Optimal Planning and Inference for Sequential Accelerated Life Testing with Two or More Experimental Factors

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SUMMARY & CONCLUSIONS

An important task before conducting Accelerated Life Testing (ALT) experiments is to specify a prior lifetime model, based on the historical data of similar products or expert opinions. The initial estimates of model parameters need to be reasonable so that the test plan can produce sufficient failure data. Though many methods have been developed to design test plans with unknown prior distributions, there is still active research in this area to obtain the best value of the final parameter estimates. A main drawback is that, in most cases, these ALT test plans consider only one stage of experimentation, which is often inadequate for building a reasonable prediction model. In this paper, we propose a modified version of sequential ALT planning and life quantile prediction framework involving multiple factors. The first stage of design is carried out based on the prior knowledge of various possible acceleration regression models for a limited testing time and experimenting at more than one level for at least one factor, followed by an adaptive second-stage ALT test planned under the given budget to improve the prediction accuracy obtained from the first stage. The proposed approach is validated through real accelerated life testing data of Multi-Layer Ceramic Capacitor (MLCC) data involving three factors: temperature, humidity and voltage.

1 INTRODUCTION

Today's manufacturers are facing increasing pressure to develop and deliver new products within a short span of time. There are various reliability tests both in product design stage as well as in manufacturing stage ranging from material and component level to a complete system level. But many times, the manufacturer does not have the luxury of having all the information about the product due to various reasons. But, how does the manufacturer decide on the warranty level for these products? It is not possible to wait until the products fail in the field and decide on the optimum warranty level.

To help industries to compete against the time and money, Accelerated Life Testing (ALT) provides a ubiquitous way to infer or predict the reliability of a product at its use condition by testing a specified number of samples at elevated stress conditions to accelerate the occurrence of failures. Many mechanical, electrical and electronic components applicable to several fields, that we come across in our everyday life (e.g., automobile parts, photovoltaic modules, aerospace components, smart phone components, etc.), are subject to ALT before being released to the market. But conducting ALT/ ADT (Accelerated Life Test/ Accelerated Degradation Test) is not an easy task since it involves a lot of factors. Meeker et al. [1] discussed the pitfalls of ALT for various phases like planning, conducting and analyzing ALT data. The most common problems quoted are: the allocation of equal number of samples for all levels, ignoring the effect of interactions between the factors, complex data analysis methods and testing protocols, etc.

In this paper, we consider the planning (design) stage as well as the inference (analysis) stage of ALT. One of the most important step is to design a statistically sound ALT test plan such as deciding on the number of factors for the test, the levels of each factor, sample size, censoring type, etc. The test results often need to be extrapolated through a physics-based and statistical model to obtain the reliability prediction at use level. The traditional design of experiments approach is inadequate for ALT planning and analysis since the test would yield censored data, non-occurrence of failure modes at some stress levels and so on. In addition, most of previous work on designing ALT plans focused on ALTs with single stress. Escobar et al. [2] designed and analyzed ALTs with two or more experimental factors, assuming a linear model without interaction between factors.

A major problem in designing ALT is that there is a need for at least some prior information about the product reliability. In some cases, the error in a prior model can lead to extremely misleading information and results in wastage of the resources. For instance, consider the Arrhenius model, the effect of temperature (usually termed as activation energy) needs to be as precise as possible since a small variation will lead to misleading results, as the effect of temperature is expressed as an exponential term. Similar problems could occur with Peck's model and modified Coffin-Manson models too. A common practice of developing an optimal test plan involves minimizing the uncertainty of failure time distribution for the product's normal use condition, which is hard to achieve with single stage of experimentation.

Bessler et al. [3] demonstrated the importance of sequential ALT and came up with the idea of optimal sequential ALT design assuming exponential failure times. The proposed sequential ALT is an important strategy for niche products in which the parameter uncertainties are quite high due to the lack of complete information. Tang et al. [4] continued with sequential testing scheme with one factor and showed that conducting the experiments in sequential stages will increase the prediction accuracy and robustness of the model. But, most of these literatures were tested and validated for only one stress factor and is designed to conduct only one set of experiments at higher level during the first stage. This will not produce satisfactory results because the experiment needs to be carried at two different levels to get an estimate of one factor.

Experimental designs for ALTs with multiple stress factors have been discussed in Monroe et al. [5-6], Yang and Pan [7], Pan et al. [8], Nasir and Pan [9-10]; however, these previous publications did not consider sequential test plans for the model uncertainty problem. Instead, they either assumed that the ALT model was fully known, or a prior distribution of model parameter was known, and a Bayesian robust plan could be derived. More recently, Zhao et al. [11] used Bayesian averaging model by performing experiments at all the stress levels for the first stage and planning the second stage using the posterior from the first stage. Their sequential plan was shown to have a better performance than one-shot plans, but computationally this strategy was not easy to implement. To alleviate the above-mentioned problems and achieve good results, we modify the sequential ALT planning and life quantile prediction framework by testing at more than one level even during the first stage. Since there is a high probability for the failures to occur at highest stress level, the allocation of samples will be adjusted so that additional stress levels can be included in the first stage for model validation. This will help in obtaining a more precise lifetime model in the first stage and then, in the second stage, the ALT experiment can focus on predicting the life distribution or life stress relationship at the use stress level.

In summary, it is important to develop a good sequential ALT design considering two or more factors to improve the model estimates, but it is also a challenging task. The following sections describe the proposed methodology followed by case study of accelerated life testing of MLCC capacitors.

2 METHODOLOGY

A typical parametric ALT model consists of two main components, the first one being the failure time or lifetime distribution and the second one being the life-stress relationship. Usually a log-location-scale family, as given in Equation (1), will be used to model the failure time distribution of the components under ALT and is linked with the life-stress model given in Equation (2).

$$F(t) = \Phi\left[(\log(t) - \mu)/\sigma\right], \quad (1)$$

where Φ is the standardized location-scale Cumulative Distribution Function (CDF), μ is the location parameter, σ is the scale parameter and t denotes the failure time. The life-stress model is chosen based on the factors involved in the experimentation. For instance, if the major cause of failure is temperature, then Arrhenius model is used to capture the relationship between failure time and stress variable (i.e., temperature). Usually, many experiments involve more than one variable such as humidity, pressure, voltage, etc., in addition to the temperature effect.

$$\mu = \beta_0 + \beta_1 s_1 + \ldots + \beta_n s_n \quad (2)$$

where 's_i', $\forall i = 0,1,\ldots, n$, denotes the stress (i) acting on the product with the corresponding effect β_i. Clearly, this model involves various parameters denoted by $\boldsymbol{\varphi} = (\beta_0, \beta_i, \sigma)$ and all these parameters should to be estimated.

The first stage of design is carried out based on the prior knowledge of various possible acceleration regression models. Usually, the sequential ALT involves testing only at highest factor level in the first stage followed by a second stage experimentation at remaining levels. Since some of the factors like activation energy are much sensitive, testing at one level during the first stage will not be helpful in getting a good estimate to proceed for second stage. In this paper, we propose designing the first stage of experimentation with more than one level, followed by an adaptive second-stage ALT test planned under the given budget to improve the prediction error obtained from the first stage. Hence the model in Equations (1) and (2) remains unchanged. This method of testing at more than one level at the first stage of testing need not be done to estimate all the factors since the test will involve several combinations if the number of factors is greater than one. However, the method can be effective for critical or more sensitive factors playing a major role in failures (ex: temperature/ activation energy).

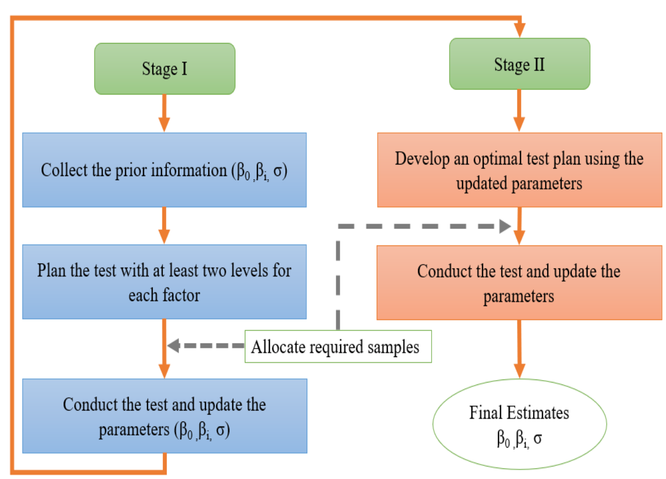

Figure 1. Flow chart of the Sequential Accelerate Life Testing (SALT) method

The flowchart in Figure 1 represents the steps involved in conducting the proposed sequential ALT methodology. Plan and conduct the first stage of experimentation with at least two levels based on the available information (expected failure time distribution and life stress model) at hand. Once the test results are available, obtain the failure time distribution for the test units and estimate the location and scale parameters (μ_i and σ_s) for the given stress levels. Once the failure time distribution parameters are available, then it's time to update the model parameters $\boldsymbol{\varphi} = (\beta_0, \beta_i, \sigma)$. The Maximum likelihood method can be used to update $\boldsymbol{\varphi}$ with details given in Equations (3) and (4) [11]. In case of more than one stress level, the first stress factor or the critical factor is tested at two different levels keeping the other factors constant with an assumed prior distribution. The model can be updated only when there is enough data available from the subsequent stages.

Let $\mu = (\mu_1, \mu_2, \ldots\ldots, \mu_n)$ be the mean vector of all the lifetime distributions and S be the diagonal matrix of variances of all μ_i's (i = 1, 2, …, n) and D be the matrix of stress variables. Then the analytical solution of β and σ is given in Equation (3) and (4) [11].

$$\beta = (D^T S^{-1} D)^{-1} (D^T S\, \mu) \tag{3}$$

$$\sigma = \left(\sum_{i=1}^{n} \mathrm{Var}^{-1}(\sigma_i)\right)^{-1} \left(\left(\sum_{i=1}^{n} \sigma_i \,\mathrm{Var}^{-1}(\sigma_i)\right)\right) \tag{4}$$

Now, the estimates of the model parameters are available and can be utilized to plan for the second stage of experimentation. In the first stage, the user can allocate equal samples or with pre-determined ratio of sample allocation for each level based on the testing limitations. If the first stage of experimentation is done at highest and lowest level, then the middle level can be chosen to run the test to check for curvature effect, and so on, but depending on the equipment capability and cost/time constraint. But, to decrease the prediction error and improve the model accuracy further, a second stage of experimentation can be performed to update the estimates using the remaining samples from the first stage. Equation (5) to Equation (8) can be helpful in determining the optimum sample size and stress levels for the second stage of experimentation [4]. In this approach, the minimum expected number of failures (Q) should be specified, which would be around 5 as suggested in [2]. Seo and Pan [12] developed the optimal test planning approach that accommodates three optimality criteria: D-Optimality, U-Optimality and I-Optimality. Usually, it is recommended that the tests to be done with 2 or 3 levels at different combination of factors to obtain robust estimates. Let n_l denotes the number of units available after the first stage of experiments, π_i denotes the proportion of units required to be allocated at stress level x_i (standardized), then the optimization problem is as follows.

Objective:

$$\text{Min } E_\beta\, (\mathrm{Var}\; y(i);\, x_i, \pi_i) \tag{5}$$

Subject to:

$$n.\pi_i.p(x_i) \geq R_i \tag{6}$$

$$0 \leq x_i \leq 1 \tag{7}$$

$$0 \leq \sum_{i=1}^{n} \pi_i \leq 1 \tag{8}$$

where $p(x_i)$ denotes the failure probability at the stress level 'i'. The estimated parameters from the first stage will be used for the unknown values in this probability density function (PDF). Once the optimization problem is solved, the second stage of experimentation is conducted and the model fitting and the final parameter estimation are carried out in a similar way as discussed previously.

3 CASE STUDY: ALT OF MLCC CAPACITORS

The proposed approach is demonstrated through accelerated life testing of Multi-Layer Ceramic Capacitors (MLCC), involving three stress factors: temperature, humidity and voltage. The failure mode is the cracking as shown in Figure 2. These MLCC capacitors find a wide variety of application in electronic devices, and the reliability can usually be determined by the performance of the capacitors (e.g., impedance/leakage in this case). While the capacitors may fail due to several reasons, most of the failures happen due to mechanical and thermal stress. The cracking may occur due to inappropriate design, assembly, operation, etc. Cracked capacitors manifest several defects like increased leakage current, intermittent open circuit or short circuit etc. In addition, when the devices are operating in an excessive humid environment, there is a high probability that the water vapor will enter the cracked regions aggravating the failure mechanism. Hence, the reliability of the capacitors operating in conditions with high temperature and humidity poses a major issue to the safe operability of the devices.

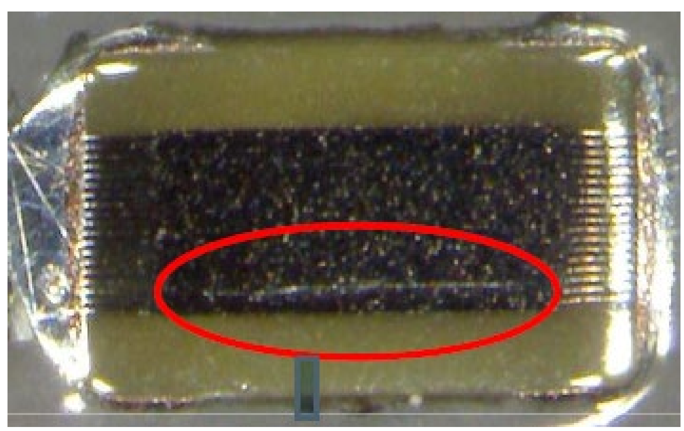
Figure 2. Cracking of MLCC capacitors

To test the reliability of the capacitors and develop a good parametric model, the ALT with three factors - Temperature, Relative Humidity and Voltage - is planned. The experiments are conducted for at least two levels for each factor. It is to be noted that due to limitations in time constraint, the experiment could not be done for all combinations of three factors (i.e., if there are 3 factors and 3 levels, then $3^3 = 27$ different sets of experiments). Since, the temperature effect was considered more critical than the other two factors, the first stage is started with the estimation of temperature effect (activation energy), but the user can choose any factor depending on the problem. The experiment is done for two levels of temperature keeping the other factors constant. Furthermore, the prior distributions were assumed for other unknown factors [13-14]. This will make the activation energy estimate closer to the true value than testing with only temperature because the effect of humidity and voltage will contribute to decrease the activation energy required to initiate the failure. We use coded variables (0 to 1) where 0 denotes the highest stress level, 0.5 denotes the middle level and 1 denotes the usage stress level. The decoded/actual values for the temperature is (85°C, 70°C, 60°C), Voltage of (4V, 2V, 1V) and RH is (85%, 70%, 50%).

The first stage of experiments is conducted, and the results are shown in Figure 3. The Weibull distribution and lognormal distribution is used to fit the failure time and the Peck's model (Temperature and Humidity) along with Voltage function given in Equation (9) is used to model the life stress relationship. The linearized form of life stress model is given in Equation (10), which is a linear function of all the stresses and can be estimated analytically.

$$TTF = A\, e^{-Ea/RT}.\, (RH)^{-m}.\, (V)^{-b} \tag{9}$$

$$\ln (TTF) = \ln A - \frac{Ea}{R}\left(\frac{1}{T}\right) - m \ln(RH) - b \ln(V) \tag{10}$$

where A is a constant, 'Ea' is the activation energy, m is the relative humidity effect and b is the effect of voltage. During the first stage, four sets of experiments were conducted with an equal sample allocation of 200 for each set with an additional set for validation. Hence, a total of 1000 samples are utilized for first stage of experimentation and an additional 1000 samples are available for the second stage. The estimates of unknown parameters of the Weibull model (shape and scale) and Peck's model (activation energy 'Ea', humidity exponent 'm' and voltage exponent 'b') are also tabulated in Table 1 and the similar results for lognormal distribution is shown in Table 2. The first row in each table consists of the parameter estimates for the lifetime distribution (location, scale and shape) fitted using the life testing data at level (0,0,1), as well as the assumed prior distributions for the unknown parameters of the life-stress distribution. Now, using the results of second set of experiments (0.5, 0, 1) along with the first set results, the value of intercept (ln (A)) and temperature effect (Ea) gets updated using the maximum likelihood estimation method (shown in the second row). Likewise, all the parameters are updated step by step in the first stage and the final estimates (highlighted in red) are obtained.

To validate the developed model, an additional set of experiments at level (1, 0.5, 0.5) is used. The actual location parameter for the Weibull failure time model is about 9.42 and the predicted location parameter is 6.17 with error of around 35%. Though the values of activation energy and other exponents fall within the wide range as stated in other literatures [13-14] of similar products, there is significant difference between the actual and predicted values using Weibull distribution. As shown in validation section of Table 2 using the lognormal failure time distribution, the prediction error is only about 10% but can still be improved. From this initial set of results, it is to be noted that if the first stage has only one set of experiments as per the usual sequential ALT methodology [3, 4] along with incorrect assumption of failure time distribution (in our case, Weibull distribution), then the parameter estimates will be far from acceptable value resulting in a poor prediction model. Therefore, it is important to have at least two sets of experiments even during the first stage and certainly, this model can be improved for better prediction using additional stages of experimentation, with the remaining resources from the first stage.

Table 1. Results of the Sequential ALT (First stage) of MLCC data using Weibull distribution

Temp	RH	Volt	Loc	Scale	Shape	ln A	Ea	m	b
Stage I									
0	0	1	10.99	59564	0.467	N(-15,5)	N(1.5,0.5)	N(-2.5,1)	N(-3,1)
0.5	0	1	9.74	17012	0.467	-18.92	0.88	N(-2.5,1)	N(-3,1)
0.5	1	1	14.2	1422014	0.467	-18.92	0.88	-5.37	N(-3,1)
0.5	1	0	13.4	663165	0.467	-18.92	0.88	-5.37	-1.04
Validation									
			Act Loc			Pred Loc			Error
1	0.5	0.5	9.42			6.177			34.43%

Table 2. Results of the Sequential ALT (First stage) of MLCC data using lognormal distribution

Temp	RH	Volt	Loc	Scale	ln A	Ea	m	b
Stage I								
0	0	1	11.46	4.93	N(-15,5)	N(1.5,0.5)	N(-2.5,1)	N(-3,1)
0.5	0	1	12.72	4.93	-17.36	0.89	N(-2.5,1)	N(-3,1)
0.5	1	1	15.28	4.93	-17.36	0.89	-4.82	N(-3,1)
0.5	1	0	16.5	4.93	-17.36	0.89	-4.82	-0.88
Validation								
			Act Loc			Pred Loc		Error
1	0.5	0.5	13.59	4.93		12.24		9.93%

Since the initial lifetime distribution and stress life relationship model and its estimates are available, an optimum test plan can be easily designed for second stage using Equations (5) to (8). In case of the samples following Weibull distribution with 'n' factors, the ALTopt package in R software by Seo [12] can be used to easily design the second stage of experiments. But, in our case, the lognormal distribution provides a better fit to the capacitors' failure time and the temperature is assumed to be the most critical factor among the others. A variation of 0.01 eV in activation energy has been proved to result in a big difference in the final model predictions of similar products [15, 16]. Also note that, after the first stage of experiments, there are additional 1000 capacitor samples available for second stage of experiments. Since we are interested in minimizing the variance of the expected lifetime of the product at its use condition, the U-optimal design is chosen. The U-optimal design minimizes the prediction variance and provides much more confidence in predicting the reliability of the product at its use condition. The optimal ALT experimental design along with the allocated samples for each experimental set is shown in Table 3. The testing is still being carried out and the results will be provided later.

Table 3. U-Optimal design for ALT of MLCC data

Stage II - U Optimal Design						
Set	Temp	RH	Volt	Censoring (hrs)	Sample allocation	Expected failures
1	0.8	0.5	0.5	48	683	20
2	0.4	0.5	0.5	48	40	2
3	0	0.5	0.5	48	277	17

4 CONCLUSION

In this paper, a modified approach for designing and analyzing the sequential Accelerated Life Testing method is presented. The proposed methodology is demonstrated using the actual life testing data of MLCC capacitors. This approach of sequentially testing with more than one stage of experimentation is advantageous when compared to the one stage experimentation since it reduces the uncertainty in failure time distribution as well as life stress model parameters by updating them systematically. In regards with the time consumption, this will take extra hours than conducting experiments all at once. Especially, this will be a hindrance for products that are tested inside the chamber for three to six months (ex: Photovoltaic modules). But, in cases when the testing is done for a couple of days or hours, this method will be helpful in getting a good estimate for the model parameters. A practical aid for applying the sequential testing framework for single stage experimentation with longer test duration would be that, even though the tests are designed for only one stage of experimentation, there will be some test runs prior to starting the actual experiments to make sure the chamber is ready for testing. Hence, the data collected from the samples during this test run could be effectively utilized for redesigning and updating the model.

Whenever possible, testing at three levels will be advisable. The advantage of testing at more than two levels is that the intermediate level(s) might provide the information about a possible curvature (if any) in the model. But, due to experimental limitations, additional testing could not be done during the first stage to check model curvature for MLCC data. But, the user is recommended to use a third set of experiments in the first stage at level (0.5, 0.5, 0.5) to get a good prior model. In addition, care should be taken to avoid zero failure problem for each level by following the compromised test plan suggested by Ma and Meeker [17], since ALT will be unsuccessful if there are no failures at one or more levels. The Equations (5) to (8) will be useful to avoid such problems by specifying the failure threshold. In our case of MLCC capacitors data, there are failures occurring at all stages of experimentation, so this problem is fortunately avoided. In future, the methodology will be extended to incorporate the effect of step stresses along with non-homogeneity in stress levels across components.

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