The Relationship Between Voltage and Life in Accelerated Life Experiment

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Abstract: The increasingly developing society has put forward higher requirements for the inspection speed of products. In order to meet the requirements for the increase of product life detection rate, the accelerated life experiment came into being. The purpose of this paper is to study the relationship between voltage and life, using the method of linear regression, through the assumption of a semi-parameter to the whole, to analyze all the data. And because the relationship between voltage and life conforms to the inverse power law model, the experiment is carried out.

Keywords: Accelerated Life; Inverse Power Law; Semi-parametric Hypothesis; Linear Regression

1. Introduction

With the intensifying global competition, manufacturers face immense pressure to produce products that offer more features and greater reliability, while reducing costs and delivery times [1]. Accelerated testing is gaining traction in the industry for its ability to rapidly gather life data. By subjecting products to higher stress levels without introducing additional failure modes, significant time and cost savings can be achieved [2]. Accelerated Life Testing (ALT) is utilized to assess product reliability by applying increased stress, and statistical analysis of ALT data involves fitting a model to data from these high-stress conditions and extrapolating it to normal use conditions. Prior to ALT, a comprehensive test plan is crafted, detailing stress types, application methods, stress levels, the number of units to test at each level, and a suitable model that links accelerated condition failures to normal condition failures [3]. Current life evaluation methods include actual life testing under typical conditions and model-based assessments [4]. American researchers developed methods like Highly Accelerated Life Testing (HALT) and Highly Accelerated Stress Screening (HASS) to quickly reveal design weaknesses and manufacturing defects. These methods apply extreme stress beyond design specifications in a stepwise manner to identify and eliminate defects, known as the stepping stress test method [5]. Ideally, models should be grounded in physical or chemical theories and validated empirically. In the absence of such theories, empirical models based on extensive experience with failure mechanisms can be used for extrapolation [6]. ALT is typically performed under constant stresses, which require lengthy periods at low stress levels to gather sufficient failure data. Ramp-stress loadings can yield faster failure times compared to constant stresses, though their reliability prediction accuracy remains unverified. We develop test plans with varying stress applications to match the statistical precision of constant-stress predictions [7]. Key experimental factors include humidity, voltage, electrical current, temperature, and thermal cycling. Voltage stress, which measures voltage per unit thickness of a dielectric, can lead to insulation breakdown if it exceeds certain levels. This breakdown occurs at weak points in the material, where dielectric strength is low, and generally, higher voltage shortens insulation life [8]. Voltage induces an electrical current, and stronger electric fields can accelerate the degradation of dielectric components, causing failures due to growing discontinuities or electrochemical reactions [9]. The inverse power relationship often describes how stresses like voltage affect lifetime. This paper collects failure time data under varying voltages through ALT, analyzes it to determine the life-voltage relationship, and uses statistical methods and regression analysis to estimate parameters in the inverse power law model. The findings provide crucial insights for product design and reliability evaluation, employing linear regression and a semi-parametric approach for robustness [10]. The section 2 introduces the specific experimental methods of this experiment. In section 3, simulation is used to prove the consistency and asymptotic normality of the method. The section 4 is the analysis of the real data. Finally, the section 5 summarizes the experimental contents and draws a conclusion.

2. Methodology

The accelerated life experiment should follow the principle of selecting the appropriate acceleration factor intensity level without changing the failure mechanism of the battery. In this experiment, voltage is used as the acceleration factor to charge and discharge the battery cycle, and the method of constant current charge and discharge is adopted. When the voltage is the single stress factor, the three voltages are selected to be arranged in an ascending order of 80V, 100V, 120V. The control variable method was used in the test to ensure that other acceleration factors were at the standard level. The relationship between the lifetime and voltage is the power law, that is: T = $\frac{A}{V^B}$. By taking the logarithm of lifetime, we have $\log(T) = \log(A) + b\log(V)$, where b = −B. 3 test groups are assumed here with V = 80, 100, 120 respectively, and we have Ni units in the ith group. We used a scale distribution family to describe the lifetime distribution in each group. The lifetime character in each test group is represented only by the scale parameter β_i. Therefore, an linear regression model

$$\log(t_{ij}) = \log(A) + b\log(V_i) + \epsilon_{ij}, i = 1, 2, 3, j = 1, 2, ..., N_i \quad (1)$$

can be used to estimate the parameters $\log(A)$ and b. Since the lifetimes follow a scale distribution family with different scale parameter and the stress factor will not influence other parameters, the condition of the Gauss-Markov theorem is satisfied. Therefore, the least square method can derive the best linear unbiased estimator, which gives accuracy of the estimate. In addition, the asymptotic normality is satisfied under the Gauss-Markov theorem, which means we can derive statistical inference of parameters by the normality of them. Since the parameter estimate process is semi-parametric, we do not assume a specific distribution family here, then we have to use acceleration factor $A_f = (\frac{V}{V'})^B$ to complete the reliability estimate.

3. Simulation Study

3.1 Simulation Setting

The Table 1 shows the simulation results. These data use the Weibull (α, β_i) and Lognormal (μ_i ,σ^2), which the sample size per group N=80, 100, 120 and α=4, σ=0.25.

Table 1. True Parameter Value

Setting	$\log(A)$	b	$A_{f(80)}$	$A_{f(100)}$	$A_{f(120)}$
Value	20.40	-2.73	3.61	6.63	10.91

3.2 MSE result

Table 2 . Bias and MSE Table of Lognormal Distribution

Lognormal		$\log(A)$	b	$A_{f(80)}$	$A_{f(100)}$	$A_{f(120)}$
N_i=20	*Bias*	0.0049	-0.0011	0.0174	0.0673	0.1742
	MSE	0.8176	0.0387	0.1132	0.8483	3.7380
N_i=40	*Bias*	-0.0032	0.0007	0.0062	0.0264	0.0709
	MSE	0.3895	0.0184	0.0533	0.3954	1.7223
N_i=60	*Bias*	-0.0089	0.0020	0.0003	0.0057	0.0200
	MSE	0.1975	0.0094	0.0269	0.1985	0.8600

Table 3 . Bias and MSE Table of Weibull Distribution

Weibull		$\log(A)$	b	$A_{f(80)}$	$A_{f(100)}$	$A_{f(120)}$
N_i=20	Bias	-0.0046	0.0011	0.0230	0.0947	0.2523
	MSE	1.3079	0.0620	0.1826	1.3817	6.1515
N_i=40	Bias	0.0031	-0.0006	0.0132	0.0515	0.1339

	MSE	0.6395	0.0303	0.0885	0.6614	2.9033
N_i=60	Bias	0.0004	-0.0001	0.0063	0.0251	0.0656
	MSE	0.3231	0.0153	0.0443	0.3283	1.4284

From the derived results in Table 2 and Table 3, the estimators we get are unbiased, and the MSE decreases as the sample size increases, so the estimators are consistent. In addition to this, our method is valid for both distributions, which reflects our method's robustness.

3.3 Asymptotic Normality

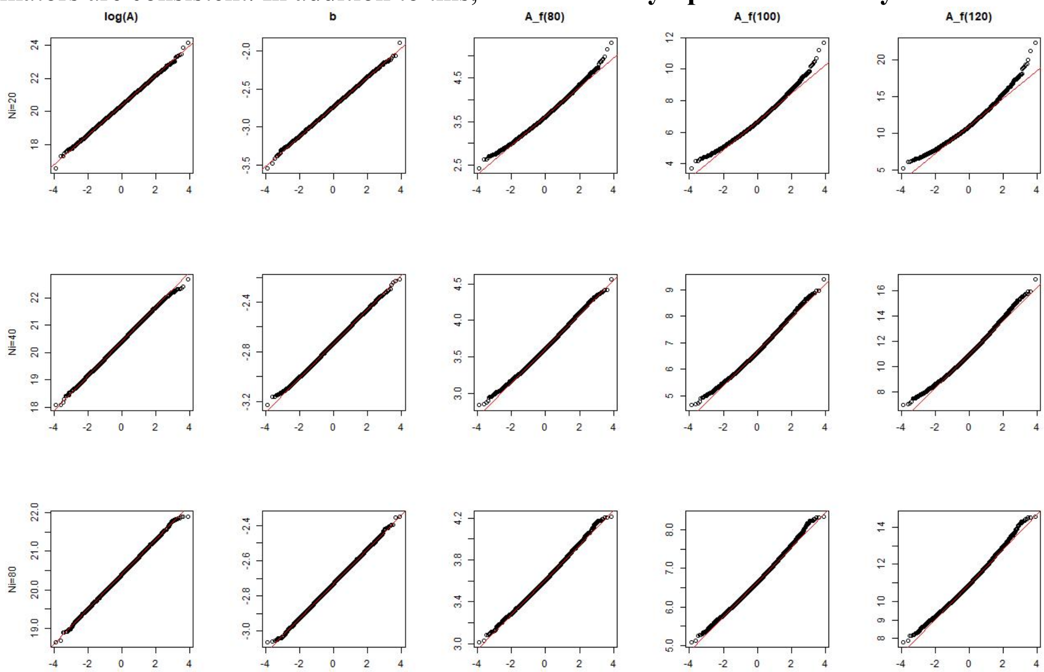

Figure 1. QQ-plots of Lognormal Distribution

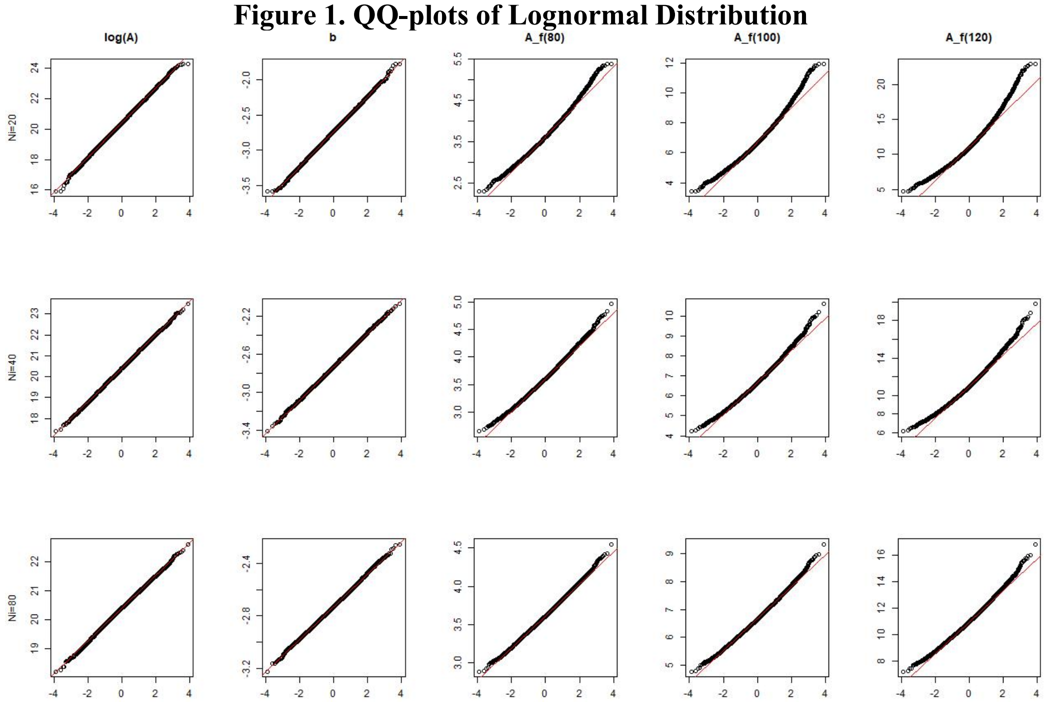

Figure 2. QQ-Plots Of Weibull Distribution

It can be seen from the Figure 1 and Figure 2 that our estimators have good asymptotic normality, and relevant inference can be completed on the basis of normality.

4. Real data analysis

Table 4. Real Accelerated Lifetime Data

	Voltage		
	80	100	120
Life (h)	1770	1090	630

	2448	1907	848
	3230	2147	1121
	3445	2645	1307
	3538	2903	1321
	5809	3357	1357
	6590	4135	1984
	6744	4381	2331
Mean Life (h)	4197	2821	1362

In Table 4, three experimental groups were set up, respectively, the service life of the battery under 80V, 100V, 120V. Each experimental group carried out eight experiments, recording the battery life at different voltages, and finally calculating the average. In this way, we get the inference below, which is shown in the Table 5. The point estimates and CIs of $\log(A)$ and b are derived along with the point estimates of $A_{f(80)}, A_{f(100)}$ and $A_{f(120)}$. In addition, the t-test shows the validity of the model.

Table 5. Inference Outcomes of the Real Data Analysis

	$\log(A)$	b	$A_{f(80)}$	$A_{f(100)}$	$A_{f(120)}$
Estimate	20.0069	-2.6699	3.5074	6.3639	10.3544
95%CI	(14.6665, 25.3474)	(-3.8322, -1.5075)	\	\	\
t-value	7.7690	-4.764	\	\	\

5. Conclusion

In this study, we systematically investigated the impact of voltage on battery life through accelerated life testing and linear regression analysis. The results indicate a significant inverse power relationship between voltage and battery life, underscoring the importance of voltage as an acceleration factor in evaluating battery performance.

The key conclusions are as follows:

The experimental findings demonstrate that as voltage increases, the battery life decreases significantly, which aligns with the inverse power law and highlights the detrimental effect of voltage on battery longevity.

By constructing a linear regression model, we successfully estimated the relevant parameters and confirmed the effectiveness and reliability of the model. The use of a semi-parametric hypothesis ensured that the analysis was not dependent on a specific distribution form, thereby enhancing the generalization ability of the findings.

This research provides a crucial theoretical foundation for battery design and reliability assessment, assisting manufacturers in optimizing voltage usage strategies during product development to extend battery life.

In summary, this study not only offers empirical evidence for understanding the relationship between voltage and battery life but also points to directions for future research in related fields. Subsequent studies could further explore the effects of other acceleration factors on battery life and conduct more in-depth analyses under varying operational conditions to achieve a comprehensive assessment of product reliability.

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