta|y)$ is the posterior distribution we want to know, $P(y|\theta)$ is the likelihood, $P(\theta)$ is the prior distribution. The posterior distribution is proportional to likelihood multiplied by the prior.

3.2.3 Markov Chain Monte Carlo (MCMC)

In reality, lots of posterior are high dimensional and which makes it hard to solve. Markov Chain Monte Carlo is a good method to solve such problem. MCMC is a stochastic simulation tool by constructing a Markov chain with equilibrium distribution $\pi(\theta)$ to generate a good sample of $\pi(\theta)$. MCMC could be divided into three steps:

1. To construct a Markov chain, make its convergence to the stationary distribution $\pi(\theta)$
2. With the sampling Markov chain simulation in step 1, produce the point sequence $\theta^{(1)}, \dots, \theta^{(n)}$.

3. Monte Carlo Integration, with large enough n, the expectation of function $f(x)$:

$$E(f) = \frac{1}{n}\sum_{t+1}^{n} f\left(\theta^{(t)}\right)$$

3.2.4 Gibbs Sampling

Stuart and Donald Geman first described Gibbs sampling at 1994, which is a sampling algorithm based on MCMC. It is one of the simplest MCMC sample methods. To select m samples out of $X = (x_1, x_2, \dots, x_n)$ from a joint distribution $p(x_1, x_2, \dots, x_n)$, and i indicates the times of sampling, like $X^{(i)} = ({x_1}^{(i)}, {x_2}^{(i)}, \dots, {x_n}^{(i)})$ represents for the ith sample from the data set. By starting with an initial sample value $X^{(0)}$, for any $i \in \{1, \dots, m\}$ and any $j \in \{1, \dots, n\}$ sample ${x_j}^{(i)}$ using the conditional distribution $p(x_j | {x_1}^{(i)}, \dots ,\ {x_{j-1}}^{(i)}, {x_{j+1}}^{(i-1)} \dots, {x_n}^{(i-1)})$. Use the most recent updated value to sample the next one. Repeating the algorithm until it converges and reaches out a good sample of X.

Gibbs sampling is a popular method used in MCMC algorithm. To apply Gibbs sampling, there are several software packages that we can use which are called BUGS. BUGS stands for Bayesian inference using Gibbs sampling. WinBUGS is one of the BUGS software that has been popular used in solving MCMC problems. It developed by a team of British data scientists at 1997.Further data analysis will be conducted using WinBUGS.

3.3 Model Explanation

From the former studies about the reliability of lead-free solder, a Weibull distribution is assumed as a good fit for studying the failure time data. In this test, assume that cycles to failure data is Weibull distributed with a shape parameter v and a scale parameter λ.

$$t \sim weibull(v, \lambda)$$

Regarding the parameters notation in WinBUGS code, the scale parameter is different from the one we widely use. In the WinBUGS code, scale parameter is:

$$\lambda = \frac{1}{\eta^{v}} = \eta^{-v}$$

In which, η represents the scale parameter we usually use of a Weibull distribution and it also represents the characteristic life of the tested data, v is the shape parameter.

According to the ccumulative distribution function of Weibull distribution, the probability of unit fails at cycle η is as follows:

$$F(\eta) = 1 - e^{-1} = 0.632$$

The characteristic life is the time when 63.2% units fail. Therefore, η or characteristic life is a good indicator to investigate the behavior of product failure time and discuss the reliability of it.

From the former studies about lead-free solder reliability shows that the shape parameter is highly related to the material of test sample. The attributes and properties of the material have a big influence of the shape parameter. In Juarez's test, since the lead-free alloy is the same for each test, a differentiation of suppliers and thermal cycle methods are been considered as influence factors for shape parameter v. A linear regression model is as follows:

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

where s_1, s_2 and s_3 are categorical variables indicating which supplier is used in for the test component. $s_1 = 1$ indicates supplier 1 is used and $s_1 = 0$ indicates supplier 1 is not used. Same as s_2 and s_3. So when $s_1 = 0$, $s_2 = 0$ and $s_3 = 0$ at the same time, it represents the second part of data without supplier information. Categorical variable $r = 1$ indicates test is under reflow preconditioning and $r = 0$ indicates test is under IST preconditioning.

For scale parameter, historical studies indicate that it's more sensitive than shape parameter. Any change of the test condition might make a difference with the scale parameter. In this study, a differentiation of suppliers and energy absorbed by coupons could affect the scale parameter. In the test, two different thermal conditioning methods were used. The ramping temperature, ramping time, cooling time and total cycle time are all different. How to make the energy quantifiable becomes a major concern. Based on Juarez's research, the energy absorbed by test samples during thermal cycle test could be calculated by the following equation:

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

where PCC represents the time of preconditioning process cycles, ΔT represents the temperature gap between ramping temperature and cooling down temperature, and RT is the ramping time while CT is the total cycle time.

By this assumption, it can easily transfer the different thermal conditions to joule equivalent energy that absorbed by coupons which is much easier to conduct a regression model with.

A linear regression model is formulated for scale parameter:

$$ln(\eta) = \beta_0 + \beta_1 s_1 + \beta_2 s_2 + \beta_3 s_3 + \beta_4 \ln(je) + \beta_5 r$$

Then numerical variable je indicates the joule equivalent energy absorbed by each coupon.

The reason for using ln for both λ and je is due to the inverse power law for Accelerated Life Testing (ALT).

Inverse Power Law

The inverse power law is widely used to express the relationship between failure life time and the stress level.

$$L(V) = \frac{1}{KV^n}$$

L is a quantifiable life time measurement, such as mean life, characteristic life, median life. In this case, is the scale parameter η, which is also the characteristic life.

V is the stress level. In this case, is the energy je, which is not exactly stress to test coupons, but assumption is made that it's has the similar impact as stress to test coupons.

$K\ and\ n$ are the parameters for the model to be determined, in this case, are the suppliers.

A natural log transformation is made to transfer the inverse power function to a linear function.

$$\ln(L) = -\ln(K) - n\ln(V)$$

According to inverse power law, a linear regression model of the characteristic life η is built.

Based on the model analysis, a Weibull regression is conducted in WinBUGS environment. The logical model for Weibull regression using Bayesian inference in WinBUGS is:

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

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

$$\lambda[i] = \frac{1}{\eta[i]^{v[i]}} = \eta[i]^{-v[i]}$$

$$ln(\eta[i]) = \beta_0 + \beta_1 s_1[i] + \beta_2 s_2[i] + \beta_3 s_3[i] + \beta_4 \ln(je[i]) + \beta_5 r[i]$$

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

WinBUGS conducted Gibbs sampling to generate a good fit of the model, and gives posterior distributions of parameters αs and βs. To do MCMC, prior distributions are needed.

3.4 Prior

Priors can be non-informative or informative distributions based on the knowledge of historical data. In this study, historical failure time data of SAC solder joint under preconditioning process is found. An informative prior distribution of coefficient of variable joule equivalence can be concluded from the former test data.

A similar test was conducted by Slough [16] with 54 coupons under IST preconditioning process for six cycles and the joule equivalence is 738J, another 58 coupons under reflow preconditioning process for six cycles with joule equivalence is 615J. Table 3.2 is a summary of the historical data.

Table 3.2 Thermal Cycle Test Data from Former Research[16]

IST 6 PCCX230C RT/CT = 0.6			RF0 6 PCCX230C RT/CT = 0.5		
235	240	401	348	294	340
287	344	243	352	604	407
331	247	318	323	551	513
135	149	196	676	393	796
317	163	142	465	1000	732
349	202	211	578	246	1000
302	210	254	665	270	963
198	144	310	388	292	395
216	208	279	290	221	568
179	167	485	183	268	617
441	183	295	329	402	453
137	145	218	472	361	579
115	124	198	319	267	
225	229		330	389	
166	296		740	477	
181	204		265	853	
418	264		254	442	
208	270		416	672	
239	147		424	446	
145	220		248	537	

Assuming the failure cycle time is Weibull distributed with shape parameter v and scale parameter η. Fit the data set with Weibull distribution, therefore, two Weibull distributions were generated because of two test conditions. Figure 3.1 represents the Minitab results of fitted distribution using prior data in Table 3.2.

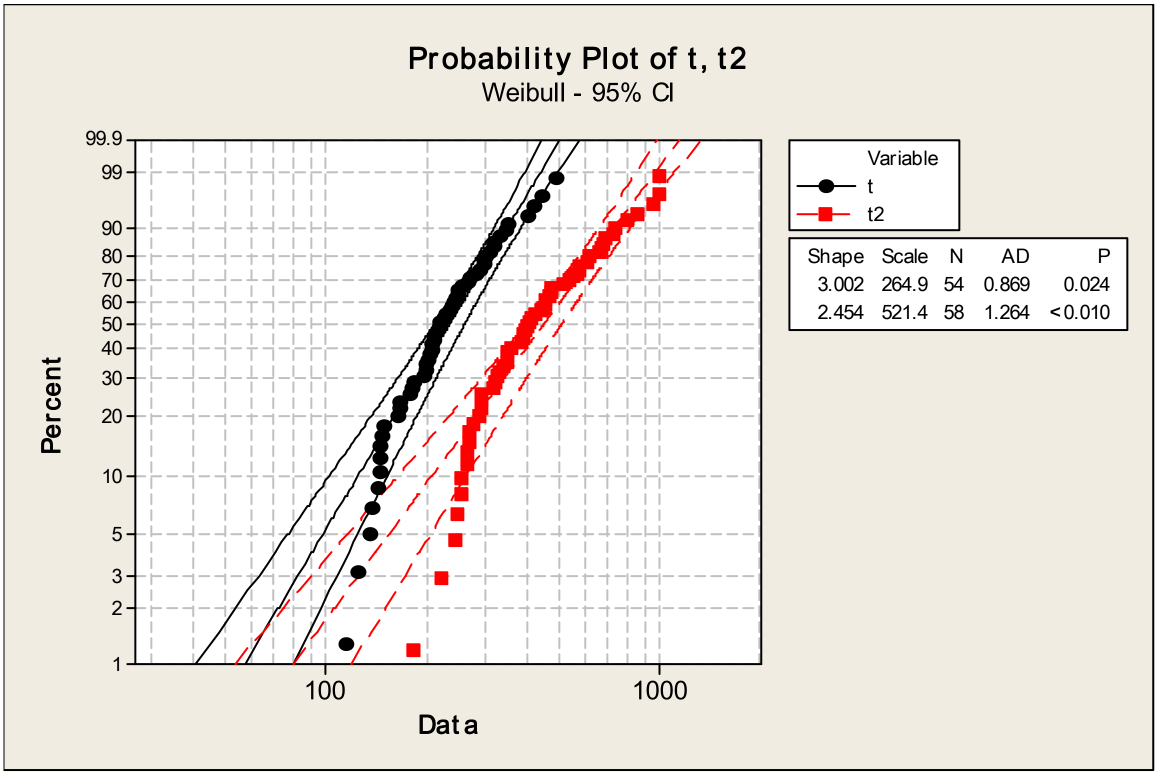


Figure 3.1 Weibull Probability Plots of Prior Data in Minitab

$$je = 738J: \qquad t_1 \sim weibull(3.002, 264.9)$$

$$je = 615J: \qquad t_2 \sim weibull(2{,}454, 521.4)$$

Assume shape parameter is only highly related to the material, and scale parameter is related to the energy absorbed by coupons during the thermal testing. A linear regression is generated as

$$\ln(\eta) = 26 - 3\ln(je)$$

So the coefficient of $\ln(je)$ is -3, based on that, a prior distribution could be assumed as

$$\beta_0 \sim dnorm(20, 1)$$

$$\beta_1 \sim dnorm(0, 1)$$

$$\beta_2 \sim dnorm(0, 1)$$

$$\beta_3 \sim dnorm(0, 1)$$

$$\beta_4 \sim dnorm(-3, 1)$$

$$\beta_5 \sim dnorm(0, 1)$$

From other lead-free solder thermal tests, the shape parameter is highly related to the solder material. In this case, all the materials are the same. Different suppliers can slightly influent the value of shape parameter. So prior distributions for $\alpha's$ could be:

$$\alpha_0 \sim dnorm(2.5, 1)$$

$$\alpha_1 \sim dnorm(0, 1)$$

$$\alpha_2 \sim dnorm(0, 1)$$

$$\alpha_3 \sim dnorm(0, 1)$$

$$\alpha_4 \sim dnorm(0, 1)$$

A doodle model in Figure 3.2 built by WinBUGS shows a good understanding of the relationships between variables and parameters.

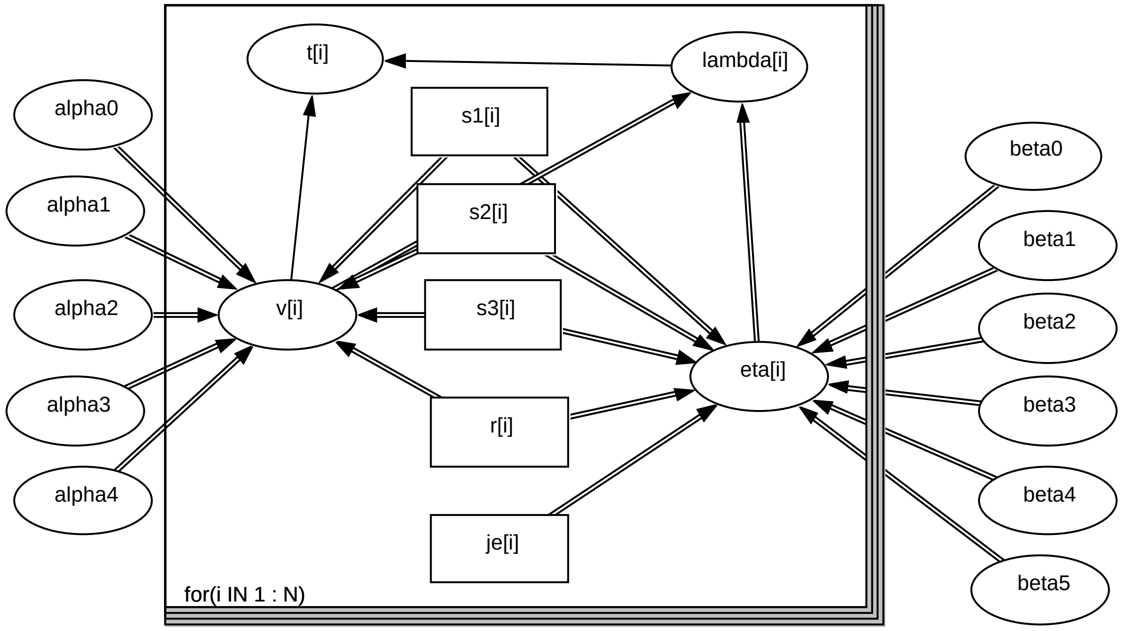


Figure 3.2 Doodle Model of Weibull Regression

3.5 Validation

Two Markov chains are set with initial value as:

Chian1: $\alpha_0 = 1, \alpha_1 = 0, \alpha_2 = 0, \alpha_3 = 1, \alpha_4 = 1, \beta_0 = 20, \beta_1 = 0, \beta_2 = 0, \beta_3 = 0, \beta_4 = -3, \beta_5 = 0$

Chian2: $\alpha_0 = 2, \alpha_1 = 0.5, \alpha_2 = -0.5, \alpha_3 = 0.5, \alpha_4 = 0.5, \beta_0 = 15, \beta_1 = 0.5, \beta_2 = -0.5, \beta_3 = 0.5, \beta_4 = -2, \beta_5 = 0.1$

With 10000 iterations and 1000 burn-in iterations for each chain, WinBUGS gave us posterior estimations. To validate the model and settings, a convergence diagnostic is taken into consideration. In WinBUGS, a bgr diag button allows us to check the convergence situation of the chains using the Gelman-Rubin convergence diagnostic.

Gelman-Rubin Convergence Disgnostic

Gelman-Rubin diagnostic is an ANOVA-type test which calculates not only the within-sample but also the between-sample variability. So it can only test multiple chains instead of single chain. Three statistic variables are been considered to determine whether the chains converge.

Average within-sample variance WSS which is in blue line in the bgr plots generated by WinBUGS.

Pooled posterior variance estimate (green line in WinBUGS plot):

$$\hat{V} = \frac{T' - 1}{T'} WSS + \frac{BSS}{T'} \frac{\kappa + 1}{\kappa}$$

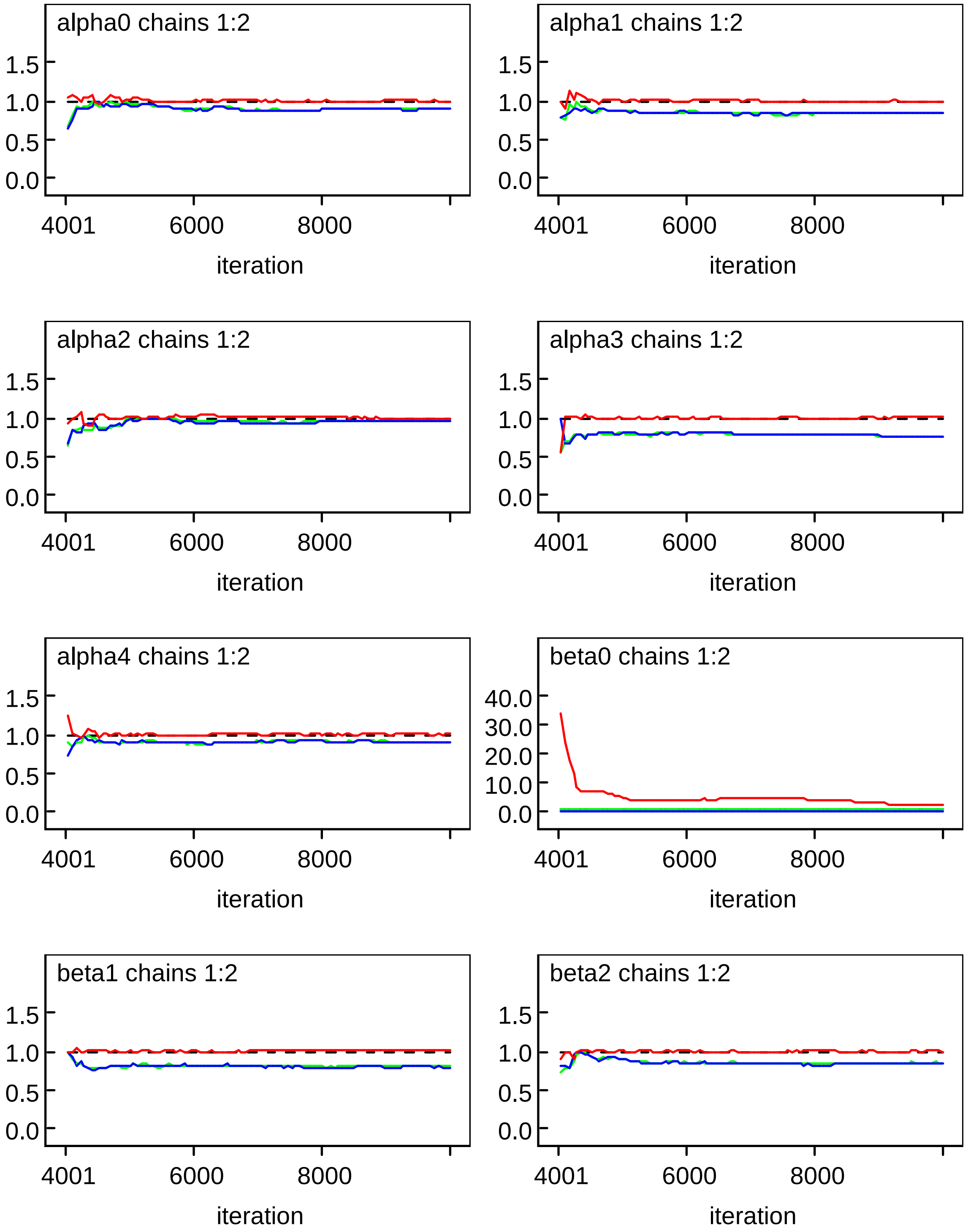
where κ is the number of chains, T' is the number of iterations kept in each chain and BSS represents the variance of the posterior mean values of each chain, so $\frac{BSS}{T'}$ represents the between-sample variance.

And statistic R is the ratio of pooled posterior variance to within sample variance and can be estimated by:

$$\hat{R} = \frac{\hat{V}}{WSS} = \frac{T' - 1}{T'} + \frac{BSS}{T' * WSS} \frac{\kappa + 1}{\kappa}$$

$\hat{R} > 1$ shows a good scattered value over the parameter space, so we expect $\hat{R} > 1$ at the beginning of the chain. However, $\hat{R} = 1$ indicates the convergence of the algorithm. So a good algorithm will has the value of $\hat{R}$ be greater than one at first few iterations and then close or equal to 1 with $\hat{V}$ and WSS being stable as the number of iterations grows.

For our model, WinBUGS plots the Gelman-Rubin diagnostic plot as Figure 3.3.



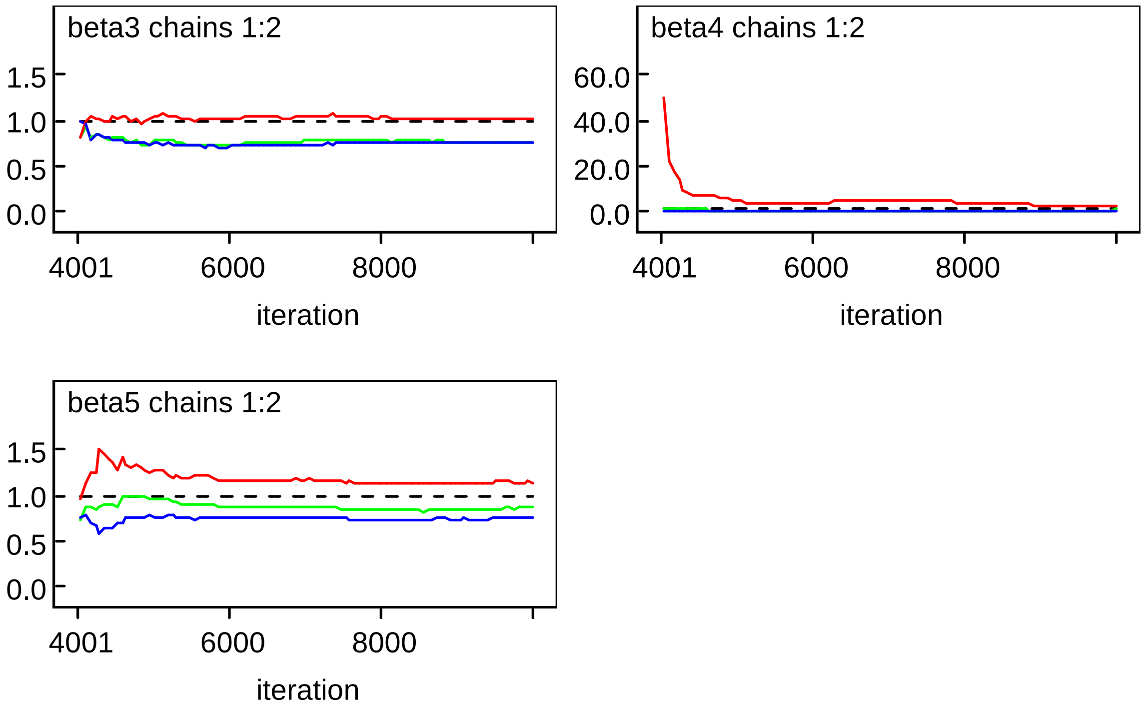


Figure 3.3 Gelman-Rubin Diagnostic Plot of Initial Run with 10000 Iterations and 1000 Burn-in Iterations

Most of the plots show $\hat{R}$ tend to be 1 after 5000 iterations which can prove the convergence, except for β_0, β_4 and β_5. Those plots show that even after 10000 iterations, $\hat{R}$ value is still away from 1. The lack of convergence will not give us a good posterior estimation for the parameters.

Furthermore, the auto correlation plots in Figure 3.4 of β_0 and β_4 also indicates the strong auto correlations of β_0 and β_4 between iterations.

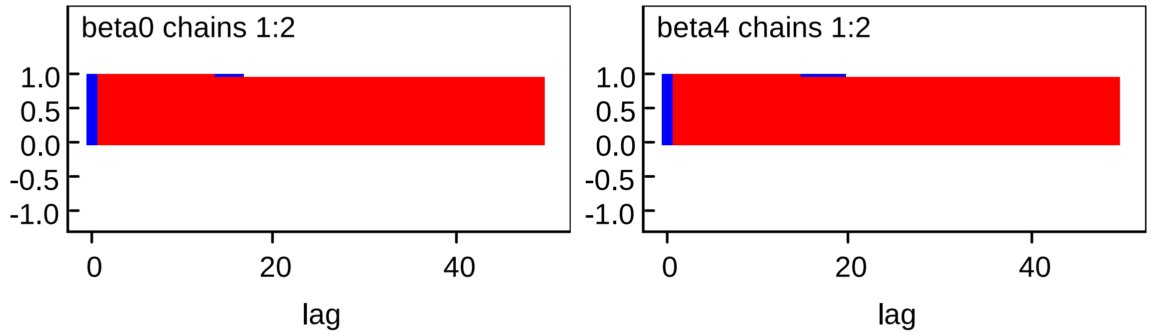


Figure 3.4 Auto Correlation Plots of Parameter $\boldsymbol{\beta_0}$ and $\boldsymbol{\beta_4}$

The reason of bad convergence performance could be a small number of iterations. To improve the convergence of those parameters, a larger number of iterations are considered by setting 100000 iterations with 10000 burn-in iterations.

The reason of high auto correlations of parameters could be low variety of je value. In this study, the total number of data samples are 132, but with only six different je values. It seems reasonable to have some auto correlations of the coefficient. Thinning interval could be used to fix the problem. A large thinning interval like 10 allow the chain to only keep the sample after every 10 iterations (i.e., only keep observations 1, 11, 21, etc.). This sample lag can efficiently avoid the autocorrelations between iterations. Moreover, it can save storage space and speed up the calculation. In order to decrease the auto correlations within the iterations, 20 thinning interval is set for each parameter. Updated auto correlation plots of β_0 and β_4 is shown in Figure 3.5. The auto correlations of β_0 and β_4 over iterations decrease from 1 to less than 0.5 comparing to the initial run. Although not perfect since the best situation would be close or equal to zero, but it's more acceptable now.

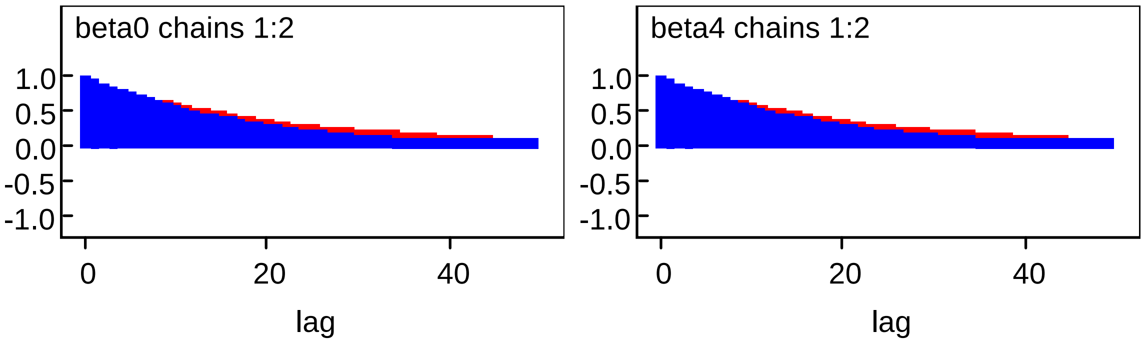
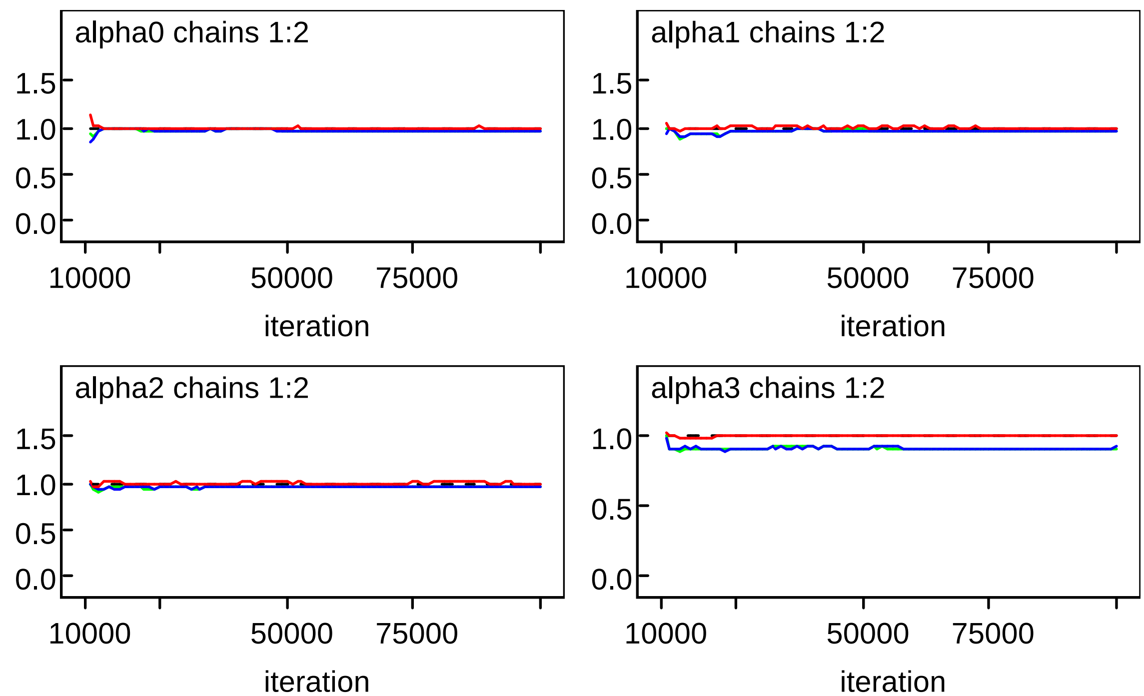


Figure 3.5 Modified Auto Correlation Plots of $\boldsymbol{\beta_0}$ and $\boldsymbol{\beta_4}$

Check the convergence of the algorithm, from Figure 3.6, all the parameters show good convergence over iterations with $\hat{R}$ values converge to one. Also, all the $\hat{R}$ values start with the value larger than one which indicates good scattered values in a sample space. $\hat{V}$ and WSS are stable after a few iterations.



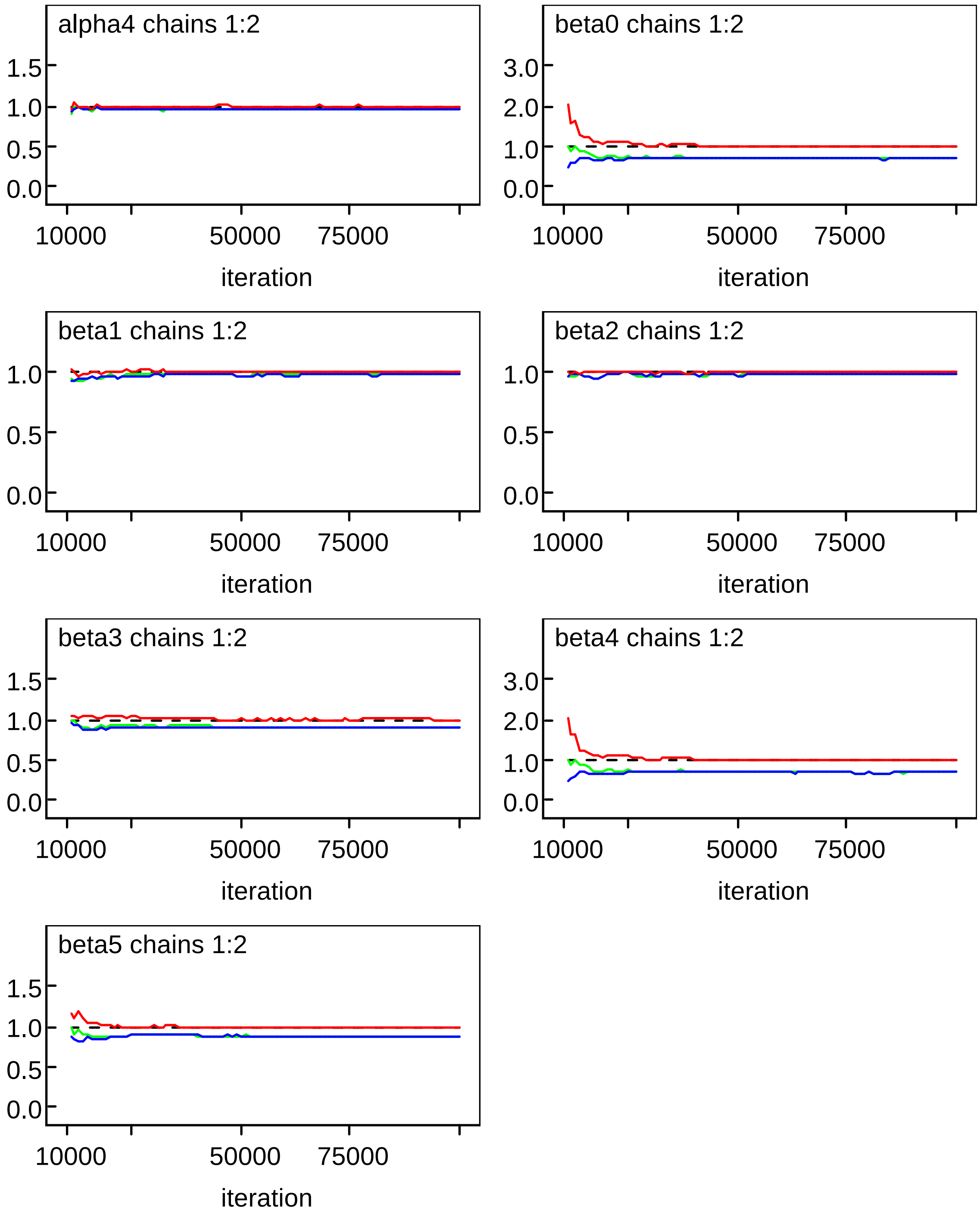
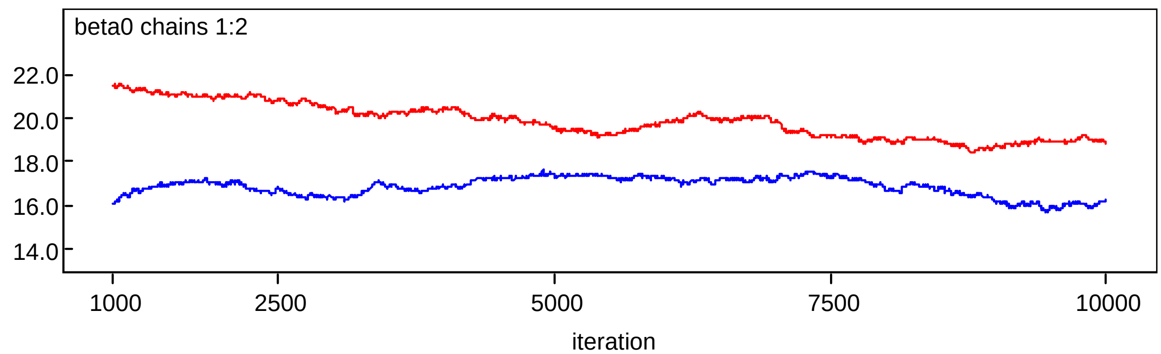
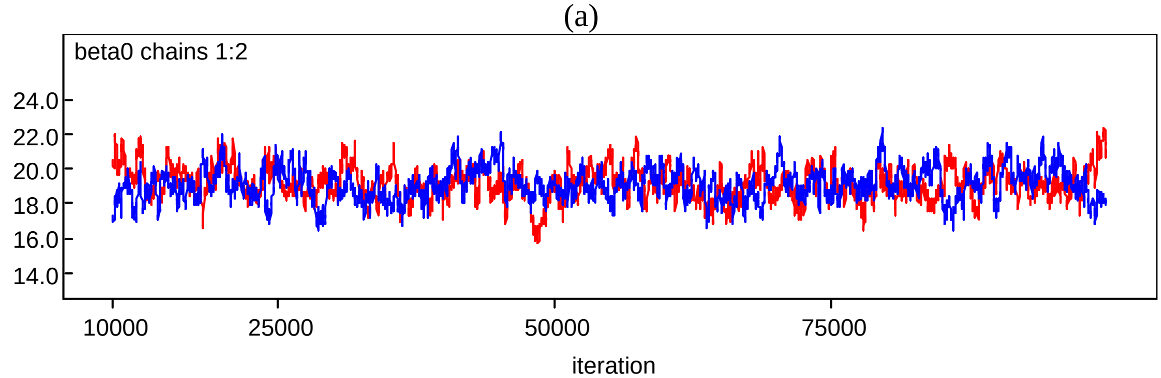


Figure 3.6 Modified Gelman-Rubin Diagnostic Plots

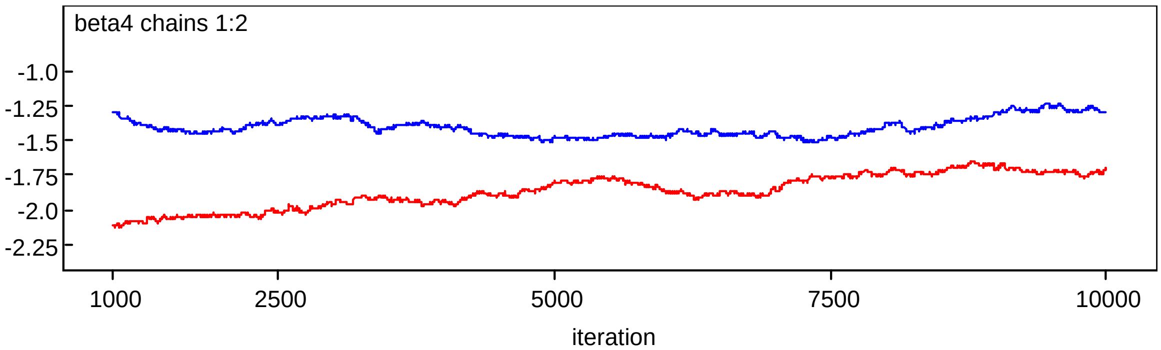
The history plot in WinBUGS plots the trace of the value of parameters over iterations. For a good model, history plots of the parameters should show no pattern which means the sample is randomly selected from the prior distribution with no correlations with each other. As in Figure 3.7, (a) and (c) are the history plots of parameters β_0 and β_4, the history trace of these two parameters are highly correlated over iterations. And two chains are separated from each other, which indicate the poor sampling of the model. However, after modifying the model with 100000 iterations and 20 thinning interval, the plots look much better. The behavior of two chains of each parameter is the same with no patterns or correlations.



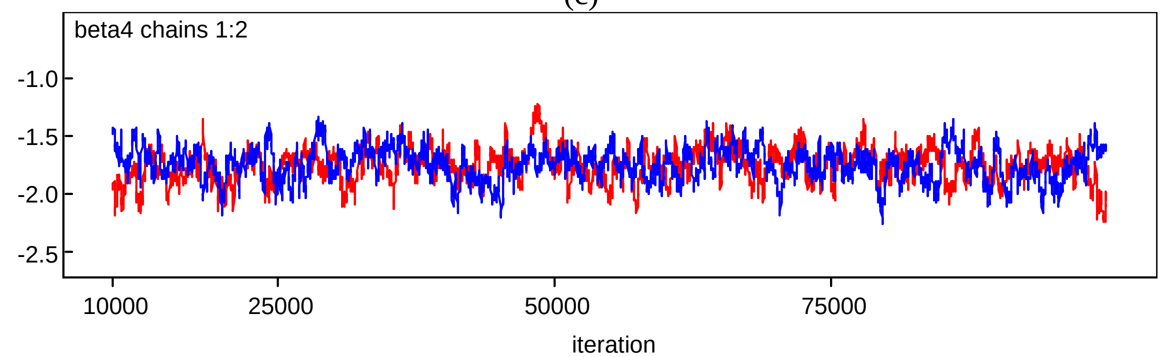
(a)



(b)



(c)



(d)

Figure 3.7 (a) Initial History Plot of β0 (b) Modified History Plot of β0

(c) Initial History Plot of β4 (d) Modified History Plots of β4

To further investigate the sampling method, the density plots of parameters are generated by WinBUGS in Figure 3.8. The kernel density plots provide a graphical view of posterior estimation density for each monitored parameters. Based on the prior distribution of parameters, the density plots of them should be in the same shape. In our model, the priors of β_0 and β_4 are normal distributed. Then the expected density plots of these two parameters should be in the similar shape like normal distribution. In comparison to the modified density plots, the initial model shows bad density plots as in Figure 3.9. Both plots are far from normal distribution shape as evidence of poor sampling of posteriors of β_0 and β_4.

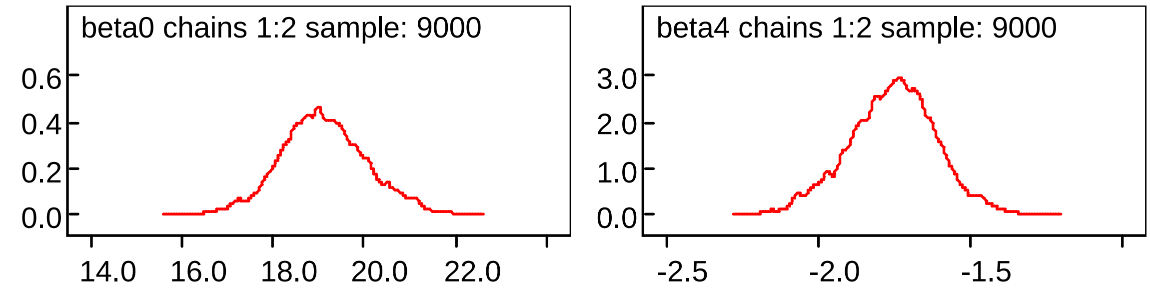


Figure 3.8 Modified Kernel Density Plots of $\boldsymbol{\beta_0}$ and $\boldsymbol{\beta_4}$

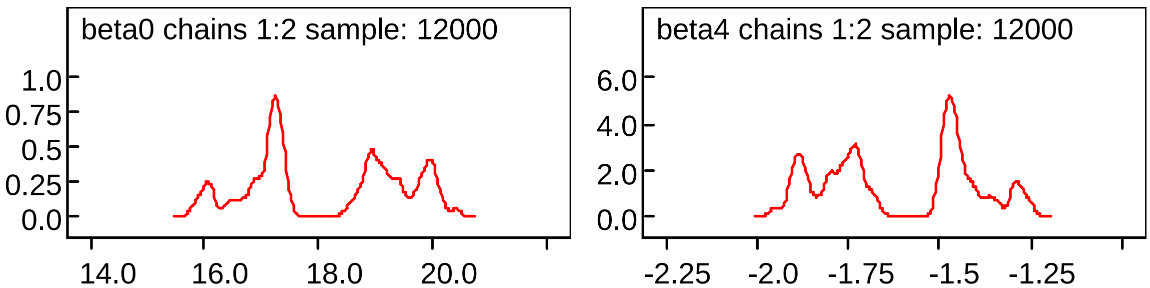


Figure 3.9 Initial Kernel Density Plots of $\boldsymbol{\beta_0}$ and $\boldsymbol{\beta_4}$

3.6 Result

After 100000 iterations with 10000 burn-in iterations, WinBUGS gives us posterior distributions of the parameters $\alpha's$ and $\beta's$ based on the informative prior distributions.

Table 3.3 summarizes the statistical results of posteriors. All the corresponding estimated posterior standard deviations are very small and acceptable in comparison to the mean. Monte Carlo errors are extremely low comparing to the corresponding estimated posterior standard deviations, which shows good performance of Monte Carlo simulation. The estimated posterior means of parameter $\overline{\beta_4} = -1.755$ presents the inverse proportion of energy absorbed by test samples and the failure life time of samples. $\overline{\beta_2} = -2.906$ shows supplier 2 performed really bad as it dramatically decreases the failure cycle time in the comparison to supplier 1 and supplier 3. $\overline{\beta_5} = 0.2382$ which is close to 0 shows that the preconditioning method only has small impact to failure cycle time while the joule equivalent has a larger influence on it.

Table 3.3 Statistical Report of Weibull Regression Model with Informative Priors by WinBUGS

node	**mean**	**sd**	**MC error**	**2.5%**	**median**	**97.5%**	**start**	**sample**
alpha0	3.353	0.3618	0.00447	2.668	3.342	4.076	10000	9000
alpha1	0.3456	0.5693	0.005455	-0.7581	0.3476	1.488	10000	9000
alpha2	-2.039	0.4438	0.004427	-2.884	-2.045	-1.147	10000	9000
alpha3	0.3183	0.5573	0.005744	-0.7455	0.3054	1.44	10000	9000
alpha4	0.9209	0.4466	0.004713	0.06004	0.9201	1.806	10000	9000
beta0	19.12	0.9538	0.05558	17.25	19.07	21.1	10000	9000
beta1	-1.104	0.06232	6.345E-4	-1.225	-1.104	-0.9813	10000	9000
beta2	-2.906	0.1896	0.002093	-3.27	-2.912	-2.513	10000	9000
beta3	-0.6304	0.05737	9.086E-4	-0.7407	-0.6305	-0.5184	10000	9000
beta4	-1.755	0.1462	0.008515	-2.06	-1.748	-1.467	10000	9000
beta5	0.2382	0.05425	0.001398	0.1332	0.2379	0.3475	10000	9000

With the result of WinBUGS, an inference of lead-free solder thermal fatigue life could be generated as

$$t \sim weibull(v, \eta)$$

$$v = 3.353 + 0.3456 s_1 - 2.039 s_2 + 0.3183 s_3 + 0.9209 r$$

$$\ln(\eta) = 19.12 - 1.104 s_1 - 2.906 s_2 - 0.63044 s_3 - 1.755 \ln(je) + 0.2382 r$$

The joule equivalent of energy absorbed by coupons plays an important role of the failure life of coupons in a negative way. The failure life decreases as the joule equivalent increases.

3.7 Model Comparison with Informative and Non-informative Prior

In this study, an informative prior is used based on the previous similar studies of lead-free solder joint. Sometimes, there is not enough information of the prior, non-informative priors might be used. However, a good informative prior will result in a better model than non-informative prior. To investigate that, non-informative priors are used. All the priors of α's and β's are set as normal distribution with mean equal to zero, standard deviation equal to 1000 as normal $(0,1000^2)$. Besides the priors, all other settings of the model remain the same. After 100000 iterations with 10000 burn-in iterations, the statistical summary of the parameters is displayed in Table 3.4. In the comparison to the summary in Table 3.3 which is generated from the model with informative priors, the standard deviation of every parameter in Table 3.4 is larger than in Table 3.3.

Table 3.4 Staitsitical Summary of the Same Weibull Regression Model with Non-informative Priors

node	**mean**	**sd**	**MC error**	**2.5%**	**median**	**97.5%**	**start**	**sample**
alpha0	4.019	0.5226	0.01061	3.041	4.002	5.066	10000	9000
alpha1	0.02555	0.7971	0.0115	-1.504	0.01986	1.623	10000	9000
alpha2	-2.829	0.5669	0.00948	-3.959	-2.83	-1.731	10000	9000
alpha3	-0.1446	0.7487	0.01052	-1.566	-0.164	1.358	10000	9000
alpha4	0.7639	0.5331	0.007735	-0.2744	0.7666	1.809	10000	9000
beta0	13.98	2.024	0.1749	11.03	13.35	18.39	10000	9000
beta1	-1.1	0.05867	0.001064	-1.218	-1.1	-0.9865	10000	9000
beta2	-3.047	0.2177	0.002477	-3.503	-3.04	-2.639	10000	9000
beta3	-0.5741	0.0603	0.002489	-0.6973	-0.5734	-0.46	10000	9000
beta4	-0.9654	0.31	0.02679	-1.641	-0.8693	-0.5136	10000	9000
beta5	0.1141	0.06483	0.004039	-0.004082	0.1102	0.2493	10000	9000

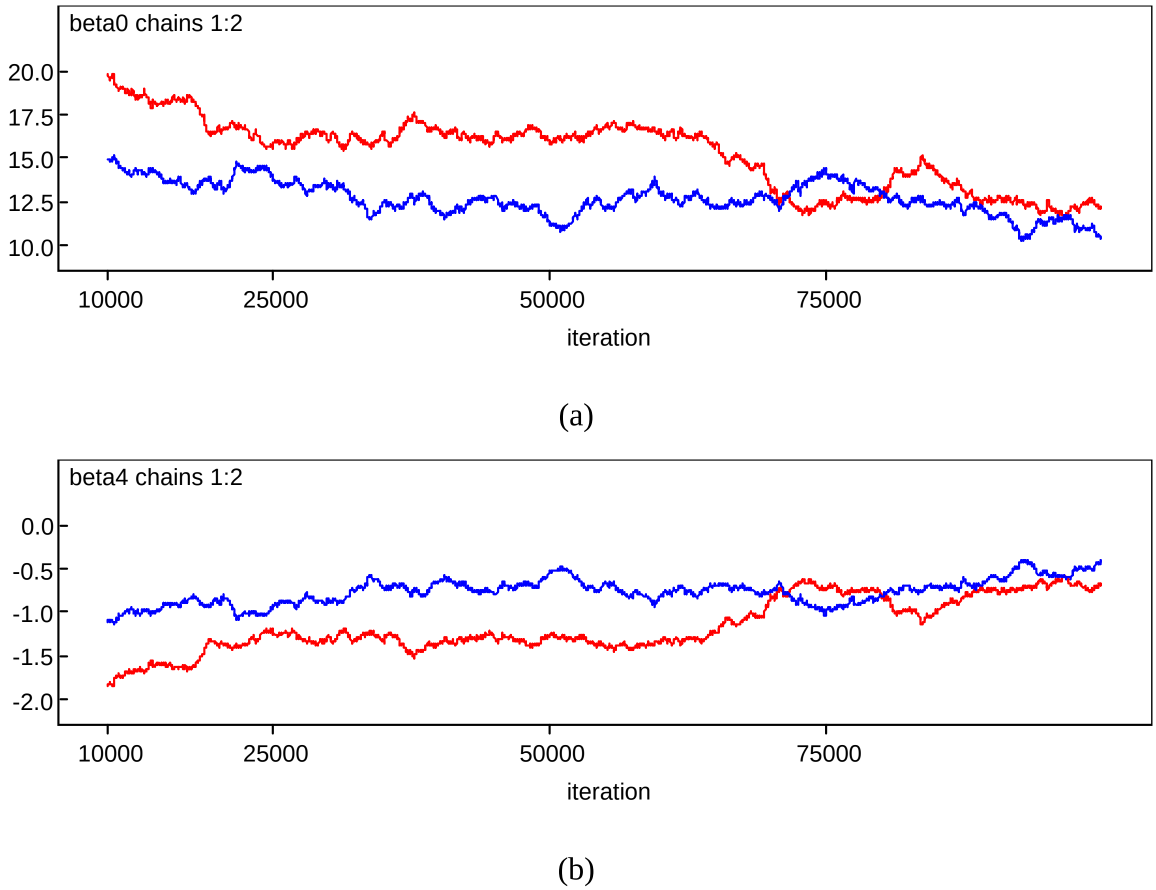


Figure 3.10 (a) History Plots of $\boldsymbol{\beta_0}$ with Non-informative Priors

(b) History Plots of $\boldsymbol{\beta_4}$ with Non-informative Priors

Furthermore, the history plots of β_0 and β_4 (Figure 3.10) are much worse than the model with informative priors (Figure **3.7**). The history plots of parameters with non-informative priors indicate a bad converge behavior of the model, which affects the accuracy of the posterior inference.

3.8 Reliability Prediction

From the model with informative priors, prediction of characteristic life η can be made based on the information of thermal cycle energy, the type of thermal preconditioning (reflow or IST) and which supplier been chosen. In the real world manufacturing, the assembly process is similar with the reflow preconditioning process in the test. To predict the characteristics life of SAC solder joint in the real life, a posterior of η in the model can be used. Table 3.5 displays the summary of η under reflow condition.

Table 3.5 Prediction of Characteristic Life of SAC Solder with Informative Prior

	mean	**sd**	**MC error**	**2.5%**	**median**	**97.5%**	**start**	**sample**
Supplier 1	670.0	38.97	0.5718	597.3	669.4	749.5	10000	9000
Supplier 2	111.2	21.73	0.2415	76.8	108.9	159.3	10000	9000
Supplier 3	1262.0	61.08	0.7298	1147.0	1261.0	1388.0	10000	9000
Unknown Supplier	2137.0	89.22	1.053	1970.0	2135.0	2324.0	10000	9000

To conclude the analysis, among the three suppliers, supplier 2 has the worst performance in the test. Coupons from the unknown supplier have the longest characteristic life among the four suppliers, which might be the best supplier choice for the company if the failure life time is the most concern when choosing suppliers.

A similar posterior of reliability probability can be concluded by adding a reliability function in the model. For example, the probability of solder joint that is not fail after 1000 cycles is generated in Table 3.6. It demonstrates the similar supplier ranking result as Table 3.5. The probability of coupons from supplier 1 and 2 fail is extremely small, and conclusion can be made that coupons produced by supplier 1 and 2 cannot survive after 1000 thermal cycles. Meanwhile, the same probability of unknown supplier is high as 0.9594, which is very close to one, and indicates there is high probability that coupons from supplier 3 will not fail after 1000 thermal cycles.

Table 3.6 Reliability Prediction of SAC Solder Joint for 1000 Cycles

	mean	**sd**	**MC error**	**2.5%**	**median**	**97.5%**	**start**	**sample**
Supplier 1	0.005002	0.009351	3.312E-5	6.275E-6	0.001563	0.03116	10000	9000
Supplier 2	1.98E-5	9.933E-4	3.227E-6	0.0	0.0	1.287E-8	10000	9000
Supplier 3	0.7029	0.06844	2.414E-4	0.5584	0.7069	0.8251	10000	9000
Unknown Supplier	0.959	0.01597	5.603E-5	0.9211	0.9615	0.9827	10000	9000

4 DISCUSSION AND CONCLUSION

4.1 Conclusion

In this thesis, a qualitative study about lead-free solder joints reliability under different test conditions is carried out. Failure modes of lead-free solder joint under drop test, bend test, thermal cycle test and vibration test are summarized. Over all, lead-free solder alloy shows a good failure life. Low Ag content alloy results in higher failure life under stress while high Ag content alloy has a longer failure life under thermal conditioning process.

Weibull regression model is built in WinBUGS busing Bayesian inference with meta-analysis of test data from previous studies to further investigate the failure cycle of lead-free solder joint under thermal test. IST and reflow are the two types of preconditioning processes used in the test. The Weibull regression model simulates the characteristic life of test samples with three independent variables: suppliers of components, type of preconditioning process and energy absorbed by samples. As a conclusion, the energy absorbed by the test sample is inverse proportional to the failure time while the type of preconditioning is not very significant to the characteristic life.

Comparison of model performance with informative and non-informative priors is analyzed. With informative priors, model presents more precise posterior inference.

Further research is necessary if test conditions changes. The model is flexible and easy to adjust to any similar situations.

4.2 Usage of the Weibull Regression Model

Since lead-free solder is very important to the electronic and electrical industry, it can be used to every electronic device like laptops, desktops, smartphones, etc. Those devices can be heated up in response to an electric current after use a while. Lots of the electronic devices have fans in it to cool down the temperature which makes it a “real” thermal cycle for the circuit boards in the devices. Different device have different thermal cycle condition and cycle time. To make a prediction of the fatigue life of the lead-free solder under this kind of conditions, the Weibull regression model could be used by changing some of the settings and prior distributions of the model to adjust particular situations. With the regression model, a characteristic life of a solder involved product can be inferred. And more detailed and product oriented reliability analysis based on the generated characteristic life can be conducted to reduce the failure risk.

4.3 Future Research

As mentioned above, an inference of thermal fatigue life of SAC lead-free solder alloy could be made based on the built Weibull regression model, but the shape parameter of Weibull distribution of failure life time is mainly decided by the material of solder. In Juarez’s tests, the solder alloy used is SAC. Although SAC is the most popular lead-free solder alloy for the industry, different lead-free solder alloy might be used in the real world manufacturing. Different regressors can be generated when different solder alloys are tested for thermal cycle fatigue. Not only the lead-free solder alloy, but also other solder materials can be taken into consideration. With that information, the model would be more flexible for different uses.

Also the supplier information is based on particular situation. In electronic industry, there could be many suppliers who produce the components. The enormous diversity of suppliers makes it difficult to just use one model to fit all situations. So in real life, when compare different suppliers of components, the same regression strategy could be used to adjust the model with new test data set. The model is useful to help a company to make decision about choosing among multiple suppliers.

Moreover, the prior distributions of parameters can be further instigated if more information or tests are found. With different test conditions, different priors are needed. With the appropriate priors, regression model can provide useful inferences of the posteriors.

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APPENDIX A

WINBUGS CODE

```
model{

    # regression model
    for (i in 1:132){
        t[i] ~ dweib(v[i], lambda[i])I(,censor[i]);
        v[i] <- alpha0 + alpha1 * s1[i] + alpha2 * s2[i] +alpha3 * s3[i]+alpha4*r[i];
        lambda[i]<-pow(eta[i],-v[i]);
        log(eta[i]) <- beta0+ beta1 * s1[i] + beta2 * s2[i] + beta3 * s3[i]+beta4
*log(je[i])+beta5*r[i];
        R[i]<-pow(2.71828, -pow(1000/eta[i], v[i]))
    }

    # priors
    alpha0 ~ dnorm(2.5, 1)
    alpha1 ~ dnorm(0, 1)
    alpha2 ~ dnorm(0, 1)
    alpha3 ~ dnorm(0, 1)
    alpha4 ~ dnorm(0, 1)

    beta0 ~ dnorm(20, 1)
    beta1 ~ dnorm(0, 1)
    beta2 ~ dnorm(0, 1)
    beta3 ~ dnorm(0, 1)
    beta4 ~ dnorm(-3, 1)
    beta5 ~ dnorm(0, 1)
}

#Initial value for chain 1
list(
    alpha0=1, alpha1=0, alpha2=0, alpha3=1, alpha4=1
    beta0=20, beta1=0, beta2=0, beta3=0, beta4=-3, beta5=0
)

#initial value for chain 2
list(
    alpha0=2, alpha1=0.5, alpha2=-0.5, alpha3=0.5, alpha4=0.5,
    beta0=15, beta1=0.5, beta2=-0.5, beta3=0.5, beta4=-2, beta5=0.1
)
```