# Statistical Methods for Reliability Data Using SAS® Software

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## Abstract

In the past decade there has been a high degree of interest in improving the quality, productivity, and reliability of manufactured products. Global competition and higher customer expectations for safe, reliable products are driving this interest. After the areas of experimental design and statistical process control the one of reliability is the next to receive a high degree of emphasis. Industry's current concern is on how to move rapidly from product conceptualization to a cost-effective highly reliable product. Part of the reliability assurance process requires conducting tests and studies to obtain reliability data and to turn these data into useful information for making decisions.

In this paper we consider the use of modern methods for analyzing time-to-failure data that can be implemented using SAS software. We provide an appropriate mix of proven traditional techniques, enhanced and brought up to date with some modern computer-based methodology. The methodology will be illustrated using PROC RELIABILITY to analyze some applications of product reliability.

**Key words**: Life data; Censored data, Quality, Survival analysis; PROC RELIABILITY.

# 1 Introduction

## 1.1 Importance of reliability data analysis

Proper reliability data analysis are needed in diverse areas like design for reliability, reliability modeling, reliability budgeting, reliability prediction and assessment, reliability demonstration. Some major objectives in obtaining reliability data include: (i) Obtaining early identification of failure modes and understanding and removing their root causes–and thereby improving reliability. (ii) Determining how long each unit should be run prior to shipment in order to avoid likely premature field failures. (iii) Quantifying reliability to determine whether or not a product is ready for release.

## 1.2 Common types of reliability data

It is important to distinguish between the following types of reliability data: (i) A sequence of reported system failure times (or the times of other system-specific events) for a repairable system. (ii) The time of failure (or other clearly specified event) for nonrepairable units or components (including data in *nonrepairable* components within a *repairable* system).

We describe methods for data analysis for nonrepairable units or components as well as for analyzing system reliability data using SAS software. Data from *nonrepairable* units arise from many different kinds of reliability studies see Meeker, Escobar, Doganaksoy, and Hahn (1997) (MEDH) for a detailed account.

## 1.3 Censoring

Reliability data are typically censored (exact failure time is not known). The most common reason for censoring is the need to analyze data before all units fail. The analysis of censored data is more complicated when the censoring times of unfailed units differ. This would happen when different units of the product enter into the field at different times, as is usually the case in analyzing field failure data. It may also be the case when units have different degrees of exposure over time or when one is evaluating failures due to a particular failure mode (in which case, failures from other independent modes are treated as censored observations).

An important assumption needed for standard analysis of censored data is that the censoring time for a unit is chosen independently of when that unit would have failed. For example, if a unit were removed from the field because it is about to fail, treating it as a censored observation would bias the analysis.

### 1.4 Computer software

Although it is possible to do some of the simplest reliability data analyses by hand, for effective analyses with real problems, computer processing with modern high-resolution graphics should be used. PROC RELIABILITY provides capabilities that facilitate the analysis of reliability data.

## 2 Life Data Models

This section deals mainly with unrepairable components or other products that are replaced rather than repaired (or time to failure of first failure on repairable products). We describe: (i) a summary of alternative statistical models for representing time to failure of non-repairable products; (ii) two parametric models commonly used in the analysis of reliability data.

### 2.1 Time-to-failure models

The distribution of time to failure $T$ can be characterized by a cumulative distribution function (cdf), a survival function (sf), a probability density function (pdf), or a hazard function (hf). These functions are illustrated, for a typical time-to-failure distribution, in Figure 1. The choice of which function of functions to use depends on con-

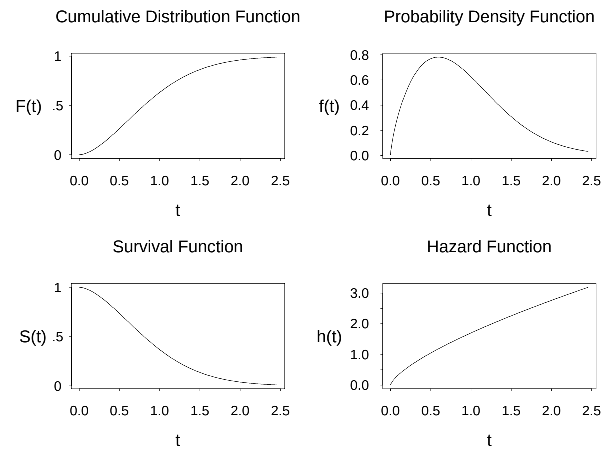


Figure 1: Typical time-to-failure cdf, pdf, sf, and hf.

venience of model specification, interpretation, or technical development. All are important for one purpose or another. In Section 2.3, we give the cdfs for the lognormal and Weibull families.

### 2.2 Parameters of interest in reliability analysis

Often, the traditional parameters of a statistical model (mean and standard deviation) are *not* of primary interest in reliability studies. Instead, design engineers, reliability engineers, managers, and customers are interested in specific measures of product reliability or particular characteristics of a failure-time distribution, e.g., quantiles of the time-to-failure distribution. The quantile $t_p$ is the time at which a specified proportion $p$ of the population will have failed. Also, $F(t_p) = p$. For example $t_{.20}$ is the time by which 20% of the population will have failed. Alternately, frequently one would like to know the probability of failure associated with a particular number of hours, days, week, months, or years of usage.

### 2.3 Some useful parametric models

Here we give the cdfs and the log-quantiles for two very useful parametric models commonly used in reliability analysis. For a complete detailed description of these and some other parametric models see Chapters 4 and 5 of Meeker and Escobar (1998) and MEDH (1997).

**Lognormal distribution.** For the lognormal distribution the cdf and the quantiles are

$$\begin{aligned} F(t;\mu,\sigma) &= \Phi_{\text{nor}}\left[\frac{\log(t)-\mu}{\sigma}\right], \quad t>0 \\ \log(t_p) &= \mu + \Phi_{\text{nor}}^{-1}(p)\sigma, \quad 0<p<1 \end{aligned}$$

where $\Phi_{\text{nor}}$ is the cdf for the standardized normal distribution.

The logarithm of a lognormal random variable $Y = \log(T)$ follows a normal distribution with mean $\mu$ and standard deviation $\sigma$. This relationship between the lognormal and normal distributions is often used to simplify the process of using the lognormal distribution.

**Weibull distribution.** For the Weibull distribution the cdf and the quantiles are

$$\begin{aligned} F(t;\eta,\beta) &= 1-\exp\left[-\left(\frac{t}{\eta}\right)^{\beta}\right], \quad t>0 \\ \log(t_p) &= \mu + \Phi_{\text{sev}}^{-1}(p)\sigma, \quad 0<p<1 \end{aligned}$$

where $\mu = \log(\eta)$, $\sigma = 1/\beta$, and $\Phi_{\text{sev}}(z) = 1-\exp[-\exp(z)]$ is the cdf for a standardized smallest extreme value distribution.

The logarithm of a Weibull random variable $Y = \log(T)$ follows a smallest extreme value distribution with location-scale parameters $(\mu, \sigma)$.

# 3 Strategy for the Analysis of Censored Life Data

This section briefly discusses two examples to illustrate some useful methods for analyzing life data. The first example are single censored data from a laboratory life test. The second example illustrates the analysis of multiply censored data from a field tracking study. In both cases we follow the following simple strategy

- Examine the data graphically, using a nonparametric estimate plotted on special probability paper (giving a probability plot).
- If a parametric distribution provides an adequate description of available data, its parameters are estimated and the distribution model are used to provide estimates and confidence intervals for distribution quantiles and population proportion failing.

## 3.1 Simple life test data (single censoring)

**Chain link fatigue life.** Parida (1991) gives the results of a load-controlled high-cycle fatigue test conducted on 130 chain links. The 130 links were randomly selected from a population of different heats used to manufacture the links. Each link was tested until failure or until it had run for 80 thousand cycles, which ever came first. There were 10 failures—one each reported at 33, 46, 50, 59, 62, 71, 74, and 75 thousand cycles and 2 reported at 78 thousand cycles. The other 120 links had not failed after 80 thousand cycles.

A nonparametric estimate of $F(t)$ is computed as

$$\widehat{F}(t) = \frac{\#\text{ of failures up to time } t}{n}. \qquad (1)$$

$\widehat{F}(t)$ is a step function that jumps by an amount $1/n$ at each failure time (unless there are ties, in which case the estimate jumps by the number of tied failures divided by $n$). For details see Meeker and Escobar (1998) or MEDH (1997)

Figure 2 was generated with PROC RELIABILITY, the nonparametric estimate of the cdf fall nearly along a straight line, indicating that the Weibull distribution will provide a good fit to these data. A similar lognormal plot (not shown here) had showed some curvature but the degree of departure was small relative to the sampling uncertainty exhibited by the confidence bands, indicating the chain link fatigue data could have come from either distribution.

Figure 2 also shows a Weibull Maximum Likelihood (ML) estimate plot for the chain link data. The dotted lines are drawn through a set of *pointwise* normal-approximation confidence intervals for $F(t)$ (computed as described in Chapter 8 of Meeker and Escobar 1998).

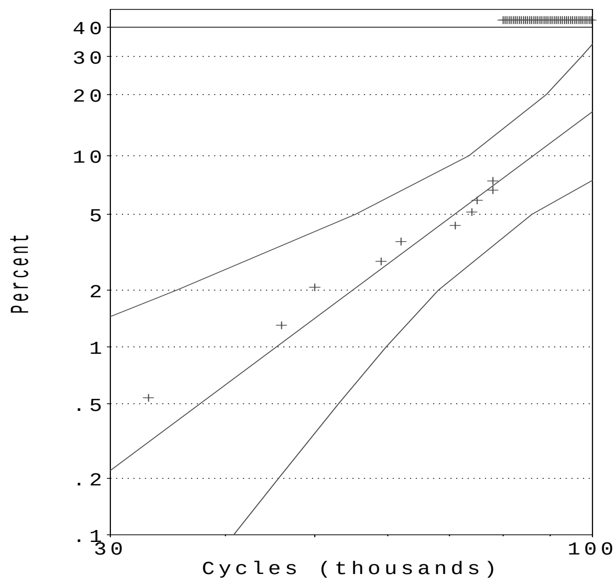


Figure 2: Weibull probability plot with the Weibull ML estimate and a set of approximate 95% confidence intervals for $F(t)$ for the chain link failure data.

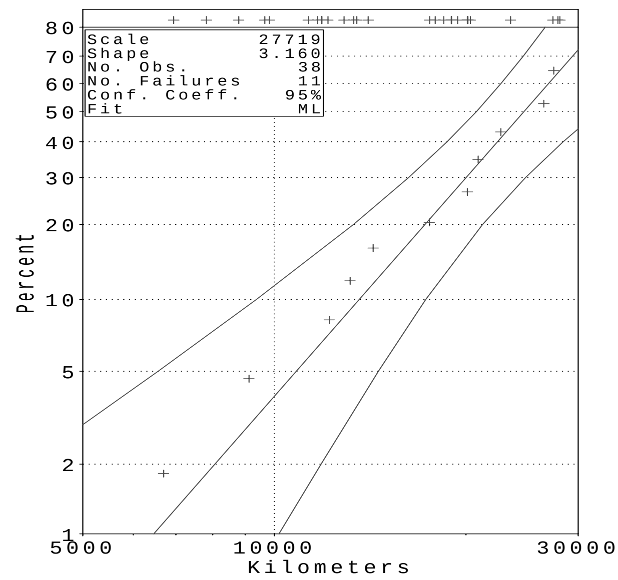


Figure 3: Weibull probability plot of shock absorber failure times with ML estimates and approximate 95% pointwise confidence intervals for quantiles.

## 3.2 Analysis of staggered field data entry (multiply censored data)

Multiple censoring can arise when units go into service at different times so that some running times are less than some censoring times. For such data, the cumulative fatigue probability $F(t)$ cannot be estimated directly using (1).

**Shock absorber failure data.** O'Connor (1985) gives failure data for shock absorbers. At the time of analysis, failures had been reported at 6700, 9120, 12200, 13150, 14300, 17520, 20100, 20900, 22700, 26510, and 27490 km. There were many units in service that had not failed. The running times for these units were 6950, 7820, 8790, 9660, 9820, 11310, 11690, 11850, 11880, 12140, 12870, 13330, 13470, 14040, 17540, 17890, 18450, 18960, 18980, 19410, 20100, 20150, 20320, 23490, 27410, 27890, and 28100 km.

To estimate $F(t)$ with multiply censored data we use the following procedure. Let $t_1$, $t_2$, ..., $t_m$ denote the times where failures occurred, let $d_i$ denote the number of units that *died* or failed at $t_i$, and let $n_i$ denote the number units that are alive just before $t_i$. The nonparametric estimator of $F(t)$ for values of $t$ between $t_i$ and $t_{i+1}$ is

$$\widehat{F}(t_i) = 1 - \prod_{j=1}^{i}\left[1 - \frac{d_j}{n_j}\right] \quad i = 1, \ldots, m. \qquad (2)$$

This is the well-known product-limit or Kaplan-Meier (KM) estimator. It can be shown that the KM estimator simplifies to (1) when the data are complete or single censored. Figure 3 obtained using PROC RELIABILITY gives a Weibull probability plot for the shock absorber data along with approximate 95% pointwise likelihood confidence intervals for selected quantiles $t_p$ of the life distribution (for details see Meeker and Escobar 1998).

# 4 Accelerated Life Test Data Analysis

Estimating the time-to-failure distribution or long-term performance of components of *high reliability* products is particularly difficult. Most modern products are designed to operate without failure for years, decades, or longer. Accelerated Life Tests (ALTs) are used widely in manufacturing industries, particularly to obtain timely information on the reliability of simple product components and materials, and to provide early identification (and removal) of failure modes, thus improving reliability.

### 4.1 Strategy for analyzing ALT data

This section outlines and illustrates a strategy that has been useful for analyzing ALT data consisting of a number of subexperiments, each having been run at a particular set of conditions. The basic idea is to start by analyzing the subexperiments separately and then to progress to fitting a model that ties together the data at different conditions. Briefly, the strategy is to

- Examine the data graphically, especially through probability plots, to suggest and explore the adequacy of possible distributional models.
- At test conditions with two or more failures, fit models individually to the data at separate levels of the acceleration variable. Plot the ML lines on a multiple probability plot showing the individual nonparametric estimates at each level of the accelerating factor. Use the plotted points and fitted lines to assess the reasonableness of the constant-$\sigma$ assumption and of the model relating life different levels of the accelerating factor (e.g. Figure 4).
- Fit an overall model with the assumed relationship between life and the accelerating variable (e.g. Figure 5).
- Perform residual analyses and other diagnostic checks of the model assumptions.
- Assess the reasonableness of using the ALT data to make the desired inferences.

For further examples and further discussion of methods for analyzing ALT data, see Nelson (1990) or Meeker and Escobar (1998).

**New Technology Device.** Table 1 gives the results of an ALT on a new-technology integrated circuit (IC) device. The device inspection process involved an electrical diagnostic test that required much time on a machine requiring expensive measurements. Thus only a few inspections could be conducted on each device. The first inspection was after one day with subsequent inspections at two days, four days, and so on. Tests were run at 150, 175, 200, 250, and 300°C. The analysis of these data requires special statistical methods that are described in Chapter 9 of Nelson (1982), Chapter 3 of Nelson (1990), and Chapters 3, 7, and 21 of Meeker and Escobar (1998).

Table 1: Hours versus temperature data from an ALT experiment on a new-technology integrated circuit device.

| Hours | | | Number | Temp |
|---|---|---|---|---|
| Lower | Upper | Status | of Obs | Degrees C |
| – | 1536 | Censored | 50 | 150 |
| – | 1536 | Censored | 50 | 175 |
| – | 96 | Censored | 50 | 200 |
| 384 | 788 | Failed | 1 | 250 |
| 788 | 1536 | Failed | 3 | 250 |
| 1536 | 2304 | Failed | 5 | 250 |
| – | 2304 | Censored | 41 | 250 |
| 192 | 384 | Failed | 4 | 300 |
| 384 | 788 | Failed | 27 | 300 |
| 788 | 1536 | Failed | 16 | 300 |
| – | 1536 | Censored | 3 | 300 |

The developers were interested in estimating the activation energy of the suspected failure mode and the long-life reliability of the components as characterized by the proportion of devices in the product population that would fail by 100 thousand hours (about 11 years).

The analysis here was done using PROC RELIABILITY. Figure 4 is a lognormal probability plot of the failures at 250 and 300°C along with the ML estimates of the individual lognormal cdfs. The different slopes in the plot suggests the possibility that the lognormal shape parameter $\sigma$ changes from 250 to 300°C. Such a change could be caused by a change in failure mode. Failure modes with a higher activation energy, that might never be seen at low levels of temperature, can appear at higher levels of temperature (or other acceleration factors). A 95% confidence interval on $\sigma_{250}/\sigma_{300}$ is $[1.01, \quad 3.53]$ (calculations not shown here), suggests that there could be a difference.

These results also suggested that detailed physical failure mode analysis should be done for at least some of the failed units and that, perhaps,

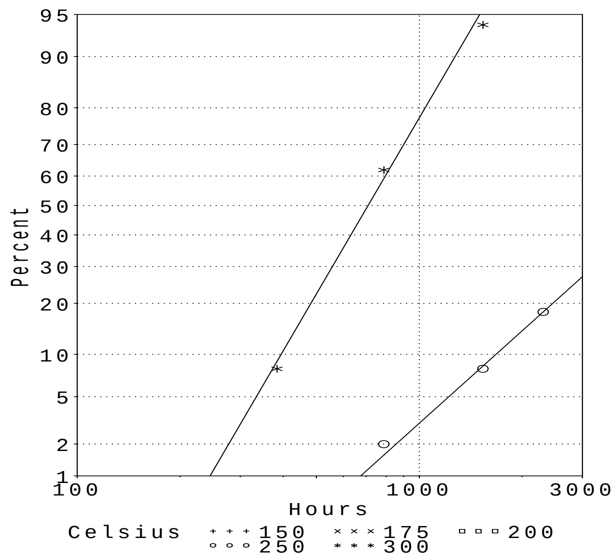


Figure 4: Lognormal probability plot of the failures at 250 and 300°C for the new-technology integrated circuit device ALT experiment.

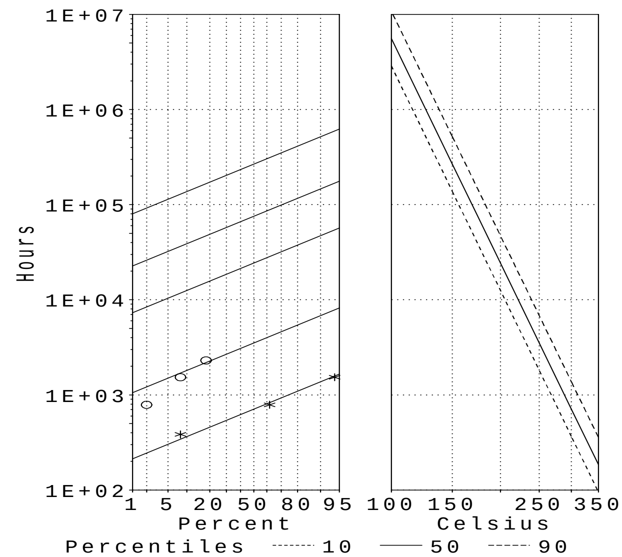


Figure 5: Lognormal probability plot showing the Arrhenius-lognormal model ML estimation results for the new-technology IC device.

Table 2: Arrhenius-lognormal model ML estimation results for the new-technology IC device.

| Parameter | ML Estimate | Standard Error | 95% Approximate Confidence Intervals Lower | Upper |
|---|---|---|---|---|
| $\beta_0$ | −10.2 | 1.5 | −13.5 | −7.4 |
| $\beta_1$ | 9.6 | .85 | 8.05 | 11.45 |
| $\sigma$ | .52 | .06 | .42 | .64 |

The loglikelihood is $\mathcal{L} = -88.36$. The confidence intervals are based on the likelihood ratio approximation method.

the accelerated test should be extended until some failures are observed at lower levels of temperature.

Table 2 gives Arrhenius-lognormal model ML estimation results for the new-technology IC device assuming a constant $\sigma$. The confidence interval for $\beta_1$ indicates that the temperature has an accelerating effect on the failure of the devices. The right hand side in Figure 5 is an Arrhenius plot of the Arrhenius-lognormal model fit (quantiles $t_{.10}$, $t_{.50}$, and $t_{.90}$) of the new-technology IC device ALT data. Because failures were only observed at 250 and 300°C, the plot shows the rather extreme extrapolation needed to make inferences at the use conditions of 100°C. If the projections are close to the truth, it appears unlikely that there will be any failures below 200°C during the remaining 3000 hours of testing and, as mentioned before, this was the reason for starting some units at 200°C. The lognormal probability plot on the left hand side of Figure 5 shows estimated lognormal cdfs for all of the test levels of temperature as well at the use-condition of 100°C. The slopes of the lines are the constant $\sigma$ assumption.

# 5 Repairable System Data

The purpose of some reliability studies is to describe the failure trends and patterns of an *overall system* or collection of systems. System failures are followed by a system repair and data consist of a sequence of system failure times for similar systems.

Repairable system data can be viewed as sequence of reported failure times $T_1, T_2, \ldots$ in time. Some applications have data on only one system. In other applications there may be data from a collections of systems. In either case failures are typically observed in a fixed observation interval $(t_0, t_a)$, where, typically, $t_0 = 0$. In some cases the numbers of failures in intervals are reported and

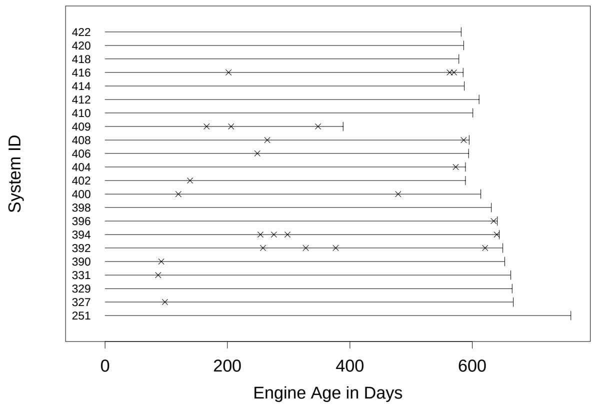


Figure 6: Valve seat event plot.

in other cases, exact times are recorded. System reliability data are collected to estimate quantities like: (i) the distribution of the times between failures, $\tau_j = T_j - T_{j-1}$ $(j = 1, 2, \ldots)$ where $T_0 = 0$; (ii) the number of failures in the interval $(0, t]$ as a function of $t$; (iii) the expected number of failures in the interval $(0, t]$ as a function of $t$; (iv) the rate of occurrence of failures (ROCOF) as a function of time $t$.

**Times of replacement of diesel engine valve seats.** Repair records for a fleet of 41 diesel engines were kept over time. Table 3 gives the the times of replacement (in number of days of service) of the engine's valve seats. This is an example of data on a group of systems. The data were originally given in Nelson and Doganaksoy (1989) and also appear in Nelson (1995). Questions to be answered by these data include the following: (i) Does the replacement rate increase with age? (ii) How many replacement valves will be needed in the future? (iii) Can valve life in these systems be modeled as a renewal process (so that simple methods for independent observations can be used for analysis)?

Simple data plots provide a good starting point for analysis of system repair data. Figure 6 is an event plot of the valve seat repair data showing the observation period and the reported repair times.

Table 3: Times of replacement diesel engine valve seats. From Nelson and Doganaksoy (1989).

| System ID | Days Observed | Replacement Time Days | | | |
|---|---|---|---|---|---|
| 251 | 761 | | | | |
| 403 | 593 | | | | |
| 252 | 759 | | | | |
| 404 | 589 | 573 | | | |
| 327 | 667 | 98 | | | |
| 405 | 606 | 165 | 408 | 604 | |
| 328 | 667 | 326 | 653 | 653 | |
| 406 | 594 | 249 | | | |
| 329 | 665 | | | | |
| 407 | 613 | 344 | 497 | | |
| 330 | 667 | 84 | | | |
| 408 | 595 | 265 | 586 | | |
| 331 | 663 | 87 | | | |
| 409 | 389 | 166 | 206 | 348 | |
| 389 | 653 | 646 | | | |
| 410 | 601 | | | | |
| 390 | 653 | 92 | | | |
| 411 | 601 | 410 | 581 | | |
| 391 | 651 | | | | |
| 412 | 611 | | | | |
| 392 | 650 | 258 | 328 | 377 | 621 |
| 413 | 608 | | | | |
| 393 | 648 | 61 | 539 | | |
| 414 | 587 | | | | |
| 394 | 644 | 254 | 276 | 298 | 640 |
| 415 | 603 | 367 | | | |
| 395 | 642 | 76 | 538 | | |
| 416 | 585 | 202 | 563 | 570 | |
| 396 | 641 | 635 | | | |
| 417 | 587 | | | | |
| 397 | 649 | 349 | 404 | 561 | |
| 418 | 578 | | | | |
| 398 | 631 | | | | |
| 419 | 578 | | | | |
| 399 | 596 | | | | |
| 420 | 586 | | | | |
| 400 | 614 | 120 | 479 | | |
| 421 | 585 | | | | |
| 401 | 582 | 323 | 449 | | |
| 422 | 582 | | | | |
| 402 | 589 | 139 | 139 | | |

### 5.1 Nonparametric model for point process data

For a single system, simple point process starting at time 0, data can be expressed as $N(t)$, the cumulative number of failures up to time $t$. The corresponding model, used to describe a population of systems, is based on the mean cumulative function (MCF) at time $t$. The MCF is defined as $\mu(t) = \mathrm{E}[N(t)]$, where the expectation is over the variability of each system and the unit-to-unit variability in the population.

**Point estimate of the MCF.** Nelson (1988) provided an unbiased estimator of the MCF, allowing for different lengths of observation among systems. Nelson's estimate of the population MCF can be computed as follows

- Order the unique $t_{ij}$ among all of the $n$ systems. Let $m$ denote the number of unique times. These ordered unique times are denoted by $t_1 < \ldots < t_m$.
- Compute $d_i(t_k)$ the total number of repairs for system $i$ at $t_k$.
- Let $\delta_i(t_k) = 1$ if system $i$ is still being observed at time $t_k$ and $\delta_i(t_k) = 0$ otherwise.
- Compute

$$\widehat{\mu}(t_j) = \sum_{k=1}^{j} \frac{d.(t_k)}{\delta.(t_k)} = \sum_{k=1}^{j} \bar{d}(t_k),$$

  for $j = 1, \ldots, m$ where $d.(t_k) = \sum_{i=1}^{n} \delta_i(t_k) d_i(t_k)$, $\delta.(t_k) = \sum_{i=1}^{n} \delta_i(t_k)$, and $\bar{d}(t_k) = d.(t_k)/\delta.(t_k)$.

Note that $d.(t_k)$ is the total number of system repairs at time $t_k$, $\delta.(t_k)$ is the size of the risk set at $t_k$, and $\bar{d}(t_k)$ is the average number of repairs per system at $t_k$ (or proportion of repaired systems if individual systems have no more than one repair at a point time). Thus the estimator of the MCF is obtained by accumulating the mean number (across systems) of repairs per system in each time interval.

For information on the computation of the standard errors of $\widehat{\mu}(t_j)$ and nonparametric confidence intervals for MCF, see Nelson (1989), Nelson (1995), and Meeker and Escobar (1998).

A plot of $\widehat{\mu}(t)$ versus age indicates whether the reliability of the system is increasing, decreasing or unchanging over time.

**MCF estimate for the valve-seat replacements.** Figure 7 shows the estimate of the valve-seat MCF as a function of engine age in days. The estimate increases sharply after 650 days, but it is important to recognize that this part of the estimate is based on only a small number (i.e., 10) of systems that had a total operating period exceeding 650 hours. The uncertainty in the estimate for longer times is reflected in the width of the confidence intervals (the computation of such confidence limits is explained in Nelson 1995 and Meeker and Escobar 1998).

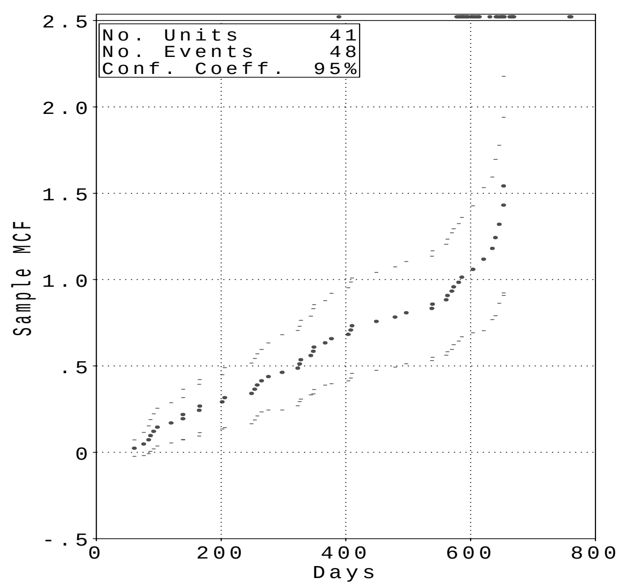


Figure 7: Estimate of the mean cumulative number of valve seat repairs.

# 6 Final Remarks and Comments

## 6.1 Other resources available in SAS

The examples here highlight some of the relevant features of PROC RELIABILITY. The procedure, however, provides many other features (no discussed here) which facilitate the analysis of reliability data. These include: comparison of two samples of repair data; analysis of Binomial and

Poisson data; and analysis of Weibull data when there are few or no failures.

PROC RELIABILITY can be useful to practitioners in other areas like biostatistics, survival analysis, etc. since it supplements the current capabilities of PROCs LIFETEST, LIFEREG, and PHREG (see Allison 1995). For this purpose, it would be necessary, however, to upgrade PROC RELIABILITY to handle inspection data (readout data or life tables data) with a general structure. Currently the procedure only admits inspection data in which all the units have the same inspection schedule, this in general is too restrictive for the analysis of time-to-event data.

### 6.2 Some other needs

As PROC RELIABILITY evolves, one would like to see some new options, within the scope of the current experimental version, that could enhance the power of the procedure. In general, it will be useful to have some options that permit a closed graphical study of the likelihood as a function of the parameters of interest. It would also be convenient to have options to plot the profile of quantities of interest like parameters, failure probabilities, and quantiles of the life distribution. Furthermore, it would be nice to have the option of requesting the computation and plotting of bootstrap confidence intervals for quantities of interest.

Finally, there are many areas in reliability data analysis that lack appropriate software. These include software for planning life tests; degradation data analysis; Bayesian methods; system reliability; planning of accelerated (degradation) life tests, etc. Relevant statistical issues related to these and other important topics in reliability are discussed at large in Meeker and Escobar (1998).

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# A SAS Code

```
%macro psfile(file);
 %***********************************;
 %* Create postscript file  'file.ps'*;
 %***********************************;
goptions reset=goptions device=psepsf
 cback=white colors=(black) noprompt
 gaccess=gsasfile gsfmode=replace;
```

```
filename gsasfile  "&file..ps";
%put %str( );
%put %str(Graphics Device is--PSEPSF);
%mend psfile;
 /************************************/
 /*   NAME: General options          */
 /************************************/
 options nodate nostimer nonumber
 source2 ls=76 ps=80;
 goptions ftext=none htext=2 cell;
 symbol1  v=plus   h=2;
 symbol2  v=x      h=2;
 symbol3  v=square h=2;
 symbol4  v=circle h=2;
 symbol5  v=star   h=2;
 title " ";
 /************************************/
 /*   NAME: Chain link data analysis */
 /************************************/
%psfile(figures/chain.link);
 filename chainid 'data/chain.link';
 data chain; infile chainid firstobs=3;
  input cycles censor units;
 run;
 ;
 proc reliability data = chain;
  label cycles='Cycles (thousands)';
  freq units;
  distribution Weibull;
  probplot cycles*censor(2)/
  lrclper pconfplt llower=30 plower=.1
  pupper=40 noinset ;
 run;
 /************************************/
 /*   NAME: Shock absorber analysis  */
 /************************************/
%psfile(figures/shock.absorber);
 filename shockid 'data/shock.absorber';
 data shock; infile  shockid firstobs=4;
  input vehicle distance censor1 censor2
  censor;
  keep vehicle distance censor;
 run;
 ;
 proc reliability data = shock;
  label distance='Kilometers';
  distribution Weibull;
  probplot distance*censor(2)/lrclper
  llower=5000 lupper=30000  plower=1
  pupper=80;
  inset/height=2 cfill=white;
 run;
 /************************************/
 /*   NAME: new technology analysis  */
 /************************************/
%psfile(figures/new.tech.arrh);
 filename newid 'data/new.technology';
 data newtech; infile newid firstobs=9;
  input time fail temp units;
 run;
 ;
 proc reliability data=newtech;
  label time='Hours';
  label temp='Celsius';
  freq fail;
  nenter units;
  distribution lognormal;
  model time = temp / readout
  relation = arr lrcl;
  rplot time  = temp / readout
  relation = arr
  plotfit 10 50 90 fit=model
  lupper=1e7 llower=1e2
  slower=100 pplot noconf
  plower=1   pupper=95 nopplegend;
 run;
%psfile(figures/new.tech.pplot);
 proc reliability data = newtech;
  label time='Hours';
  label temp='Celsius';
  freq fail;
  nenter units;
  distribution lognormal;
  probplot time=temp /
  readout scale=.7 scinit overlay
  pupper=95  plower=01
  lupper=3000 llower=100
  noconf;
 run;
 /************************************/
 /*   NAME: valveseat analysis       */
 /************************************/
%psfile(figures/valveseat);
 symbol v=dot h=.7;
 filename valveid 'data/valve.seat';
 data valve;
  infile  valveid  firstobs=3;
  input id days value @@;
 run;
 ;
 proc reliability;
  label days='Days';
  unitid id;
  mcfplot days*value(-1);
  inset / cfill = white;
 run;
```

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