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Accelerated Testing In An Electronic Device With Censored Data

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ABSTRACT: To study the reliability of a product or system, it is important to know about the product's lifespan. In this case, accelerated tests are used in order to accelerate the process of equipment degradation due to exposure to high levels of stress. In this work, an example of a rapid test on an electronic device is presented. The maximum likelihood method is used to obtain the increased statistical model for the lifetime of this device, as a function of temperature. The objective is to estimate the risk as a function of time and temperature, using a model that relates failure times to the stress factor.

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I. INTRODUCTION

An important characteristic of quality is reliability. To obtain information regarding the reliability of a product, it is necessary to conduct lifetime tests. This time is usually very long, making it impractical to carry out such tests. In this context, accelerated life tests are introduced (Nassar; Nadarajah (2021)).

The purpose of accelerated life testing is to expedite the occurrence of failure by applying stressful conditions (examples: usage rate, temperature, voltage, and stress). This tool results in rapid estimates of the variable of interest, which is the time to failure (Sabri-Laghaie; Noorossana (2021)).

Accelerated life testing can be divided into two areas: qualitative and quantitative (Freels et al. (2015)). In qualitative accelerated testing, the engineer is interested in identifying failures and failure modes without needing to make predictions regarding the product's life under normal conditions. In contrast, quantitative accelerated testing involves predicting the product's life under normal conditions based on the data obtained from accelerated testing.

Qualitative testing is done gradually, with the product subjected to a single severe stress level for various stressors. If the product withstands this, it passes the test. However, qualitative accelerated testing is not designed to yield data that can be used subsequently. Therefore, quantitative accelerated testing is necessary.

Unlike qualitative accelerated testing, quantitative accelerated testing is designed to quantify the product's life characteristic and provide information about its reliability. Quantitative accelerated testing uses acceleration methods such as accelerated usage rate and increased stress. The example in this article utilizes accelerated testing on an electronic product with data from the literature.

In the analysis of life data, it is necessary to know all the available data, which can sometimes be incomplete or have some uncertainty about when the failure occurred. Therefore, life data can be divided into two types: complete data and censored data (Cook et al. (2017); Singh (2013)). Complete data means that all information is known. On the other hand, censored data, in many cases, may involve units from the samples that have not failed, or the exact time of failure is not known.

There are three types of censored data: right-censored, left-censored, and mixed. Right-censoring, which will be seen later in the example, is the most common case. In this case, the data consists of units that have not failed due to an interruption. In other words, if the units were to continue being tested, the failure would occur at some point after the collected data.

This work will present an example of an accelerated test from Hooper and Amster (as cited in ESCOBAR; MEEKER, 2007), in which the stress factor is the increase in temperature in an electronic device. Applications of accelerated tests in electronic devices are common (Catelani et al. (2021)). The goal is to estimate risk as a function of time and temperature, using a model that relates failure times to the stress factor. To achieve this, it is necessary to: find a physical-statistical model for the experiment; estimate the parameters through Maximum Likelihood Estimation; test the model's fit with experimental data and use the model to infer risk, reliability, Mean Time To Failure (MTTF), maintenance policies, inspection, and warranty.

II. MATERIAL AND METHODS

2.1 Data

The example developed in this article is the accelerated life test from the Hooper and Amster (1990) paper, in which an experiment with an electronic device is conducted. The authors analyzed accelerated life test data by temperature on an electronic device used in submarine digital repeaters. Since the authors do not specify the specific device, it is referred to as Device A. The data is available in (Meeker and Escobar (1998, page 637)). The objective of the experiment was to determine whether Device A meets a reliability target at 10,000 hours (1.14 years) and at 30,000 hours (3.4 years) for its operational temperature of 10°C (the nominal temperature at the bottom of the Atlantic Ocean).

The experiment had 165 devices available for testing. However, the test only lasted for 5,000 hours, and it was known that failure was unlikely to occur at this temperature within the first 5,000 hours. Therefore, data from this type of experiment is collected under a stressful condition, in this case, at a higher temperature.

During the accelerated test on Device A, the following information was obtained:

- Out of 30 devices placed at a temperature of 10°C, no unit failed.
- Out of 100 devices placed at a temperature of 40°C, 10 units failed.
- Out of 20 devices placed at a temperature of 60°C, 9 units failed.
- Out of 15 devices placed at a temperature of 80°C, 14 units failed.

The number of test units allocated at 40°C is much higher than the numbers allocated at 60°C and 80°C. This is a good statistical practice and was done to ensure that there would be a reasonable number of failures, given the low probability of failure before 5,000 hours.

2.2 Physical-Statistical Model

One of the most important physical relationships that applies to the majority of problems is the Arrhenius relationship. The Arrhenius model is used to relate the mean time to failure of units to their operating temperature (Shin (2023)).

Assuming that the times to failure of a component are proportional to the inverse of the reaction rate (of the failure-causing process). This relationship is described by the Arrhenius acceleration model:

$$L(V) = Ce^{\frac{B}{V}} \tag{1}$$

where L(V) denotes some percentile of interest in the distribution of times to failure (MTTF), V is the stress level, and C and B are physical parameters of the model to be determined. Temperature is typically measured in degrees Celsius. Therefore, it needs to be converted to Kelvin. The conversion can be done as follows:

$$°K = °C + 273{,}15 \tag{2}$$

where ºK is temperature in degrees Kelvin, and ºC is temperature in degrees Celsius.

From a statistical perspective, the Weibull Distribution is the primary model for estimating the distribution of the useful life times of a product. Additionally, it is also the most commonly used distribution for modeling reliability data. Depending on the values of its parameters, it can resemble the characteristics of various types of distributions, including the exponential distribution. Due to its versatility, it is the one that may best fit the experimental data in the example. Therefore, we will use the Weibull Distribution as follows:

$$f(t) = \frac{\beta}{\eta}\left(\frac{t-\gamma}{\eta}\right)^{\beta-1} e^{-\left(\frac{t-\gamma}{\eta}\right)^{\beta}} \tag{3}$$

Where the parameter γ is the location parameter, β is the shape parameter, and η is the scale parameter. Assuming the Weibull distribution with γ = 0, we have:

$$f(t) = \frac{\beta}{\eta}\left(\frac{t}{\eta}\right)^{\beta-1} e^{-\left(\frac{t}{\eta}\right)^{\beta}} \tag{4}$$

The Arrhenius-Weibull model is constructed by setting η = L(V). Therefore, the physical-statistical distribution is given by:

$$f(t) = \frac{\beta}{Ce^{\frac{B}{V}}}\left(\frac{t}{Ce^{\frac{B}{V}}}\right)^{\beta-1} e^{-\left(\frac{t}{Ce^{\frac{B}{V}}}\right)^{\beta}}. \tag{5}$$

The functions of the mean time to failure (MTTF), reliability function, and hazard function are, respectively:

$$MTTF = Ce^{\frac{B}{V}}\,\Gamma\left(\frac{1}{\beta}+1\right) \tag{6}$$

$$C(T,V) = e^{-\left(\frac{t}{Ce^{\frac{B}{V}}}\right)^{\beta}} \tag{7}$$

$$h(t,V) = \frac{\beta}{Ce^{\frac{B}{V}}}\left(\frac{t}{Ce^{\frac{B}{V}}}\right)^{\beta-1} \tag{8}$$

Having the relevant functions of the physical-statistical model, the next step is to find the parameters.

2.3 Parameter Estimation

To estimate the parameters, the Maximum Likelihood Estimator (Meeker and Escobar (1998)) is used. The general likelihood function is given by:

$$L(\theta; x1; \dots; xn) = \prod_{i=1}^{r} f(t_i;\theta) \prod_{j=1}^{n} \left[C(t_j^{+},\theta)\right] \prod_{k=1}^{m} [F(t_k;\theta) - F(t_{k-1};\theta)], \tag{9}$$

where r isthenumberofknownfailure times t_i, n isthenumberofright-censoredunitsatt_j^+, m isthenumberofintervals [t_(k-1) , t_k] containing q failureswhosefailure times are notknownexactly.

In thecitedexample, there are only complete data andright-censoring; therefore, onlythefirsttwofactorsoftheMaximumLikelihoodEstimator are used. Tocalculatetheparameters, theArrhenius-Weibullfunctionandthereliabilityfunctionof Arrhenius-Weibull are substitutedintotheestimator. Thus, thelikelihoodfunctionassociatedwiththemodelis:

$$L = \prod_{i=1}^{r} \frac{\beta}{C\,e^{\frac{B}{V}}}\left(\frac{T_i}{C\,e^{\frac{B}{V}}}\right)^{\beta-1} e^{-\left(\frac{T_i}{C\,e^{\frac{B}{V}}}\right)^{\beta}} \prod_{j=1}^{n} e^{-\left(\frac{T_j}{C\,e^{\frac{B}{V}}}\right)^{\beta}} \tag{10}$$

To solve the maximization problem (10), which lacks an analytical solution, a Differential Evolution method is applied. As described in Kienitz and Wetterau (2012), the Differential Evolution method is a population-based search algorithm that belongs to the class of genetic algorithms. It mimics the process of Darwinian evolution using techniques such as inheritance, mutation, recombination, selection, and crossover. The algorithm is designed to converge to the global optimal solution. The algorithm is described in Chapter 9 of Kienitz and Wetterau (2012).

III. RESULTS

To estimate the parameters, MATLAB was used. The values found for the parameters of the physical-statistical model were C = 1.646543X10^(-6), B = 7355.23, and β = 1.41.

Using these parameter values, it is possible to plot graphs that aid in the interpretation of the problem. The MTTF graph helps us understand the device's performance at temperatures under normal operating conditions up to stressful temperature levels.

Reliability defines the probability of a specific item performing its function within a specific time interval. Through the graph in Figure 2, it is possible to analyze the reliability of Device-A at a fixed ambient temperature (V= 300K). Note that at time 0, it starts at 1, and as time progresses, reliability decreases until it reaches 0.

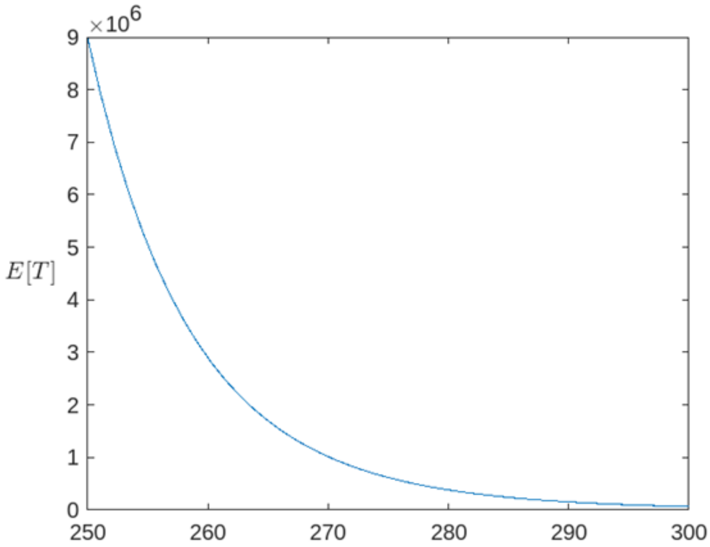

Figure 1 – MTTF Arrhenius-Weibull with respect to the temperature (K)

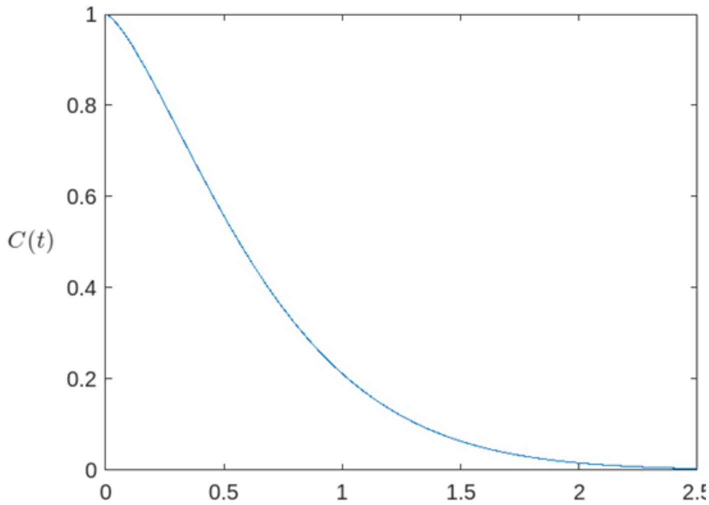

Figure 2 –Arrhenius-Weibull Reliability Function

In Figure 3, it is possible to observe the surface of the reliability function over time and temperature. In the case of an Arrhenius-Weibull model, reliability is also a function of stress, hence the need for a three-dimensional graph to illustrate the effects of stress and beta, as in the figure below, which has this shape because beta is greater than 1.

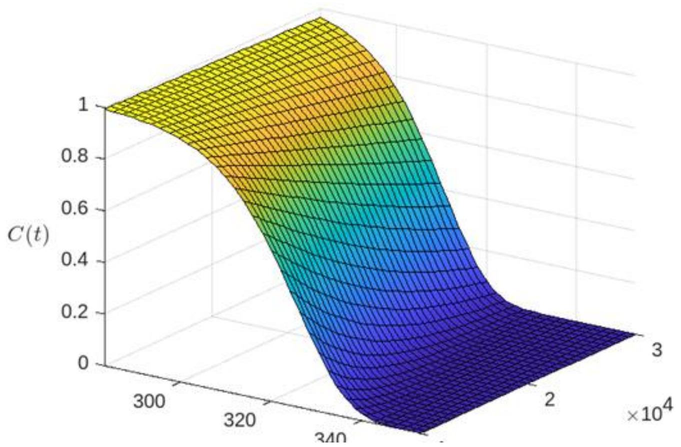

Figure 3 –Arrhenius-Weibull (3D) Reliability Function with respect to temperature (K) and time (hours).

IV. DISCUSSION AND CONCLUSION

In conclusion, this paper has demonstrated the application of accelerated life testing and statistical modeling techniques in assessing the reliability and performance of Device-A under varying stress conditions. By adopting the Arrhenius-Weibull model and utilizing the Maximum Likelihood Estimator, the study successfully estimated key parameters (C, B, and β) that characterize the device's behavior.

The analysis and interpretation of the results, illustrated through graphs of Mean Time To Failure (MTTF) and Reliability, offer valuable insights into the device's performance across different temperature levels and times. The reliability graph vividly portrays how the device's reliability decreases over time, providing crucial information for decision-making regarding maintenance, inspection, and warranty policies.

Furthermore, the three-dimensional representation of the reliability function over time and temperature highlights the complex interplay between stress and beta values, emphasizing the importance of considering these factors in reliability assessments.

Overall, this paper exemplifies a comprehensive approach to accelerated life testing and statistical modeling, offering a framework for evaluating and improving the reliability of electronic devices. The methodology presented here can be extended to various industrial applications, enhancing our understanding of product performance and contributing to informed decision-making in the field of reliability engineering.

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