Models and data used for assessing the ageing of systems, structures and components

(European Network on Use of Probabilistic Safety Assessment (PSA) for Evaluation of Ageing Effects to the Safety of Energy Facilities)

C.Atwood, O.Cronval, M.Patrik, A. Rodionov

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Contact details:
Andrei Rodionov
Tel. +31 (0) 224 56 54 57
E-mail : Andrei.rodionov@jrc.nl

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Abstract

This report summarizes and presents the results of the studies conducted in the frame of European Network on Use of Probabilistic Safety Assessment (PSA) for Evaluation of Ageing Effects to the Safety of Energy Facilities (EC JRC IE Ageing PSA Network). The Network was initiated and will be operated within the framework of the JRC FP-6/7 Institutional Action "Analysis and Management of Nuclear Accidents" (AMA).

Report is focussed on the reliability models and data could be used for assessing the ageing of systems, structures and components including statistical and physical ones. The results of the case study on demonstration of possible application of statistical evaluation of ageing trend in case of I&C and electrical components presented in Appendix B.

Context

1. General aspects related to ageing of NPP systems, structures and components

Ageing, which could be understood as a general process in which characteristics of components, systems and structures ("equipment") gradually change with time or use, eventually leads to degradation of materials subjected to service conditions and could cause a reduction in component and systems safety margins.

Ageing affects all materials in nuclear power plants (NPPs) to some degree and therefore may lead to degradation of safety state /i.e. integrity and functional capability/ of plant components.

Ageing as cumulative degradation occurs with the passage of time. However, the amount of degradation within given period of time depends on the spectrum of degrading conditions present. These conditions are created by the operational environment, which includes the effects of operational procedures, policies and maintenance, etc.

The amount of degradation and the rate at which degradation accumulates can be mitigated /change/ by maintenance activities. If maintenance results in complete renewal /replacement of all degraded parts, then the component may be considered as good as new. If it results in the renewal /replacement of only subset of the degraded parts, the component may be considered better than old. If the activity results in the return of the component to a condition nearly equivalent to that before /repair or replacement of single part/ then the component may be considered as good as old. The component may be even better than new if parts which were replaced with better than original ones or worse than old as a result of faulty parts or improper maintenance /Wolford (1992)/.

NPPs, as large operating complexes, cover a broad spectrum of materials and designs and operate in a variety of different environments. A number of **factors** can cause degradation of the functional capability of components, systems and structures /Vora (1991)/:

- **Material degradation mechanisms** /neutron embrittlement, fatigue, erosion, corrosion, oxidation, thermal embrittlement, chemical reactions/
- Irradiation, primary and secondary chemistry, vibration loads are the typical **stressors** for operating environment, Freezing, brackish water and humidity are typical examples of stressors for external environment.
- Accumulation of fatigue damage due to plant operational cycling, wear of rotating equipments or wear of drive rod assembly are typical examples of **service wear.**
- Frequent testing of equipment – **excessive testing** of diesel generators is a typical example
- **Improper installation, application or maintenance** – investigations indicates significant contribution of improper maintenance

Also operating experience shows that age related component failures have occurred because of degradation processes such as general and local corrosion, erosion, erosion-corrosion, radiation and thermally induced embrittlement, fatigue, corrosion fatigue, creep, binding and wear.

Examples of some significant ageing related component failures include /IAEA (1992)/:

- Carbon steel feedwater line rupture caused by single phase erosion-corrosion
- Wall thinning (metal loss of 1-9 mm/a) of carbon steel bodies of boiler feed pumps and valves caused by single phase erosion-corrosion,
- Zircaloy pressure tube rupture caused by hydride blistering
- Failures of primary pump motors due to degradation of high voltage epoxy mica insulation of stator windings caused by electrical stress (partial discharge),
- Failures of electrical cable insulation caused by thermal embrittlement.
- Failure of control rods to scram due to degradation of BUNA-N disc material of the scram pilot valve solenoids.
- Failure of cables, attributable to temperature induced accelerated aging and degradation of cable insulation, resulting in loss of off-site power.
- Failure of inverters due to thermal degradation of capacitors, fuse and solid state device
- Degradation of bodies of motor operated valves due to cavitation induced erosion
- Thimble tube thinning due to flow induced vibration and wear.
- Boric acid induced corrosion of the high pressure injection nozzle of the reactor coolant system
- Fatigue cracks in pressurized surge lines induced by thermal stratification.
- Failure of steam generator tubes due to intergranular stress corrosion cracking, pitting, denting, fretting and wastage.
- Degradation of station batteries due to erosion of plate to bus bar connections.
- Failures of check valves due to wear, vibration and stress corrosion cracking.
- Erosion and vibration induced failures of emergency service water pumps.
- Damage to pipe supports due to vibration.
- Rupture of the carbon steel feedwater line caused by single phase erosion-corrosion.

Such ageing related failures may significantly reduce plant safety since they may impair one or more of the multiple levels of protection provided by the defence in depth concept. Ageing may lead to a large scale degradation of physical barriers and redundant components resulting in an increased probability of common cause failures. This could cause a reduction in component safety margins below limits provided in plant design bases or in regulatory requirements and thus could cause impairment of safety systems.

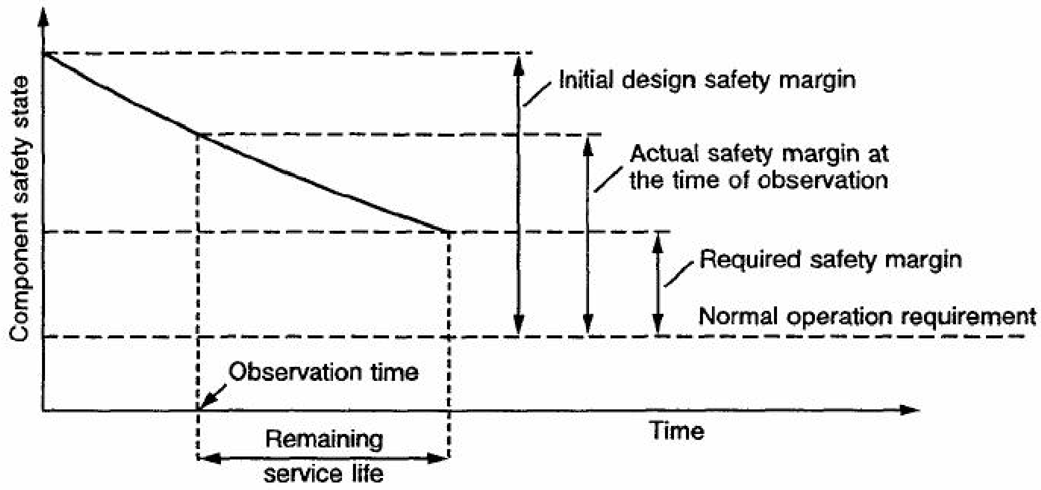

Figure1. Component safety state and safety margin as functions of time (IAEA (1992)).

It is then possible that degradation not revealed during normal operation and testing could lead to failure or even multiple common cause failures of redundant components under special loading and environmental stresses associated with an operational upset or accident /IAEA (1992)/.

Overview of main PWR and BWR components and their degradation mechanisms is presented in Appendix A1 /Smith (2001)/.

Ageing phenomena are modelled differently, depending on the rate of the functional degradation of a component and the availability and quality of data (both failure and condition monitoring). /NEA(1995)

The general theory of aging of active components includes three regimes:
-early failures
-relatively constant failure rate
-increasing failure rate over time

In case of short-term ageing, the identification and evaluation of component ageing is mainly based on the operating experience including both failure and maintenance information. The quantitative analyses can be based either on the modelling of the physical degradation process or on the statistical analyses of failure data. The short-term ageing models include renewal processes and non-homogeneous Poisson processes.

Passive components are also of ageing analysis concern because they may be weakening, and yet the deterioration may not be recognized until a catastrophic failure occurs. Most passive components do not provide adequate numbers of failures to analyse statistically. Long term ageing models include random crack growth models, strength-time models, and Markov modelling for cumulative damage.

The relevant data for statistical analysis would consist of condition monitoring (Simola 1992). As the collection of data relevant in-situ measurements for passive components can be very costly, passive components are sometimes studied by simulations.

There are many references where ageing of particular type of components and related ageing degraded mechanisms are described and discussed in detail, for example IAEA (1990, 1992, 2003), EPRI (1980), NUREG/CRs 5632 (Smith et al. 2001) and 6157 (1994), EUR 19843 EN (2001), OTA-E-575 (1993), HSE Health & Safety Executive (2001), etc./

Taking into account the fact that in each NPP are thousands of components, the ageing cannot be assessed for every one of them, but the components that should be subject to ageing evaluation and management should be very carefully selected. Also in PSA, where we are talking about components important to safety, a selection should be performed to take into account components and ageing effects with clear impact to plant risk level. This could help to assure analysis efficiency and reasonable resources could be used.

Outcome from components selection process, based for example on safety importance measures and evaluation of potential for significant degradation, could be used here also as a base for scope definition of data extraction and analysis and definition of reasonable level of incorporating ageing effects into PSA tools. The selection includes both active and passive components of a plant.

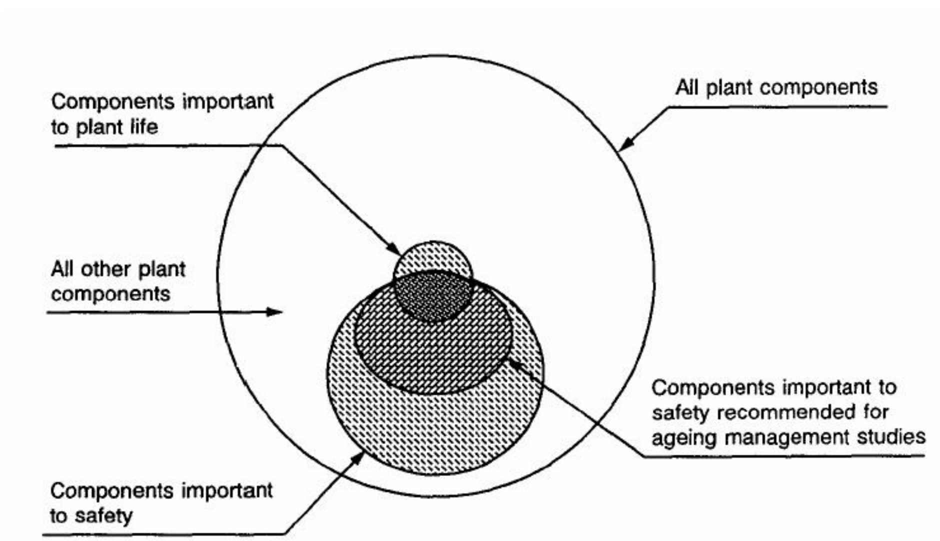

Figure 2. Selection of components important to safety for further activities /IAEA (1992)/.

In general, we could say that data needs and the attributes of appropriate data collection and record keeping systems are related to objective connected with evaluation and management of NPP ageing and service life and are determined by the scope of particular activities, and for example according to /IAEA (1991)/ as:

- Prediction of future performance

- Preventive maintenance support
- Identification and evaluation of degradation, failures and malfunctions of components and systems caused by ageing effects /also plant risk level assessment/
- Optimization of operating conditions and practices to reduce ageing degradation
- Identification of new emerging ageing effects
- Assessment concerning continued operation on NPPs, including reviews of license renewal applications
- Etc.

We will probably not need to organize specific data collection for incorporating ageing effects into PSA applications. Existing plant database systems and data could be used, together with public international failure databases, e.g. NUREG/CR-5750 (Poloski et al. 1999) and SKI database (2000). The main problem here could be lack of data for particular components and observed period of time.

Usually the databases used in life and ageing management programmes include three categories of data:

- Base information data
  ID, population, expected degradation mechanisms, data of installation, qualification data, design modification, etc.

- Operating experience data
  ID, system and component service conditions, testing data, component failure data, etc.

- Maintenance data
  ID, condition monitoring data, maintenance data /type, date and duration, description of work…/, costs of repair, replacement, etc,

What kind of data are really needed to extract from databases and use for incorporating ageing effects into PSA for evaluation of ageing impact and other applications will be dependent on scope and type of application, but mainly on models and approaches being used for addressing ageing effects in PSA models, for more details see following subchapters.

2. Data – availability and analysis

There are three qualitatively different settings for data collection and analysis,

(1) Frequent or periodic data collection over time. The purpose of the analysis is to discover the existence and magnitude of a trend.

(2) Single data collection under current conditions. The obtained measurement data are included in the input data of physics based ageing analysis, performed with a suitable analysis code. The purpose of the analysis is to estimate the probability of failure in the future.

(3) Infrequent data collection, such as non-destructive testing of materials. The analysis can have two purposes. It may be intended to characterize the current state of the material, or, as in setting (1), the analysis may be intended to discover and quantify the existence of a trend.

The discussion here emphasizes the first setting because some general analysis methods can be given. For the second setting, every type of ageing requires a major effort to develop an effective mechanistic model; by comparison, the effort of data collection is relatively minor. The third setting is new and still requires development and application. The three settings are discussed below in this chapter.

The issue of how to use the data in a PSA will be developed in the future stages of the project. However, we point out here that evidence of ageing requires the following:

- as a minimum, the basic event probabilities must be modified in a PSA.
- more changes may also be needed in the PSA, such as
  - new initiating events
  - new basic events
  - new common-cause initiators
- cutsets that were truncated from the original PSA because of their low probabilities may now need to be restored.
- finally, one must be wary of extrapolation into the future if the fitted trend model was chosen primarily for simplicity and mathematical convenience. It is safer to let evidence of a trend alert the analysts and decision-makers to the need for frequent reassessment of the initiating event frequencies and basic event probabilities.

2.1 Data for frequently tested components

The typical example of this setting is a changing frequency of failures of a type of active component. The goal of the analysis is to discover whether such a change is present, and if so to quantify it for PSA. The following process is suggested here:

1. Identify the parameter of interest, such as failure rate λ or failure probability p.
2. Collect relevant data: failure times, demand counts or exposure times, and ages of components during this history.
3. Perform very simple investigations, such as creating graphs and/or performing simple tests of hypotheses, to see if there is evidence of a trend.
4. If the evidence justifies further work, either
   (a) Choose a recent time period in which the trend is apparently minimal, and work only with data from this time period, using a model in which the parameter of interest is constant, or

(b) Let the parameter of interest be time-dependent, and fit this trend model over the entire data period.

5. Estimate the unknown constants in the chosen model. Also, quantify the uncertainties in the unknown constants, and obtain a Bayesian uncertainty distribution for the parameter of interest. This distribution can be used in a PSA.
6. Perform checks on the validity of the model, such as goodness of fit checks. Perform checks on the sensitivity of the results to the choice of the model. If the model survives this validation process, use the results found in Step 5. Otherwise, go back to an earlier step and reconsider the decisions made.

The above six steps are discussed below in Sections 2.1.1 through 2.1.6.

2.1.1. Identify parameter of interest

Typically, the concern is that an active component fails to operate when demanded. There are two common ways to model failure on demand.

- The standby-failure model. Pr(failure on demand) = λt, where t is the time since the last repair or successful demand.
- The failure-on-demand model. Pr(failure on demand) = p, a number that does not depend on the time since the last demand.

These two models are discussed and compared in Section 2.3 of the Handbook of Parameter Estimation for Probabilistic Risk Assessment (Atwood et al. 2003), denoted HOPE in this document. The main point of the discussion below is that the random number of failures in an extended period can be treated as approximately Poisson, whichever of the above two models is used.

Consider the first bullet above, in which a component that is normally in successful state occasionally fails. In principle a failure occurs at some random time, then it is discovered, and the component is repaired and returned to service. When it after a time fails again, this process is repeated. Under some simple assumptions given in the above reference, this is a **homogeneous Poisson process** (HPP). (See HOPE or Cox and Isham 1980 for more information.) The random number of failures in some fixed time s is Poisson(λs). If the component is only known to be failed when a demand occurs, then failures are not discovered immediately. However, if demands are frequent (in practice, if there are many more demands than failures), then the random number of failures in time s can be treated as approximately Poisson(λs). The time s is called the **exposure time**, i.e. the elapsed time when failures could occur. The parameter λ is called the **failure rate** or the **Poisson intensity**.

Now suppose that the failure rate λ is a function of component age, $\lambda(t)$, where t denotes component age. Then, under simple assumptions given in Section 7.2.2.1 of HOPE or in Thompson (1981), the model is a **non-homogeneous Poisson process** (NHPP), and the random number of failures between ages a and b is Poisson with mean:

$$\int_a^b \lambda(t)dt \quad . \tag{1}$$

If λ is constant and $b - a = s$, this integral reduces to λs, and the NHPP is an HPP.

Consider now the second bullet above, the failure-on-demand model, with p constant. The random number of failures in n demands is binomial(n, p). However, when the number of demands during exposure time s is large, the binomial distribution is approximated by a Poisson distribution with $\lambda s = np$ (HOPE, Sec. A.6.2). Therefore, most of the discussion below treats the number of failures in exposure time s as approximately Poisson(λs), either because the standby-failure model is used or because the failure-on-demand model is approximated.

The above approximation may require some adjustment. Suppose that the failure-on-demand model is considered truly correct. Then the number of failures will be roughly proportional to the number of demands, not to the exposure time. If the data come from components with very different demand counts per unit time, or from a time history in which the frequency of demands changed greatly, then we should model the failure counts as binomial, and construct a fictitious exposure time s that is proportional to n, the number of demands. If we set $s = n$, then the binomial(n, p) distribution is approximately Poisson(λs), and the estimate of λ can be used as an estimate of p.

If ageing occurs in the failure-on-demand model, p is a function of time, $p(t)$. Suppose demands occur at time points t_i. Then the expected total number of failures is

$$\Sigma p(t_i). \tag{2}$$

If the number of demands is large and each $p(t_i)$ is small, it can be shown that the random number of failures is approximately Poisson distributed, with mean given by Expression (2). Finally, if the demands are equally spaced between ages a and b at intervals $\Delta t = (b - a)/n$, then Expressions (1) and (2) are virtually equal, with $p(t)$ corresponding to $\lambda(t)\Delta t$. For these reasons, most of the discussion below is in terms of λ rather than p.

2.1.2. Collect relevant data

The data may consist either of information about the individual failures or aggregated counts of failures in time bins.

In the first case, the data must contain the failure history of each component during the data period: the age of the component at the start of data recording, the component age when each failure occurred, and the age of the component when the data ends, either because data were no longer recorded or because the component was removed from service.

Sometimes such detailed information has not been recorded. Instead, the ages are grouped into ranges, or **bins**. In this case, the data must state the total number of component-years that correspond to each bin, and the number of failures of components for that bin. For example, each bin might correspond to one year. Then the data would need to specify the number of components observed in their first year of age and the number of failures occurring during the first year, and so on for each succeeding year.

In either type of data, if differences between the components might affect the failure rate, this information must be given. Such differences might be in construction, environment, or testing and maintenance of the components.

The components can be grouped in categories using the following criteria:

- component types

- failure modes taking into account the component types
- the modelled primary events (in function, in stand-by or in demand)
- system in which the component is located
- design and operating characteristics
- operating experience and behaviour

It is typically considered acceptable to assume components as joined in the same category if they have similar design and if they have comparable operating practices. It was not recommended to consider components as being in the same component category, if they have:

- large differences in the design,
- different operating modes,
- different operating environment, or
- major differences in testing and maintenance practices.

Few if any data analyses have shown statistically significant ageing. Several reasons can be suggested. One is that maintenance is successful, removing degraded components before they reveal ageing in a statistically significant way. Another possibility is that for many years the data were not adequate for an analysis of ageing. The discussion in Chapter 3.4 mentions a few studies that have been carried out, and then lists a few data sets that may be useful in future ageing studies.

For binned data, the failure and component counts must be given for each homogeneous subset of the components.

When constructing the bins, it is usually desirable for them all to have approximately the same exposure time. For crude analyses, it may be enough to have only two bins. For more sophisticated analyses, it is generally desirable to have more bins, so that $\lambda(t)$ does not curve much within any bin. However, for the goodness-of-fit investigations that accompany any analysis, the expected number of failures in a bin should not be too small. Thus, we have competing desires for small bins and for many failures per bin.

2.1.3 Perform simple investigations of possible ageing

Two such kinds of investigation are to construct simple graphs and to perform simple tests of hypotheses. They are discussed here.

Graphs. The type of graph depends on the type of data, either data for the individual failures or binned data.

Data for individual failures

.

If the data are given in terms of the individual failures, a cumulative failure plot is simple and informative. Consider here the simple case when all the components are observed for the same age range. First, order the failures from the earliest age to the latest. Then, for each failure, plot the age of the component at the time of failure on the horizontal axis, and the cumulative number of failures on the vertical axis. Figure 3, from HOPE, gives an example of initiating events at one NPP.

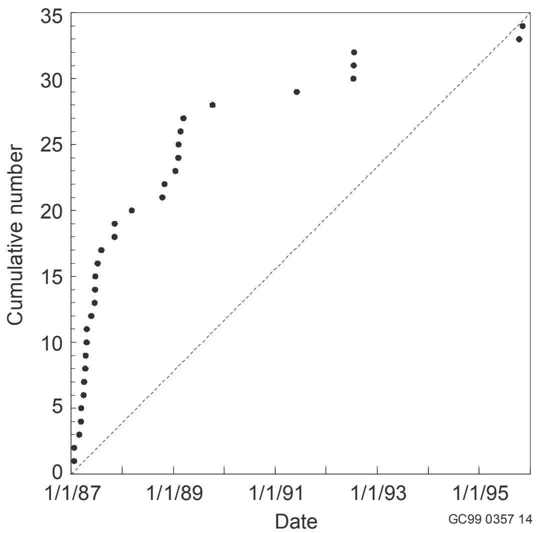

Figure 3. Cumulative plot for initiating events at one NPP (From HOPE).

The plant shown had its initial criticality on 3 January 1987. In this example, there is only one "component", the entire plant, and a "failure" is an initiating event. The scatter plot can be mentally interpolated to form a line. The **slope** of any portion of the line is defined as the change in height divided by the change in horizontal distance. The slope, therefore, is the number of failures divided by number of years, so the slope estimates λ, the failure rate. The slope can be approximated in any region of the graph.

In this example, the line rises to about height 19 in the first year, so the slope, the estimate of λ, is 19 events per year. In the second year the line rises much less, so the slope, the estimate of λ, is much smaller. This graph shows that λ was decreasing - the plant was in the burn-in stage of its life, not ageing and approaching the end of life. If, instead, the slope had been small on the left and larger on the right, the graph would have shown evidence of deterioration, presumably caused by ageing.

Now consider a more complicated situation, with several components that are not necessarily all observed over the same age range. For example, suppose that 8 components are observed for five years, starting when they are five years old. However, after one year one of the components is replaced by a new component. We then have:

- 1 component observed from age 0 to 4,
- no data between age 4 and 5,
- 8 components observed from age 5 to 6,
- 7 components observed from age 6 to 10.

The slope should estimate λ, which now has units of failures per component-year. One way to accomplish this is to let the horizontal axis show age, just as before, but to adjust the vertical scale so that it displays failures per component. During the first 4 years of age, each point marking a failure should be 1 unit higher than the previous point, because there is 1 component in that age range. The graph has a discontinuity between ages 4 and 5. Between age 5 and age 6, each point should be 1/8 unit higher than the previous point, because there are 8 components in that age range.

And between ages 6 and 10, each point should be 1/7 higher than the previous point. In this way, the slope in any period estimates the rate, with units of failures per component-year.

When viewing such a plot, one must remember that some portions of the plot correspond to a lot of data and some to only a little data.

Binned data.

Now let us consider the other kind of data, with component counts and failure counts aggregated into bins. For each bin, calculate an estimate of λ, treating λ as if it were constant within the bin. The simplest such estimate is the maximum likelihood estimate (MLE), which is the number of failures divided by total exposure time for the bin. Also, for each bin construct a confidence interval for λ. (One presentation of how to do this is in Section 6.2.1 of HOPE.) Then plot the estimates and confidence intervals side by side, and look for a trend.

Table 1 shows the data from Figure 3 with bins corresponding to calendar years. The exposure time is the time that the reactor was critical, because an initiating event was considered to be an event that causes a reactor trip, which can only occur when the reactor is critical. Each exposure time is expressed as a fraction of a year. These exposure times were obtained from records reported by the plant. The “bin” column shows the calendar year, and the “age” column shows the age at the midpoint of the bin.

Bin	Age	Events	Exposure time
87	0.5	19	0.7094
88	1.5	3	0.7517
89	2.5	6	0.7949
90	3.5	0	0.8960
91	4.5	1	0.8153
92	5.5	3	0.7513
93	6.5	0	0.9961
94	7.5	0	0.8274
95	8.5	2	0.8376

Table 1. Binned Data for Initiating Events.

Figure 4 shows the data from Table 1. In this graph 90% confidence intervals are used. For this graph, the horizontal axis is labelled as age rather than calendar year.

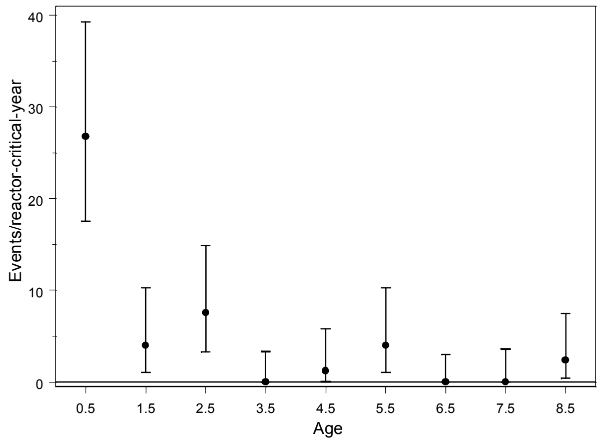

Figure 4. Plot of side-by-side confidence intervals for λ, using data from Figure 3. (adapted from HOPE).

The simple plot of the estimates and confidence intervals shows that the first year had a much higher failure rate than did the later years. Also, if we restrict consideration to ages 3.5 through 8.5, there is no evidence of a trend in those years - in spite of minor variation, the confidence intervals overlap a lot.

In addition to looking for trends, one should in general look for other sources of variation. If the components are constructed differently, or if they are in different systems (with different environments), or if they are operated under different test-and-maintenance procedures, these differences might lead to different failure rates. In this case, one can group the components into separate classes, or categories. For each class, construct the estimate and confidence interval for λ. Then plot these estimates and confidence intervals side by side, and look for marked differences. At this preliminary stage of the investigation, one can probably ignore the possible ageing within each class. The purpose right now is only to see if the data must be split into subsets that must be analyzed separately. If substantial differences are seen between classes, this fact must be kept in mind during the rest of the analysis, and it is quite possible that the data will need to be analyzed separately for each class.

Hypothesis tests. An alternative to a plot is a hypothesis test. The hypothesis can give a quantitative answer to the question of whether ageing appears to be present, by measuring the strength of the evidence against the hypothesis H_0: no ageing occurs.

This contrasts with plots, which give a visual impression but nothing quantitative. Several hypothesis tests are mentioned here, first when the data contain information on the individual failures and second when the data are aggregated in bins.

Data for individual failures.

A simple test for ageing when the individual failure times are given is the so-called Laplace test, presented in Section 6.2.3.2.2 of HOPE, and also discussed by Cox and Lewis (1978, p. 47). Ascher and Feingold (1984) attribute the test to Laplace.

Consider first a single component, with n failures reported in some age range (a, b). If there is no ageing, the failure times should be independent of each other, and uniformly distributed from a to b. This is the null hypothesis:

H_0: failure times are independent and uniformly distributed from a to b.

When the null hypothesis is true, the average of the *observed* failure times should be not far from the midpoint $(a + b)/2$. If the average failure time is much larger, this is evidence of an increasing failure rate.

If the final failure results in the component being taken out of service, so that b is not fixed in advance, then we must condition on the final failure time. Set b to the final failure time and only consider the earlier failures as random; n is then defined as the number of failures excluding the final one.

To make all this both precise and fully general, consider m components, with the ith component observed from age a_i to b_i and having n_i failures at random times during that time period. Denote the random failure times by T_{ij}, for $i = 1$ to m and $j = 1$ to n_i. The null hypothesis, corresponding to no ageing, is

H_0: failure times are independent, and each T_{ij} is uniformly distributed on (a_i, b_i).

Let c_i denote the centre of the ith interval, $(a_i + b_i)/2$, and let w_i denote the width of the interval, $b_i - a_i$. Then $(T_{ij} - c_i)/w_i$ is uniformly distributed on (−1/2, +1/2), with mean 0 and variance 1/12. The sum of all these random quantities,

$$\sum_{i=1}^{m}\sum_{j=1}^{n_j}\left(\frac{T_{ij}-c_i}{w_i}\right) \tag{3a}$$

has mean 0 and variance $\Sigma n_i/12$. Therefore,

$$\sqrt{12/\Sigma n_i}\sum_{i=1}^{m}\sum_{j=1}^{n_j}\left(\frac{T_{ij}-c_i}{w_i}\right) \tag{3b}$$

has a mean of 0 and a variance of 1, and by the Law of Large Numbers it is approximately normally distributed. Denote Expression (3b) by $T_{Laplace}$. The normal approximation is very good when the T_{ij}'s are uniform and there are 6 or more of them. A table of the normal distribution shows that 1.28 is the 90th percentile and 1.645 is the 95th percentile. Therefore if the H_0 is true, we have
$\Pr(T_{Laplace} > 1.645) = 0.05$ and
$\Pr(T_{Laplace} > 1.28) = 0.1$.

The above results assume that no ageing occurs. If, on the other hand, ageing is occurring, then more failures are expected late than early, and Expression (3b) will tend to be larger than if no ageing were occurring. Thus, large values of Expression (3b) give evidence of ageing. A value > 1.645 shows evidence that is significant at the 5% level, and a value > 1.28 shows evidence that is significant at the 10% level.

Binned data.

The above approach used the individual failure times. Now consider binned data. A very simple test is to partition the data into just two segments, corresponding to the early and late portions of the component histories, with approximately half of the exposure time (component-years, say) in the early segment and the other half in the late segment. Denote these early and late exposure times by s_E and s_L, and let the total exposure time be $s_T = s_E + s_L$. Denote the number of failures in the late period by X_L. If no ageing is occurring, a failure is equally likely at any time. Therefore, conditional on the total number of failures n, X_L is a binomial(n_T, p) random variable, where $p = s_L/s_T$. If, on the other hand, ageing is occurring, then X_L will tend to be larger. This leads us to reject the hypothesis of no ageing, in favour of the alternative hypothesis of ageing, if X_L is large. In particular, if n is large a value of

$$(X_L - np)/\sqrt{np(1-p)} \qquad (4)$$

greater than 1.645 shows evidence for ageing that is significant at the 5% level, just as with the Laplace test. A value greater than 1.28 shows evidence that is significant at the 10% level.

The above use of X_L assumes implicitly that all the components are observed over the same age range, or if not, that all the components have the same failure rate function $\lambda(t)$. We might not wish to make this assumption. For example, we might believe that some components inherently fail more frequently than others, and then ask if, in addition, the failure frequencies are increasing. In such a case, modify the above method as follows. Suppose that component i is observed from age a_i to age b_i. Let $X_{L,\,i}$ be the number of "late" failures for the ith component, that is, the number of failures occurring in the second half of the age range, between ages $(a_i + b_i)/2$ and b_i. The total number of late failures is now defined as

$$X_L = \sum X_{L,i} \quad .$$

If each component has a constant failure rate, failures are equally likely to be early and late. Therefore, conditional on the total number of failures n, X_L has a binomial(n, 0.5) distribution. If instead the failure rates are increasing, X_L will tend to be larger. Therefore, a large value of X_L causes us to reject the null hypothesis of constant failure rates in all the components. The binomial distribution can be used for calculating the details. When the number of failures is moderately large, the normal approximation can be used exactly as in the previous paragraph, with p defined as 0.5.

To compare different classes of components, a chi-squared test can be used. See many statistics books, or Section 6.2.3.1.2 of HOPE, for the formulas. Section 2.1.6 below illustrates the method.

Interpretation of Findings. It is common to point out that lack of statistically significant evidence against a hypothesis does not prove that the hypothesis is true. There may just not be enough data to draw firm conclusions. In the present setting, lack of strong evidence for ageing does not prove that no ageing is occurring.

The converse also applies, however: Any evidence against the hypothesis of no ageing or no differences between classes must be interpreted carefully. Difference between classes of components might be evidence of ageing, if the average ages of the components are different in the different classes. Alternatively, a cumulative plot could conceivably appear to show improving performance, if the components are ageing at different rates and the worst components are being systematically removed from service while the best components are allowed to remain and age.

In summary, any statistical findings must be interpreted carefully and thoughtfully.

2.1.4 Assume a model for a trend – a review of statistical ageing models

If the evidence from the previous section justifies further work, assume a model for the data and for the trend. As discussed in Section 2.1.1, we assume that the data come from a Poisson process, with a failure rate λ that may be a function of age. Several functional forms have been assumed in the literature for $\lambda(t)$.

Piecewise constant failure rate. In this very simple model, the failure rate is assumed to be constant in some recent time period:

$\lambda(t) = \lambda_0$ for t in a restricted age range.

Then λ_0 is estimated based only on data from that age range. For example, Figure 3 and Figure 4 show that $\lambda(t)$ appears to be constant over 1990-1995 (ages 3.5 to 8.5). At the end of 1995, one could reasonably use an estimate based on that restricted range of data to forecast performance in 1996.

Clarotti et al. (2004) is a recent reference that uses a piecewise constant failure rate. That paper discusses the issue of determining the change-point (somewhere between the years 1987 and 1990 in the example of Figures 3 and 4), and estimates the change-point with Bayesian methods, though the details are not given.

Linear ageing. The failure rate is of the form:

$$\lambda(t) = \lambda_0 + bt\ .$$

Vesely (1987) assumes that damage accumulates at a constant rate, and uses this to motivate linear degradation of λ. Here, λ_0 is the baseline rate and bt is the additional portion resulting from ageing. Wolford et al (1992) and Atwood (1992) rewrite the formula as

$$\lambda(t) = \lambda_0(1 + \beta t), \qquad (5)$$

with $\beta = b/\lambda_0$. The reason for this change of notation is to make the analysis more comparable to analyses using other functional forms. To keep $\lambda(t)$ non-negative throughout the observed data period, β must satisfy the constraint:

$$\beta \geq -1/t_{\max}$$

where $t_{\max}$ is the maximum time in the observed data set.

Linear ageing is simple, an obvious natural way to give a first-order approximation to changes in the failure rate. It does seem to have one practical disadvantage, however. Wolford et al. (1992) analyzed two data sets using several functional forms for $\lambda(t)$; one such analysis is reported by Atwood (1992). They found that a Bayesian distribution for $\lambda(t)$ was approximately lognormal when a log-linear or power-law model was used for $\lambda(t)$, but not when a linear model was used. Apparently, the approximate lognormality required a much larger data set when linear ageing was assumed than when power-law or exponential ageing were assumed.

When two parameters are estimated from data, the estimators may be statistically correlated. In Equation (5), if β is overestimated then λ_0 will tend to be underestimated. To minimize this correlation, the data can be **centred**, that is, age can be measured not from 0 but around some value t_0 other than 0. Equation (5) then becomes:

$$\lambda(t) = \lambda_0[1 + \beta(t - t_0)]. \tag{5'}$$

The constraints on β, to force $\lambda(t)$ to be non-negative, are:

$$-1/(t_{\max} - t_0) \le \beta \le 1/(t_0 - t_{\min}),$$

where $t_{\min}$ and $t_{\max}$ are the smallest and largest ages in the observed data set.

In this parameterization, λ_0 no longer represents the failure rate at age 0 but at age t_0. To minimize the correlation between the estimators of λ_0 and β, t_0 should be defined as the mean of all the component ages in the data. The exact formula is given in Table 1 of Atwood (1992). The intuitive idea is that it is relatively easy to estimate the failure rate in the middle of the data, λ_0. Having done this, the linear trend line pivots around that middle value. The slope of the line determines β, and the estimators of the two parameters are statistically uncorrelated.

Exponential or log-linear ageing. Rather than assuming that λ increases linearly, assume that $\ln\lambda$ increases linearly:

$$\ln\lambda(t) = a + \beta t, \text{ or equivalently}$$

$$\lambda(t) = \lambda_0 \exp(\beta t) \tag{6}$$

where $\lambda_0 = \exp(a)$.

This use of logarithms ensures that $\lambda(t)$ is always positive, regardless of the values of t and β, so the constraint on β is the trivial one:

$$-\infty < \beta < \infty \ .$$

This model is favoured by theoretical statisticians, because it fits most neatly into the theory of generalized linear models (e.g. McCullagh and Nelder 1989). As a result, it is the default model for Poisson regression in statistical software packages such as SAS® and S-plus®.

In terms of practice, linear ageing and log-linear ageing are probably indistinguishable, except for unrealistically large data sets. Indeed, the first order Taylor approximation of $\exp(\beta t)$ is $1 + \beta t$, showing that Equation (5) is a first-order approximation of Equation (6). Linear and log-linear functions give different extrapolations into the distant future, but no function that is chosen purely on the basis of simplicity and convenience should be used for long-term extrapolation.

Centring the data as described for linear ageing does not result in perfectly uncorrelated estimators in this case - the curvature of the trend line complicates the formulas. However, centring the data reduces the correlation of the estimators, and is therefore recommended. The resulting equation for $\lambda(t)$ is

$$\lambda(t) = \lambda_0\exp[\beta(t - t_0)] \qquad (6')$$

As with linear ageing, λ_0 now represents the failure rate at age t_0.

Power-law or Weibull ageing. Both terms, "power-law ageing" and "Weibull ageing", are used in the literature. The failure rate is of the form:

$$\lambda(t) = \lambda_0 t^{\beta} , \qquad (7)$$

with

$$\beta > -1.$$

The constraint on β does not arise from the need to keep $\lambda(t)$ non-negative, but from the need to keep Equation (1) finite when the integral has lower limit 0. Various authors write Equation (7) in various ways. Those accustomed to using the Weibull distribution would write:

$$\lambda(t) = \lambda_0 t^{B-1} \text{ , with } B > 0,$$

defining $B - 1 = \beta$.

Equation (7) is very sensitive near $t = 0$. If β is positive (that is, increasing failure rate) then $\lambda(t) = 0$ at $t = 0$. If β equals 0 exactly (that is, constant failure rate) then $\lambda(t) = \lambda_0$ everywhere, including as $t \to 0$. Finally, if β is negative then $\lambda(t) \to \infty$ as $t \to 0$. If the sign of β is uncertain, then $\lambda(t)$ is extremely uncertain near $t = 0$. This fact means that one must be careful in defining the age that we call 0. Different results are obtained if age t is measured from the component's installation or, instead, from the start time of the data recording.

In the parameterization of Equation (7), λ_0 is the failure rate at age $t = 1$. This is dependent on the scale used. For example, if ageing takes place over years but age t is expressed in hours, λ_0 will be the failure rate at age one hour, a difficult quantity to measure. For this reason, and to reduce the statistical correlation of the estimators of λ_0 and β, Atwood (1992) recommends centring with t_0 chosen as in the previous sections, using the formula:

$$\lambda(t) = \lambda_0(t/t_0)^{\beta} \text{ , with } \beta > -1 . \qquad (7')$$

Then λ_0 is the failure rate at the age t_0.

HOPE points out that Equation (7′) can be rewritten as:

$$\lambda(t) = \lambda_0\exp[\beta(\ln t - \ln t_0)] . \qquad (8)$$

This is the same form as Equation (6′), but using the logarithm of age instead of age itself. Therefore, if ages are converted to logarithms, a formal analysis based on log-linear ageing will give estimates for the power-law parameters.

Modified Weibull ageing. Following Pörn (1990), the Swedish I-book (Pörn et al. 1994) uses an additional base rate, so that:

$$\lambda = \lambda_0 + at^{\beta} .$$

Diffuse priors are updated using Bayesian methods. This topic will not be considered further here, because it is hard enough to estimate two parameters with the limited available data. Estimating three parameters involves even more uncertainty.

Thresholds. Some authors (Rodionov 2005) introduce a threshold at which ageing is assumed to begin. Then $\lambda(t)$ is assumed to be constant before the threshold age is attained, and to increase following one of the above formulas afterwards. The threshold is generally unknown, and must be estimated from the data. For example, if linear ageing with a threshold θ is modelled, the formula (5) would be changed to:

$$\lambda(t) = \lambda_0 \qquad \text{for } t < \theta ,$$

$$\lambda(t) = \lambda_0[1 + \beta(t - \theta)] \qquad \text{for } t \geq \theta .$$

Thresholds cause difficulty in classical statistics, because the assumptions for the asymptotic theory of maximum likelihood estimation are typically violated. Therefore, it is difficult to quantify the uncertainty in the estimate of the threshold. Bayesian estimation, using some simulation package such as BUGS® (Spiegelhalter et al. 2003), is still possible. However, just as with modified Weibull aging, a model with a threshold involves three parameters, and it is difficult to find enough data to estimate even two parameters. Therefore, threshold models will not be considered further here.

Note, all of the above forms can be written as:

$$\lambda(t) = \lambda_0 g(t; \beta), \tag{9}$$

where $g(t)$ is a function of the age t, one or more parameters such as β, and perhaps one or more known quantities such as t_0. This fact will be used below.

1.1.5 Estimate the parameters.

The goal here is to obtain estimates so that $\lambda(t)$ can be used in a PSA. This means that a Bayesian uncertainty distribution must be obtained for $\lambda(t)$. It is highly desirable to obtain a simple parametric distribution, such as lognormal, because then the distribution can be specified by just a couple of parameters, which can be entered into the code for the PSA.

In principle, one must:

1) Construct the likelihood, with either binned or unbinned data. This job will be performed with some suitable software.
2) Then, EITHER

a. Perform a Bayesian update, with a diffuse prior or perhaps an informative prior, using BUGS or some other software, and obtain a distribution for $\lambda(t)$.
   If possible, approximate this by a standard distribution in terms of a few parameters.

OR

b. Find the MLE and the asymptotic variance of the MLE. Treat the resulting approximate confidence interval for $\lambda(t)$ as a Bayes interval corresponding to a diffuse prior.

The posterior distribution for $\lambda(t)$ has a simple form in the following cases:

- $\lambda(t)$ is a piecewise constant function of t, and the prior distribution for $\lambda(t)$ is the conjugate prior, a gamma distribution. In particular, the Jeffreys noninformative prior is gamma(0.5, 0). Then the posterior distribution of $\lambda(t)$ is also a gamma distribution. These assertions ignore the uncertainty in the location of the discontinuities in $\lambda(t)$.
- In the examples of Wolford et al. (1992) and Atwood (1992), for each t, $\lambda(t)$ was found to have an approximately lognormal uncertainty distribution, if $\lambda(t)$ was assumed to be a log-linear or power-law function of t.

The above steps are now discussed in detail.

The likelihood function. The likelihood function may be found with the software. If, however, the analyst is working only with a spreadsheet, the likelihood will need to be constructed.

Binned data.

With binned data, counts of failures and exposure times for various ranges of ages, the number of failures in the ith bin is

$$\text{Failure count in } i\text{th bin} \sim \text{Poisson}(\lambda(t_i)s_i) \qquad (10)$$

The failure counts in the different bins are assumed to be independent. Therefore the likelihood is a product of Poisson probabilities. More precisely, let the ith bin consist of components within some age range, and let t_i be the midpoint of this range. Let the total exposure time for all these components be s_i, and let x_i be the number of failures for the bin.

For example, suppose that the ith bin consists of components with age from 5 yrs to 6 yrs, and suppose that 10 components were observed for the full year and one component was removed from service at age 5.4 yrs. Then the exposure time s_i would be 10.4 yrs. Let x_i be the number of component failures between ages 5 yrs and 6 yrs, and define the midpoint t_i to be 5.5 yrs. (Section B1.2.3 of Appendix B1 gives a more sophisticated way to define the "midpoint" to account for the fact that one component was present at the beginning of the year but not the end. When that method is used, t_i is set to 5.49.)

If brute-force calculations are performed with a spreadsheet, the following formulas are needed. The likelihood is:

$$\prod_i e^{-\lambda(t_i)s_i}[\lambda(t_i)s_i]^{x_i} / x_i!$$

where $\lambda(t)$ is defined by one of the equations in Section 2.1.4. The likelihood is considered a function of λ_0 and β. A somewhat simpler expression is the logarithm of the likelihood:

$$L = \sum_i -\lambda(t_i)s_i + \sum_i x_i \ln\lambda(t_i) + J \quad , \tag{11}$$

where J is "junk", a quantity that does not depend on the unknown parameters. In principle, this function (ignoring J) can be programmed explicitly into a spreadsheet such as Microsoft Excel® or Quattro Pro®, with λ_0 and β assigned initial values based on an eyeball fit to the data.

Data for individual failures.

With unbinned data, information is given for each failure and each component. This situation is explained in detail by Cox and Lewis (1966) for the log-linear ageing model. Building on that work, Atwood (1992) presents the results for the linear and power-law models as well. A rather complete mathematical presentation, with derivations and proofs, is given in Appendix A of Wolford et al. (1992). The formulas for unbinned data were programmed in PHAZE, a Fortran 77 program used for the work of Wolford et al. (1992). This program still runs, and is available from the author (cory@statwoodconsulting.com).

However, for most applications it is much easier to use binned data. As long as the bins are not too few and too wide, little information is lost by the binning. (Use of binned data approximates the Poisson mean for the bin by the exposure time multiplied by $\lambda(t_{mid})$, where t_{mid} is the midpoint of the bin. Relevant information is lost if this approximation is inaccurate, for example if $\lambda(t)$ is strongly curved within the bin.)

Bayesian analysis. A simple method for Bayesian analysis of binned data, using any of the functional forms for $\lambda(t)$, is based on BUGS® (Spiegelhalter et al. 2003), a very flexible program that is available for free download. The Windows version is called WinBUGS®. BUGS uses a technique called Markov Chain Monte Carlo (MCMC) sampling, and approximates the posterior distribution of the unknown parameters by a large sample of simulated values from this distribution. A sequence of such simulated sample values is called a **chain** by WinBUGS. Successive elements of the chain are statistically correlated, but the whole sample covers the entire distribution with close to the right probabilities, becoming more accurate as the sample increases in size.

Because the successive elements are correlated, the first several hundred elements may be influenced by the possibly unrealistic initial values. Therefore, it is usual to look at a graph of the chain, and to drop the first part of the chain, the part before the values have stabilized at the posterior distribution. To help accomplish this, it is also useful to begin chains from several widely scattered initial points, and to only use the portion of the chains that overlap each other. WinBUGS offers diagnostic graphs to help to show when the chains overlap, as discussed in Appendix 3.3.

Non-Bayesian analysis. Users who prefer to use non-Bayesian software can approximate the Bayesian posterior that would result from updating a diffuse prior. The idea goes as follows. For a large sample, the log-likelihood is approximately quadratic in the unknown parameters (a Taylor series approximation), so the form of the likelihood is approximately proportional to a normal density, with the parameters as the normally distributed variables. When graphed, the likelihood has the familiar bell shape, at least approximately when the sample size is large. The maximum likelihood estimate (MLE) is the value of the parameter at the centre, where the likelihood is largest, and a confidence interval is based on the spread of the likelihood; well-known formulas exist, based on derivatives of the log-likelihood. This is the standard frequentist manipulation.

If one were doing a Bayesian analysis, the likelihood would be multiplied by the prior density, to produce a multiple of the posterior density. If the prior density is diffuse, essentially constant, then the posterior density would be essentially proportional to the likelihood. Because the likelihood is approximately normal, the posterior distribution of the parameter is approximately normal, and (for example) a 90% credible interval for the parameter is numerically the same as the frequentist 90% confidence interval.

This is valid for large data sets, but "large" depends on the details. In particular, it depends on how the parameters are specified. For example, consider log-linear ageing, introduced above. If the parameters are specified as (a, β), approximate normality is attained with a moderate sized sample. If the model is instead parameterized in terms of (λ_0, β), a larger sample is required to achieve approximate normality. Also, the linear ageing model seems to require larger samples than do the log-linear and power-law models, to achieve the same degree of approximate normality.

The details are now sketched, for various software packages.

When using a spreadsheet, one can find the maximum likelihood estimators of λ_0 and β as follows. Write the log-likelihood as a function of these two parameters. The log-likelihood was given in Equation (11) for binned data and general $\lambda(t)$, and particular functions of λ_0 and β can be written for the different assumed forms of $\lambda(t)$. Then the expression can be maximized by the spreadsheet. In Excel®, click on *Tools/Solver*. In Quattro Pro® click on *Tools/Numeric Tools/Optimizer*.

This programming is unnecessary when binned data are analyzed by a statistical package such as SAS® or S-Plus®, because they have the generalized linear model programmed. Suppose the bin midpoints are named AGE, the failure counts are called FAILURES, and the exposure times are called EXPOS.

- In SAS, also define a variable LNEXPOS = ln(exposure time).
  Use *Proc Genmod*. Set
  model FAILURES = AGE / *dist* = *poisson*
  offset = LNEXPOS

- In S-Plus for Windows, also define a variable FperEXPOS = (failure count)/ (exposure time).
  Click on *Statistics/Regression/Generalized Linear Models*. Then set *family* = *Poisson*, *weights* = EXPOS, *dependent variable* = FperEXPOS, and *independent variable* = AGE.

Both of these packages also require a *link*. Set it to *log* if log-linear ageing is assumed, and set it to *identity* if linear ageing is assumed.

Finally, power-law ageing can be treated by using the relationship between Equation (8) and Equation (6′). Define a variable LNAGE, equal to ln(AGE). In SAS, model FAILURES = LNAGE, and in S-Plus set the independent variable to LNAGE. Here is one place where the distinction between exposure time and age is important. The logarithm of age is used, because that describes how λ changes with age. The exposure times are unchanged, however, because the Poisson counts have means that depend on exposure time in the usual units.

2.1.5 Checks for model validity and sensitivity.

The above work assumed that all of the components have a common failure rate, which depends on age through a specified function involving parameters β and λ_0. If possible, the analyst should check whether:

- the components have the same β,
- the components have the same λ_0, and
- the assumed functional form of $\lambda(t)$ is correct.

The analyst should also perform a sensitivity study on the choice of model, asking:

- would a different functional form of $\lambda(t)$ fit equally well?

The sensitivity study may not invalidate the chosen model, but it may affect application of the results. For example, suppose several trend models are consistent with the data, so there are no solid grounds for choosing one model over the others. Then it would be unwise to extrapolate far beyond the range of the observed data, out to where the models diverge in their extrapolations.

Instead of comparing components, one could compare sets of components. In the discussion below, the full data set of components will be partitioned into subsets, and the subsets will be compared. One possible partition lets each component be its own subset, but other partitions are also possible. The advantage of partitioning the data into subsets larger than single components is that individual components often do not have enough failures to allow statistically significant conclusions to be drawn.

The only requirement is that the subsets are not based on the failure data. The components can be partitioned based on manufacturer, design, location, operating environment, etc., but they may not be partitioned retrospectively based on their numbers of failures.

Test for common β in all subsets. The following test works with binned data when all the components are observed over the same age range. If that age range is from *a* to *b*, let us cut that range somewhere in the middle, at some age *c*. Call failures before age *c* the "early" failures, and failures after age *c* the "late" failures. Combining Equations (1) and (9), we see that for any one component the expected number of early failures is:

$$\int_a^c \lambda(t)dt = \lambda_0 \int_a^c g(t;\beta)dt$$

and the expected number of late failures is:

$$\int_c^b \lambda(t)dt = \lambda_0 \int_c^b g(t;\beta)dt \ .$$

The ratio of these two quantities is independent of λ_0, and depends only on the ageing constant β. Thus, if all the components have a common β, each subset of the components should have, on average, the same ratio of late to early failures. This is true whether or not the components have the same value of λ_0, and whether or not the subsets have the same numbers of components.

The above assumption can be generalized somewhat. If the components are all observed over a portion of the time, such as whenever the reactor is operating, this does not affect the above argument, as long as the unobserved periods are about the same for all the components. Then the expected ratio of late to early failures remains the same for all components.

This justifies the following **contingency table**. That is, divide the age range into two pieces, early and late. For efficiency of the test, the division between early and late should be chosen so that the total numbers of early failures and late failures are roughly equal. Construct a two way table of the failures in the various subsets of components:

	Subset 1	Subset 2	…	Subset J	Total
Early failures	x_{11}	x_{12}	…	x_{1J}	x_{1+}
Late failures	x_{21}	x_{22}	…	x_{2J}	x_{2+}
Total	x_{+1}	x_{+2}	…	x_{+J}	x_{++}

The central part, with 2 rows and J columns, is a $2\times J$ contingency table. If all the subsets have the same β, the expected number of failures in the ijth cell is estimated by:

$$e_{ij} = x_{i+}x_{+j}/x_{++} \ .$$

The chi-squared statistic is:

$$X^2 = \sum_{i=1}^{2}\sum_{j=1}^{J}\frac{(x_{ij}-e_{ij})^2}{e_{ij}} \ .$$

If all the subsets have a common value of β and if the number of failures is “large”, the distribution of X^2 is chi-squared with $J-1$ degrees of freedom. A value in the upper tail of the chi-squared distribution, such as larger than the 95th percentile, indicates that β is not the same in all the subsets.

According to p. 6-24 of HOPE, each cell should have an expected count of at least 1. This is the reason for defining “early” and “late” to have roughly equal counts of failures. If the components have been partitioned into too many subsets, some of the subsets will need to be combined.

The above approach assumed that every component was observed for the same age range, so that the expected proportion of late failures is the same for all components.

If some components were observed for one age range, and others were observed for a different age range, the above test should probably be performed separately on the two groups of components.

Test for common λ_0 in all subsets. Suppose that the above test finds no strong evidence of different values of β, so that we are willing to accept the model with a common β. The following approach can be used to test whether all the subsets of the components have a common λ_0. We assume, as before, that all the components are observed over a common age range. If the components are not observed during portions of this age range, such as during plant outages, assume that these unobserved periods are about the same for all the components. Form a one-way table as shown here.

	Subset 1	Subset 2	…	Subset J	Total
Failures	x_1	x_2	…	x_J	x_+
No. of components	n_1	n_2	…	n_J	n_+

Under the above assumptions, the number of failures for a subset of components should be proportional to the number of components in the subset. Therefore, the estimate of the expected number of failures for subset j is:

$$e_j = x_+ n_j / n_+ \ .$$

The chi-squared statistic is:

$$X^2 = \sum_{j=1}^{J} \frac{(x_j - e_j)^2}{e_j} \ .$$

If the number of failures is "large" and the above assumptions are true, X^2 has a chi-squared distribution with $J-1$ degrees of freedom. As before, we take "large" to mean that the e_j values are all at least 1 in size. A value of X^2 in the upper tail of the chi-squared distribution is evidence of failure of the assumptions, most likely the assumption of a common λ_0.

Checks of form of the function $\lambda(t)$. Both graphical checks and statistical hypothesis tests can be performed to investigate whether the assumed form of $\lambda(t)$ is correct. One graphical check consists of comparing the side-by-side confidence intervals, such as shown in Figure 4, with the fitted values for $\lambda(t)$. When this is done with the data from Figure 4, Figure 5 results.

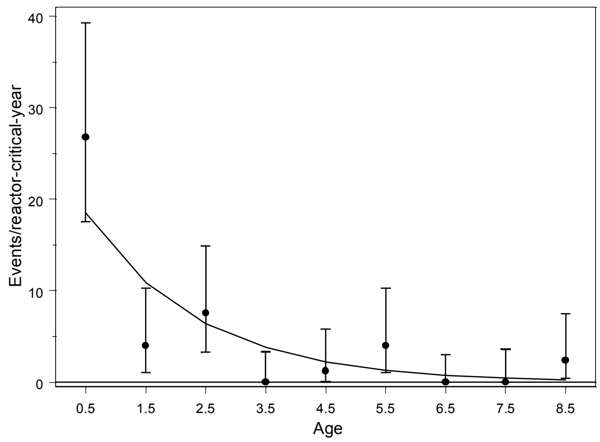

Figure 5. Figure 4 with fitted curve for $\lambda(t)$.

Figure 5 shows that three of the confidence intervals fail to contain the curve, and two others almost fail. These are 90% confidence intervals, so only 10% of them, on average, should fail to contain the true value. Therefore, this plot shows evidence of lack of fit.

A statistical hypothesis test can be constructed as follows. Let x_i be the number of failures in the ith bin, and let e_i be the expected number of failures, $e_i = s_i\lambda(t_i)$, where s_i is the exposure time for the bin and $\lambda(t_i)$ is the fitted value at the midpoint of the bin, t_i. The chi-squared statistic is:

$$X^2 = \sum_{i=1}^{I} \frac{(x_i - e_i)^2}{e_i} \ .$$

If the form of the curve is correct, and the number of failures is "large", X^2 has a chi-squared distribution. The degrees of freedom are the number of bins minus the number of estimated parameters. In the example of Figure 3.5 there are 9 bins and 2 estimated parameters, λ_0 and β. Therefore, the number of the degrees of freedom in that example is 7. With the data for Figure 3.5, X^2 can be found to equal 28.9, beyond the 99.5th percentile of the chi-squared distribution; this confirms the conclusion from the picture, that the log-linear model does not fit well.

Comparison of various functional forms of $\lambda(t)$. This sensitivity study consists of fitting various models to the data, and comparing how well they fit. If may be that some models can be ruled out, as was the case in the above example. Alternatively, it may be that the data are consistent with several models. In this latter case, the results should not be extrapolated to an age where the models give divergent results.

2.2 Data and models for components that are never tested

2.2.1. Mathematical model and basic data analysis

The typical example is a piping segment that is never tested after its initial installation. If it is discovered to have failed, such as by a leak, the piping segment is replaced or repaired so thoroughly that it can be regarded as "new". Thus, the model of a Poisson process, used in such a fundamental way in Section 2.1, is no longer appropriate. Instead, whenever a component fails, the process ends for that component. In the reliability literature, the components are called **non-repairable**.

For nonrepairable components, the analogue of a failure rate is the **hazard rate** or **hazard function**. We will again denote it by $\lambda(t)$, but its definition is somewhat different. Let T be the time of failure. The hazard function is defined by:

$$\lambda(t)\Delta t \approx \Pr(T < t + \Delta t \mid T > t)$$

for small values of Δt. Thus $\lambda(t)\Delta t$ is approximately the probability that the component fails in the next interval of length Δt, given that it has not failed by time t. A more formal definition of $\lambda(t)$ can be given as a derivative.

If the hazard function is constant, then the component is not ageing — at any time t it is as good as new. Ageing corresponds to an increasing hazard function.

A simple graph for showing evidence of ageing is the **cumulative hazard plot**. This is very similar to the cumulative failure plot discussed in Section 2.1.3 in connection with Figure 3. The difference, as presented in Sections 6.5.2 and 6.6.1.2.4 of HOPE, is as follows. Consider the age t_i of each component when it fails, sorted from smallest to largest. Begin with t_1, the earliest age for a failure, and plot a point at (t_1, $1/n_1$), where n_1 is the number of components of age t_1 in the data set. If there were many components of age n_1, then a single failure is not very surprising, and the plotted point is not high above zero. On the other hand, if there were few components of that age and one failed, the plotted point is relatively high above zero. Now consider the next age when a failure occurred, t_2, and let n_2 be the number of components in the data set having age t_2. Plot the next point at t_2 on the horizontal axis, and at height $1/n_2$ above the previous point. Continue this for all the failures. Now look at the slope of the plotted points, just as with Figure 3. If the slope is increasing, this indicates an increasing hazard rate, and thus possible evidence of ageing. If the slope is constant or decreasing, there is no graphical evidence of ageing.

If thousands of components (such as pipe segments) have been observed, and only a few have ever failed, then all the n_i values are virtually the same, and the cumulative hazard plot has the same visual shape as the cumulative failure plot discussed earlier. Unfortunately, a few failures are usually not enough to show curvature, so the simple cumulative plot cannot give much evidence one way or the other.

Lydell (2000) collected and published in his work for Swedish Nuclear Inspectorate (SKI) the operating experience data regarding piping failures from many countries. These data represent the international experience for PWR and BWR reactors. The

Table 2 presents the distribution of the number of occurred events by failure mechanism and by failure mode. Vibration fatigue, flow accelerated corrosion and water hummer are the major causes for pipe line ruptures. On the basis of results and approach developed in SKI, OCDE has opened a project called Pipe Failure Data Exchange (OPDE) Database. It is not clear if these data could be used for statistical estimation of initiating event frequencies. Further researches are needed.

Failure mechanism		**Pipe diameter < DN50**				**Pipe diameter > DN50**			
ID	**Description**	**Failure mode**				**Failure mode**			
		All	Crack	Leak	Rupture	All	Crack	Leak	Rupture
SC	Stress corrosion	152	20	132	0	794	587	207	0
TF	Thermal fatigue	36	7	27	2	63	31	32	0
E/C	Erosion by cavitations	3	0	3	0	7	0	7	0
C/F	Corrosion-fatigue	9	0	9	0	11	4	7	0
E/C	Flow accelerated corrosion	208	2	193	13	236	11	180	45
COR	Corrosion attack	84	1	80	3	80	3	74	3
VF	Vibration fatigue	670	14	592	65	96	6	85	5
D&C	Design and fabrication failures	148	2	140	6	68	5	61	2
WH	Water hammer	71	7	47	17	89	14	31	44
HE	Human errors	45	0	44	1	16	0	15	1
URC	Unknown	103	0	102	1	86	0	83	3
	All failure mechanisms	153 0	53	1369	108	1546	661	782	103

Table 2. Piping failure distribution [Lydell (2001)].

2.2.2 Estimating degradation without data, using models

Data for such components are typically quite sparse, with only a few failures. Therefore, one usually does not try to estimate the hazard function from data. Instead, several computer programs or calculational procedures have been constructed to model the degradation of particular materials from various mechanisms. Among others Smith et al. (2001) give a survey of the status of these models. The brief summary here is taken from that report and several other reports. For more details, see e.g. Smith et al. (especially Chapter 2 and Appendices A and C), and the references cited below in Table 3.

Table 3. Models for Ageing of Pipes.

Ageing Mechanism	**Model or Code and Status**	**Basis**	**Comments**	**References**
Radiation embrittlement of ferritic low-allow steels	VISA-II Code, public domain	Analytical models for processes. Data for flaw distribution.	Can perform deterministic analysis (heat transfer, stress, and fracture mechanics), with user's input temperature and pressure transient. Also can perform Monte Carlo simulation to estimate probability of vessel failure.	Simonen et al. (1986), Appendix C of Smith et al. (2001)
Thermal ageing of cast stainless steels	ANL procedure, limited validation	Laboratory test results	Estimates lower-bound facture toughness after long-term thermal ageing; and fracture toughness and other mechanical properties at a given service time and temperature.	Chopra (1992a, 1992b)
Low-cycle fatigue: crack initiation	ASME (1995), Section III. Limited validation	Laboratory test results	Generally conservative. Does not include effect of LWR environment.	Many reports cited by Smith et al. (2001)
Low-cycle fatigue: flaw growth	ASME (1995) Section XI Appendix A and C. Validated with laboratory test results	Laboratory test results	Separate topics considered: Fatigue crack growth in carbon steel and low-alloy steel. Fatigue crack growth in austenitic stainless steels. Fatigue crack growth in cast stainless steels Models for stainless steel do not include effect of LWR environment.	Many reports cited by Smith et al. (2001)

Table 2 (cont.). Models for Ageing of Pipes.

Ageing Mechanism	Model or Code and Status	Basis	Comments	References
High-cycle vibrational fatigue of welded pipe connections	ASME Section III. Vecchio work fits data.	Test data for small polished specimens and use of strength reduction factors. Requires test data for full-size components	ASME approach requires complex stress analysis, and is not necessarily conservative. Vecchio uses empirical, data-based approach of American Association of State Highway Transportation Officers (AASHTO).	ASME (1995) Section 3, Vecchio (1996), Barsom and Vecchio (1997)
Primary water stress corrosion cracking of Alloy 600 components:	Industry models	Laboratory and field data	Needed data on residual stress and grain boundary carbide distribution may not be available.	Scott (1991) and other references cited by Smith et al.
Flow-accelerated corrosion (FAC)	CHECWORKS, WATHEC, Verified and validated	Laboratory and field data	Requires adequate training and appropriate application. CHECKWORKS, developed by EPRI, is used in all U.S. plants. WATHEC is based on Kastner (Siemens/KWU) model, in cooperation with European utilities.	Chexal and Horowitz (1995), Chexal et al. (1996), Kastner and Riedle (1986)
Growth of flaws in piping weldments	PRAISE, Widely used.	Laboratory and field data.	PC version available from www-rsicc.ornl.gov. Initiation is probabilistic, based on data from laboratory tests and austenitic stainless steel in BWRs. Crack growth is deterministic, based on fracture mechanics. The latest version of the code is WinPRAISE.	Harris et al. (1992), Harris et al. (1998)

Table 2 (cont.). Models for Ageing of Pipes.

Ageing Mechanism	**Model or Code and Status**	**Basis**	**Comments**	**References**
Stress Corrosion Cracking (SCC)	PIFRAP The code has been extensively reviewed	Probabilistic fracture mechanics based analysis code	The code is limited to analyses of inner circumferential surface cracks in piping components. The only randomised parameter is the length of the crack, otherwise calculation procedure is deterministic. Procedure takes into account POD. Crack growth model has been verified against measured data.	Brickstad (2000), Nilsson et al. (1990), NKS (1998), Bergman and Brickstad (1995)
Several degradation mechanisms can be considered	STRUREL Commercial code, developed by Univ. of Munich	General purpose reliability analysis code	The code enables appropriate distributions to be derived for datasets input from e.g. spreadsheets. Goodness of fit tests are also included to demonstrate the best fitting method to be used. The code comprises 44 models and limit state equations can be input for failure modes not addressed. It includes e.g. MC simulation, FORM and SORM methods.	Univ. of Munich (2002), Das et al. (2000)
Several degradation mechanisms can be considered	NESSUS Commercial code, developed by Southwest Research Institute (SwRI)	General purpose reliability analysis code	The code allows the user to link traditional and advanced probabilistic algorithms with analytical equations, external computer programs including commercial finite element codes and general combinations of the two. The finite element codes NESSUS has interface to include ABAQUS, NASTRAN and PRONTO. Eleven probabilistic algorithms are available in NESSUS. These include MC simulation, FORM, SORM, FPI, MV, AMV and LHS.	SwRI (1995), Riha et al. (2000)

Table 2 (cont.). Models for Ageing of Pipes.

Ageing Mechanism	**Model or Code and Status**	**Basis**	**Comments**	**References**
Flow Accelerated Corrosion (FAC)	BRT-CICERO Version 2 Developed by EDF, proprietary analysis code	Probabilistic analysis of pipe wall thinning	The probabilistic module calculates the evolution of the 1E-3 fractile of the residual thickness distribution until it reaches the critical thickness. The probability for thickness being smaller than critical is evaluated after this. If the 1E-3 fractile estimate appears to be higher than the critical value, crude MC simulation is applied. If not, MC variance reduction technique is applied.	Ardillon et al. (1997)
Degradation caused by crack growth	PROPSE The code has been verified against other similar codes	Probabilistic fracture mechanics based analysis code	The code contains two different algorithms to calculate the probability of failure: simple MC simulation with an error estimate on probability of failure, and application of FORM with sensitivity factors using the most probable point of failure in a standard normal space.	Dillström (2000)
High and low cycle fatigue, SCC, FAC	SRRA The code is eveloped by WOG for RI-ISI of piping, it has been benchmarked against PRAISE	Probabilistic fracture mechanics based analysis code	The code uses recognised deterministic failure models in conjunction with MC routine to simulate the action of time dependent degradation mechanisms and infrequent loading events and to derive the probability of piping failure by a variety of failure modes. The code calculates the lifetime failure probability for three different types of piping failure: small leak, large leak, full break. Based on inputs for ISI interval and probability of detection (POD), for the applicable NDE technique the code also calculates the reduced failure probability.	Bishop (1997), NUREG/CR-2189 (NRC 1981), Harris et al. (1992), WCAP-14572 Revision 1-NP-A (1999)

Table 2 (cont.). Models for Ageing of Pipes.

Ageing Mechanism	Model or Code and Status	Basis	Comments	References
Fatigue and SCC	ProSACC Developed by DNV	Probabilistic fracture mechanics based analysis code, includes MCS and FORM	The code includes both deterministic and probabilistic flaw evaluation procedures. The deterministic part of ProSACC is based on the R6-method. A wide range of components and crack geometries may be analysed. Many parameters are treated as random parameters: fracture toughness, yield strength, ultimate tensile strength, primary stresses, secondary stresses, defect depth given by ISI, defect distribution, POD-curve, constants in the fatigue crack growth equation and constants in the SCC crack growth equation.	Dillström (2003)
Fatigue	PRODIGAL Developed by Rolls Royce	Probabilistic fracture mechanics based analysis code, applies MCS	The code evaluates leak and break probabilities for circumferential or axial cracks in piping components. Weld defect distributions and densities are generated by the code. The code assesses growth of surface breaking and buried defects. Leak rate calculations are not included.	Bell and Chapman (2003)

General assumptions applied for mechanical probabilistic models are

- both the strength or resistance of the component, $R(t)$, and the applied loads or stress, $S(t)$, are functions of time;
- $R(t)$ and $S(t)$ are statistically independent random variables;
- the component fails under the condition that $R(t) - S(t) < 0$.

Then failure probability at time t:

$$q(t) = P[R(t) - S(t) < 0] = \int_0^\infty F_R(x) f_S(x) dx \qquad (11)$$

where

$F_R(x)$ and $f_S(x)$ are the probability distribution function of R and density function of S.

Supposing R and S are distributed by a Normal low, we obtain:

$$q(t) = \Phi\left(\frac{m_R - m_S}{\sqrt{S^2{}_R + S^2{}_S}}\right) \qquad (12)$$

here

Φ is standard normal cumulative distribution function ;

m_R and m_S mean values of R and S correspondently;

S_R and S_S standard deviations of R and S.

Values of m_R, m_S and S_R, S_S can be obtained from test or operational data.

Smith (2001) demonstrates the applicability of the stress-resistance models for the purpose of evaluation of secondary pipe failure rate due to the flow accelerated corrosion (FAC) process. The model takes into account the material properties of the piping steel, the operating conditions, the velocity and chemistry of the flow and the exposure time. The model was incorporated into Surry NPP PSA model in SAPHIRE code on the level of Fault Tree.

The motivation to choose FAC ageing mechanism was the fact that several secondary pipe ruptures occurred during the NPP operation because of FAC acting on carbon steel pipes. The most significant events are the SG main feed water pipe rupture (D = 440 mm) on Surry unit 2 on December 1986, and the rupture of condensate pump line (D = 350 mm) in Trojan NPP on March 1985.

Another class of mechanical probabilistic models are probabilistic fracture mechanic ones (PFM). PFM is a commonly applied method to assess leak and break probabilities of NPP piping components. A typical PFM analysis is briefly described in the following. First, one or more model parameters are randomised, depending on the characteristics of the employed analysis model. Next, crack growth simulations are performed. Fracture mechanics models employed are based on linear-elastic fracture mechanics (LEFM), e.g. Newman-Raju solutions, influence functions and others, or elastic-plastic fracture mechanics (EPFM), or on a combination of LEFM and EPFM. During the crack growth simulation, pre- and in-service inspection are considered and failure judgements of failure states, e.g. leak or rupture, are performed. Cumulative failure probabilities are calculated as functions of operation time, see [Yagawa et al. (1997)]. A flow chart of a typical PFM analysis is shown in Figure 6.

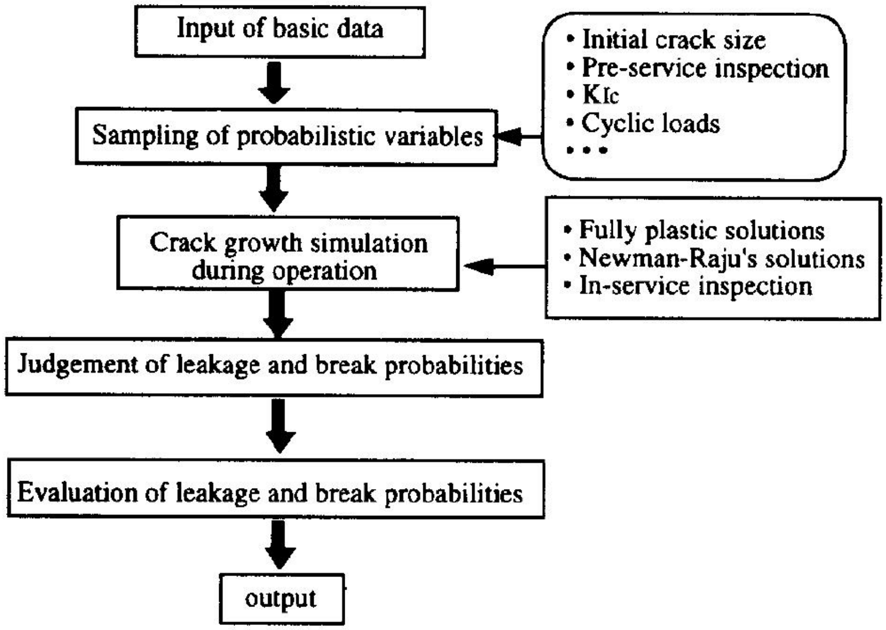

Figure 6. A flow chart of a typical PFM analysis, Yagawa et al. (1997).

Numerical techniques for generation of failure probabilities from PFM models are generally required for more complex problems. Application of these techniques does not necessarily lead to a large amount of computations or complicating factors, as workable techniques are readily available. Numerical results from the construction of PFM models are produced in a variety of ways. Techniques include: K_I /K_{Ic} overlap, variance/ covariance, convolution, Monte Carlo simulation (MCS), first-order second moment method (FORM), second-order reliability method (SORM), fast probability integration (FPI), mean value method (MV), Latin hypercube simulation (LHS) and importance sampling (IS).

There are several good sources concerning PFM theory and models, e.g. Provan (1987) and Sundararajan (1995).

In the following is a brief comparison of PFM and PSA, which is mainly based on reference [Nilsson et al. (1997)].

From a general point of view there is no need for any distinction between PRA/ PSA and PFM. The latter method, dealing with the particular phenomenon of crack growth initiation and propagation, could simply be regarded as a subclass of the former method. In fact, if crack growth is judged to be an important contributor to the total risk PFM should be applied. This follows from the simple fact that there is no better alternative than PFM to assess the risks caused by cracks. Since mechanical failures of this type are quite rare in NPPs, it often is not easy to obtain empirical failure data. Furthermore, this way of estimating failure probabilities raises problems about statistical homogeneity. Mechanical failure depends critically on local conditions such as stress distribution, material properties, loads, environment, etc. These factors are furthermore changing with time. Presumably better material is used when replacing an old component, the water chemistry is subject to changes in order to mitigate SCC. All in all this makes the use of failure statistics difficult.

A more difficult difference between PFM and PRA/ PSA is on which level the input data are based on actual observations. In PRA/ PSA the component failure probabilities, for instance for a certain valve not to function, are mostly based on direct observation albeit sometimes extrapolated by Bayesian techniques. It can be said that the primary data pertain to the component level.

The probability of a mechanical failure of a component, such as for instance for a weld in a medium or large sized pipe is seldom based on direct observation, since failure of such piping rarely occurs in NPPs. Thus the failure probability for the component in this case must be calculated, and the random properties for quantities like fracture toughness, crack size, etc. are those for which data from observations are needed. It can be said that the primary data pertain to the physical level. This procedure tends to introduce imprecision in the failure estimates for the following reasons:

1) Several different variables contribute to the component failure probability.

2) Errors in the assumptions of the PFM model will add to the uncertainty caused by input data.

Compared issue	PRA/ PSA	PFM
type of variables	discrete	continuous
mathematical modelling	well established	under development
input data and experimental verification	on component level	on physical level
data collection	possible both in service and laboratory	mostly in laboratory, some data from service

Table 4. Comparison of PRA/ PSA and PFM [Nilsson et al. (1997)].

Comments: *The stress-resistance models are widely used for reliability analyses of structures, unique components with high availability requirements, materials defect development (for example for pipes and supports), etc. In fact, resistance - load models provides much more engineering sense to the age-dependant unavailability equations than other models discussed before, but they also require more data and became more complex as soon as different stress and resistance characteristics are introduced into the model.*

When assessing leak/failure probabilities, structural reliability/probabilistic fracture mechanics based methods are often computationally the most laborious ones. However, due to very likely scarcity of leak/failure data that will be available for the analyses, these methods must be at least to some extent resorted to.

There are still methodological problems to solve and there is no standard format for how to perform PFM analyses. This is however a problem that can be overcome through the development of computational procedures. If PFM procedures are not standardised, any comparison between components that have been analysed with different methods will be questionable.

Even though most degradation phenomena are quite well known, there are still degradation phenomena the physical mechanism of which is not clear. An example of such degradation phenomena is SCC. These degradation phenomena need to researched. Through improved knowledge of various degradation phenomena, more accurate models of them can be formulated. In general, physical degradation models need development in many areas, *which include scope, range of validity, accuracy and realistic consideration of the underlying physical phenomena. One problem that needs further research as well is the modelling of several degradation phenomena acting simultaneously. This is due to known (or anticipated) dependencies and synergetic qualities between degradation phenomena that increase the propagation of detrimental effects, e.g. joint action of fatigue and SCC.*

Any engineering model that attempts to describe a process or mechanism should supply suitable documentation and evidence of its ability to accurately perform the task. These requirements are generally referred to as the verification and validation of the model. According to [Chapman (2004)] a structural reliability model could be said to be verified and validated if the following criteria are met:

1) The basic programming can be shown to have suitable quality assurance documentation.

2) That the scope, analytical assumptions and limitations of the modelling capability are well defined.

3) That the analytical assumptions in (2) are well grounded and based on theory that is accepted as representative of the situations considered by the given SRM.

4) That the model is capable of reproducing the data on which its analytical assumptions are based and examples are provided that can demonstrate its general agreement with the available experimental data.

5) Attempts have been made to show how the model compares with the world or field data, accepting the inherent limitation of this data.

6) That the model has been benchmark against other SRM models within the same field or scope and that any differences are adequately explained.

Benchmarking analyses of component failure probability analysis tools WinPRAISE, PIFRAP (included as a failure probability analysis part in risk analysis code NURBIT), PRODIGAL, ProSACC, PROST and STRUREL can be found in the final reports of the NURBIM reports, see e.g. [Brickstad, et al. (2004)].

2.2.3 Quantifying the uncertainty in a deterministic calculation

Several of the models or calculational procedures shown in Table 2 are deterministic. To estimate the probability of a pipe failure for a PSA, one must recognize at least two sources of uncertainty: the inputs to the model are uncertain, and the model is only an approximation of reality. For example, consider these two sources for the CHECWORKS code.

The code requires the user to enter various inputs. According to page A-20 of Smith et al. (2001), “the main sources of uncertainties are associated with the original thickness and thickness profile of the piping components, trace amounts of alloy content in the piping material, actual number of hours of operation, plant chemistry history, and discontinuities on the inside surface of the piping.” Once uncertainty distributions have been defined for each of these variables, they should be randomly sampled, and CHECWORKS should be run for each combination of variables. Latin Hypercube Sampling (LHS) was designed for such a setting, when each computer run is somewhat costly in terms of run time or of manual effort to set up the run. Therefore, LHS might be a useful way to perform the sampling.

Having obtained *n* outputs from CHECWORKS, each based on a different combination of input variables, one must recognize that the outputs are not perfectly accurate. According to Smith et al., CHECWORKS was based on European data and then validated with U.S. data. The comparison between the code predictions and the actual measurements indicates that “the code predicts the flow-accelerated corrosion rates within ±50%.” It is not clear how to interpret this statement - whether the ±50% spread corresponds to a 90% prediction interval (i.e. containing 90% of the predicted values) or to a prediction interval with some other confidence level. For the discussion below, suppose that the correct interpretation can be found in the code's detailed documentation, and that a 50% spread is a 90% prediction interval.

Now the two sources of uncertainty must be combined. This is accomplished most easily with a simulation, as follows.

Consider each of the n CHECWORKS runs. For example, consider the ith run. Denote the calculated corrosion rate by x_i. Now calculate a large number, m, of hypothetical values y_{ij} that are not too far from x_i, reflecting the inexactness of a CHECWORKS calculation. For simplicity, let us generate the y_{ij} values as coming randomly from a normal distribution with mean x_i and some standard deviation σ_i. Define σ_i by $1.645\sigma_i = 0.5x_i$, because 1.645 is the 95th percentile of a standard normal distribution, and we want the 5th and 95th percentiles of the y values to be $x_i - 50\%{\times}x_i$ and $x_i + 50\%{\times}x_i$.

Thus, for each x_i generate a large number, m, of values y_{ij} from a normal distribution with mean x_i and standard deviation $0.5x_i/1.645$. Now combine all the y_{ij} values into a single sample of mn numbers. These numbers are a random sample from the overall uncertainty distribution of the corrosion rate. This distribution can be used within the PSA. For convenience, we would probably try to fit a common parametric distribution to the mn values, and enter this distribution into the PSA. If that turned out to be too difficult, for example, because of weird behaviour of the CHECWORKS output, then it would be necessary to enter a discrete distribution into the PSA, based on the histogram of the y_{ij} values.

In the above example, a normal distribution was chosen because the CHECWORKS prediction interval was stated to be symmetrical around x_i. If the prediction interval had been stated to be asymmetrical, a different distribution would have been more appropriate. For example, if it had been found that the actual values were usually no more than twice the calculated value and no less that half the calculated value, we might have generated the y_{ij} values from a lognormal distribution with median x_i and error factor 2.

Some codes include a probabilistic section. For example, PRAISE models the flaw initiation probabilistically, assigning probability distributions to various parameters, including crack aspect ratio. These distributions are based on data. The remainder of the code is deterministic. If the analyst accepts the built-in probabilistic distributions of the input parameters, the only additional work would be to account for inaccuracy in the deterministic calculations, as described above.

2.2.3 Infrequently collected data on material condition

In this setting, gradual development of defects, such as cracks, must be detected by limited periodic non-destructive testing (NDT) or other indirect measurements. The NDT data are often noisy and difficult to interpret. A probabilistic approach is required, to account for the uncertainties in the NDT data and in the somewhat random development of a fault. Probabilistic models and solution techniques are presented by Simola and Pulkkinen (1998). (See also Pulkkinen and Uryas'ev 1992 and Pulkkinen 1994). The summary given here is taken from the paper by Simola and Pulkkinen.

Let d denote the thickness of the material, such as a pipe wall, and let a denote the size (actually depth in the paper by Simola and Pulkkinen) of a flaw, with $0 \le a \le d$. A non-destructive technique is used to try to detect the flaw. If the flaw is detected, the value of a is estimated by a measured value $\hat{a}$.

Calibration data are required to relate the measured flaw sizes to the true sizes. Under the assumption that $\ln(\hat{a}/d)$ is normally distributed,

$$\ln(\hat{a}/d) \sim \text{normal}(\beta_0 + \beta_1 \ln(a/d), \sigma^2) \qquad (12)$$

least squares fitting can be used to estimate the calibration parameters β_0, β_1, and σ^2. If some of the flaws are large compared to d, then a logit model must be used instead (see Sec. A.7.9 of HOPE), in which $\ln[\hat{a}/(d - \hat{a})]$ is normally distributed. The logit formulas are analogous to those involving the lognormal distribution, but they are more accurate at the price of being somewhat more complicated. For simplicity only Equation (12) is considered in the discussion below, but the logit analogue can be worked out in every case.

Consider now the probability of detection (*POD*). Two approaches are presented. In the first, we assume that a flaw is "detected" whenever $\hat{a}/d$ is above some decision threshold. (Simola and Pulkkinen point out that this assumption may not always be valid, but may still be reasonable for some inspection methods.) Then the POD can be expressed in terms of the calibration parameters, the decision threshold, and the standard normal distribution function.

In the second approach, the *POD* is estimated from "hit/miss" reference data. Here a set of n flaws is studied by several independent teams or independent measurement methods. The *POD* for a flaw with specified characteristics can be estimated from the observed number of detections. The reference data and hit/miss results are used to estimate both the parameters in Equation (12) and the *POD* as a function of a/d. Both the MLE approach and a Bayesian estimation approach are given. The MLE requires numerical maximization, and the Bayesian approach requires Monte Carlo simulation, such as can be performed by WinBUGS (Spiegelhalter et al. 2003).

Finally, Simola and Pulkkinen present a method for Bayesian updating of flaw sizes. Note, growth of the flaw between measurements is not discussed. This is Bayesian updating in the traditional sense, in which a *constant* unknown parameter a/d is estimated with ever greater precision by accumulating data.

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APPENDIX A1

MAIN PWR COMPONENTS AND THEIR DEGRADATION MECHANISMS

Degradation Mechanisms / Components	Radiation Embrittle-ment	Time-Dependent Relaxation (Creep)	Hydrogen Embrittle-ment	Stress Corrosion Cracking	Low – Cycle Thermal Fatigue	High-Cycle Mechanical and Thermal Fatigue	Corrosion Fatigue	Thermal Embrittle-ment	Mechanical Wear, Fretting and Fatigue	Corrosion and FAC
Reactor Pressure Vessel (RPV)	x			x						x
Containment and Basemat		x	x	x						x
Reactor Coolant Pipe, Safe ends, and branch					x	x		x	x	
Steam Generator tubes				x		x	x		x	x
Reactor Coolant Pump (RCP)						x		x		x
Pressurizer				x	x					
Control Rod Drive Mechanisms				x				x	x	
Safety-related Cables and Connections	x							x		x
Emergency Diesel Generators									x	x
Reactor Internals		x		x		x			x	
Reactor Pressure Vessel Supports	x			x						
Feedwater Pipe and Nozzles, and Steam Generator Shell				x	x	x				x

MAIN BWR COMPONENTS AND THEIR DEGRADATION MECHANISMS

Degradation Mechanisms / Components	Radiation Embrittle-ment	Time-Dependent Relaxation (Creep)	Stress Corrosion Cracking	Low – Cycle Thermal Fatigue	High-Cycle Mechanical and Thermal Fatigue	Corrosion Fatigue	Thermal Embrittle-ment	Mechanical Wear, Fretting and Fatigue	Corrosion and FAC
Containment			x			x			x
Reactor Pressure Vessel (RPV)	x		x	x	x				x
Recirculation Pipe and Safe Ends			x				x		
Recirculation Pumps			x		x		x		
Control Rod Drive Mechanisms	x		x				x	x	x
Safety-related cables and connections in containment	x	x					x		x
Emergency Diesel Generators	x							x	x
Reactor Pressure Vessel Internals	x		x		x	x	x		
Reactor Pressure Vessel Supports				x					
Feedwater and Main steam Pipe					x			x	x

APPENDIX A2
General goals and methodologies for monitoring system

Goals		Methodology
Prevention from failures and damages	Load (height, frequency) Verification of specified load collective	On-line measurement of global plant data (p,T) Transient book-keeping Local temperature distributions Calculations related to the load collective
	Stresses (height, frequency) Verification of calculated design limits	On-line measurement of global plant data (p, T) Local measurement of temperatures, strains, Displacements Calculation of fatigue usage
	Environment (oxygen content, pH, conductivity) Control of electrochemical potential Influence on protective oxide layers and fatigue strength	Measurement of plant data by sampling (sampling lines) Direct measurement at operating parameters Direct measurement of redox- and electrochemical potential
Early detection of damage	Loose parts monitoring	On-line measurement and analysis of structure-borne acoustic signals (impact of loose parts), using e. g. piezoelectric accelerometers
	Loose parts, cracking, damage	On-line measurement and analysis of vibrational behaviour using signals of the following categories: displacement (absolute, relative), pressure fluctuations, ex-core neutron flux noise
	Crack growth (during pressure test)	On-line measurement and analysis of acoustic emission signals
	Leakage monitoring system	Visual inspection during operation Acoustic monitoring systems, using the noise generated by a leakage flow, detected by piezoelectric resonant acoustic emission probes Localization of leaks Humidity measurement systems
Control of damage, Crack propagation	Measurement of crack depth and ligament	On-line measurement of crack growth by direct instrumentation of the affected component Potential probe Ultrasonic measurement

APPENDIX A3

Example of the use of statistical analysis code WinBUGS®

Conceptually, the steps for using WinBUGS (also known by the older name BUGS) are as follows.

1) Define the model
    a. For i denoting any bin, define the formula for lambda[i], in terms of the underlying parameters. Here, the notation lambda[i] denotes the value of $\lambda(t_i)$.
    b. Define the mean count in each bin, $\mu(i) = \lambda(i)s(i)$.
    c. Declare the distribution of the count $x(i)$ to be Poisson($\mu(i)$)
    d. Assign prior distributions to the unknown parameters. Presumably, a diffuse prior is desired for the ageing parameter β, but an informative prior might be appropriate another parameter such as λ_0.

2) Give BUGS the data.
    a. Declare the number of bins
    b. For each bin, declare the exposure time s_i, the number of failures x_i, and the mean component age t_i.

3) Define the sampling process.
    a. Decide on the number of chains. If several are used, they can be compared to help show when they have converged to stability and agreement.
    b. Assign initial values for the underlying parameters for each chain.
    c. Declare the variables for which the posterior distributions are desired. This would include λ at some current or near-future age, and it would probably include the ageing parameter β, the baseline failure rate λ_0, and perhaps others.

4) Obtain the posterior distributions of the desired variables.
    a. Let BUGS do the sampling, and produce plots and summary statistics.
    b. Drop the early part of the chains, when the initial values are still influencing the chains, before the sample values have stabilized in the posterior distribution.
    c. Perform diagnostic tests to see whether enough values have been sampled.
    d. From the program output, read summaries of the sample: mean, variance, percentiles, density estimates, and others.

As an example, consider the data from Table 3.1 in the body of this report. Figure A3.3.1 shows the input to WinBUGS for the above process, assuming a log-linear trend in λ as given by Equation (3.5′) in Chapter 3, and using b instead of β because BUGS prefers English over Greek. Also, a is used instead of λ_0, with a defined as $\ln\lambda_0$. The lines preceded by # are comments, and are ignored by BUGS.

```
# Model portion of the input
model
{
   lambda0 <- exp(a)
   for (i in 1:N) {
      lambda[i] <- exp(a + b*(t[i]-t0))
      mu[i] <- lambda[i]*s[i]
      x[i] ~ dpois(mu[i])
   }
   a ~ dnorm(0.00, 0.0001)
   b ~ dnorm(0.0, 0.0001)
}

# Data portion of the input
list(N=9, t=c(0.5, 1.5, 2.5, 3.5, 4.5, 5.5, 6.5, 7.5, 8.5), t0=4.5,
     s=c(0.7094, 0.7517, 0.7949, 0.8960, 0.8153, 0.7513, 0.9961, 0.8274, 0.8376),
     x=c(19, 3, 6, 0, 1, 3, 0, 0, 2)    )

# Initial values portion of the input
list(a=-0.7, b=0)
list(a=-0.7, b=-0.5)
list(a=3, b=0)
list(a=3, b=-0.5)
```

Figure A3.1 Input for BUGS, assuming a log-linear trend.

Consider first the model portion of Figure A3.1, and note several points of syntax. The model definition is enclosed in curly brackets. Square brackets are used for array subscripts. The symbol <-, a pair of typed characters that together are supposed to look like an arrow that points left, is used for showing definitions of numbers. The symbol ~ is used to define the distribution of a quantity. The "d" at the start of "dpois" or "dnorm" indicates a "distribution", Poisson or normal in these cases. Finally, BUGS uses the "precision", defined as 1/variance, as the second parameter of a normal distribution. Therefore, dnorm(0.0, 0.0001) indicates a normal random variable with mean μ = 0 and variance σ^2 = 10000. This is very diffuse, suggesting that the values of *a* and *b* could very plausibly be in the range (−100, +100) or wider.

Now consider the data section of Figure A3.1. The word "list" introduces the assignment of numerical values. In a vector of data, the individual numbers are combined with the c( ) function. This notation is borrowed from the original versions of S-Plus, which users of S-Plus for Windows hardly ever see.

The value of N is set to 9, the number of years (bins) of data. The plant had its initial criticality at the start of 1987, so its average age in that year was 0.5. This is shown as the first value of t, and the other values follow. The value of t_0 is set to 4.5, the age in the middle. As a result of this centred t_0, the MLEs of *a* and *b* will be less dependent, and we hope that *a* and *b* will also be approximately independent when the Bayesian joint posterior distribution of (*a*, *b*) is found. This makes their joint distribution easier to visualize. The exposure times *s* are taken from information about the particular plant, and expressed in critical years (critical hours divided by 8760), as given in Table 3.1. The failure counts *x* came from the same table.

Finally, consider the initialization section of Figure A3.1. If four chains are used, four initialization statements are needed. Examination of Figure 3.4 shows that a value of 0.5 would almost certainly be too small for λ_0, the value of λ at age 4.5, and a value of 20 would almost certainly be too large. Therefore, taking logarithms, the parameter *a* is almost certainly between -0.7 and +3. These two extreme values are used as the two initial values of *a*. Similar reasoning with the slope shows that *b* is almost surely between 0 and -0.5, so these two values are used as initial values for *b*. Taking the four possible combinations leads to the four sets of initial values shown in Figure A3.1.

To run WinBUGS, first create and save a text file containing the contents of Figure A3.1. Then open WinBUGS and perform the following steps, in the order given.

1) Click on *File/New*. A blank sheet will appear. Copy the text file here.
2) Click on *Model/Specification*. A Window labelled *Specification Tool* will appear.
3) Drag the cursor to highlight the model portion of the text, or at least the "m" in "model". In the Specification Tool, click on *check model*. At the bottom of the window, you should get the message, *model is syntactically correct*.
4) Drag the cursor to highlight the data portion of the text, or at least the "l" in "list". In the Specification Tool, click on *load data*. You should get the message, *data loaded*.
5) In the specification tool, enter the number of chains to use, 4 in the present example. Then click on *compile*. You should get the message, *model compiled*.
6) Drag the cursor to highlight the first of the data initialization lines, or at least the "l" at the start of the line. In the example, this line is "list(a=-0.7, b=0)". Click *load inits*. The number in the window *for chain* should change from 1 to 2. Repeat this with the next initialization line, until all have been loaded.
7) Go back to the main WinBugs window, and click on *Inference/Samples*. A window named *Sample Monitor Tool* will appear. Click on a desired percentile, such as the 5th. With the Ctrl key down, click on any other desired percentiles, such as the 95th and the median. These chosen percentiles will all show as highlighted.
   Specify the length of the chain. When first experimenting with WinBUGS, use a fairly short chain, such as 1000. With more experience, a longer chain, such as 100,000, may be useful.
   In the blank window *node*, enter the name of a parameter of interest, such as *a*. Click the *set* button. Repeat the selection with other parameters of interest, such as *b*, lambda0, and lambda. This will produce samples from the posterior distribution of a, β, λ_0, and $\lambda(t_i)$ for each t_i.
8) In the main WinBUGS window, click on *Model/Update*. A window named *Update Tool* will appear. Click on the *Update* button.
9) Return to the Sample Monitor Tool, and select one of the nodes that was previously defined, such as *a*. Clicking on *history* will show a plot of all the chains. If they converge, notice roughly how many iterations it took for them to converge. If they do not, then longer chains are needed. If it is hard to decide when the chains start to overlap, click on *bgr diag* to produce a diagnostic plot of Brooks, Gelman, and Rubin. As described in the WinBUGS manual (Spiegelhalter et al. 2003), the red line should converge to 1 and the other two lines should converge to stable values. It is often easier to read this plot than to decide if the chains have started overlapping.
   Do this for all of the fundamental underlying parameters, *a* and *b* in this example. When enough sampling has been done so that all the chains converge, drop the early portions of the chains, the portion before convergence; do this by changing the number in the *beg* window from 1 to a larger value.
   Clicking on *density* will show a plot of the simulated density of the selected node. Clicking on *stats* will show the mean, standard deviation, and the previously chosen percentiles.

To see box plots or side-by-side confidence intervals of an array, such as lambda in the example, click on *Inference* in the main WinBUGS window, then click on *Compare*. A window named *Comparison Tool* will appear. Type the array name where requested, and click on either *box plot* or *caterpillar*.

To see the correlation of two parameters, such as *a* and *b*, click on *Inference* in the main WinBUGS window, then click on *Correlations*. A window named *Correlation Tool* will appear. Type the two parameter names into the two blank windows, and click on *print* for the value of the Pearson correlation coefficient, and on *scatter* for a scatter plot of the two parameters.

Clicking on *coda* produces the actual sample values for the selected parameter (node). If these are copied into a spreadsheet for the different nodes, the joint posterior distribution of the parameters can be obtained. The WinBUGS manual mentions a CODA S-Plus diagnostic package for using the CODA output.

The guidance in Steps 1-8 form a detailed recipe for using WinBUGS. Step 9, on the other hand, gives only a hint of the possibilities for the analyst. Good practice at this point is learned from reading the WinBUGS manual and from trying things in practice.

APSA in risk informed applications

Appendix B1

Demonstration Examination of Failure Data from Continuously Operating I&C Components

C. ATWOOD - STATWOOD CONSULTING

October 2005

TABLE OF CONTENTS

B1.1 The Data of This Study

This demonstration study uses a data set provided by IRSN. This data set represents the "virtual" failure and replacement dates of "virtual" electrical or instrumentation and control (I&C) components. It is quite close to the real operating experience data collected in French nuclear power plants (NPPs). In particular, it is a large sample that represents one technological group of continuously operating components. The data set contains records from two types of reactors, denoted "T" and "U", which have different power levels but which are operated by a single utility with a single management philosophy. The components are all of the same type (design, manufacturer, technology, etc.). The components operate in two different environments, with the "A" environment having more stressful pressure and temperature and the "R" environment having more stressful radiation and water chemistry. The scope of the maintenance is the same for all the components. For the sake of consistency, when these combinations are analyzed in this appendix, the analyses are always presented in the order T-A, then U-A, then T-R, and finally U-R.

Eleven years of data were collected, from January 1, 1990 through December 31, 2000. Therefore the data are censored by interval, that is, the observed times in operation are truncated at the right and left ends. The components in the sample do not all have the same date of being put into service, and as a consequence do not have the same ages at the beginning and end of observation. The failure counts were taken from a review of the maintenance data, so any reported date of failure is actually the date of the periodic test. A "critical" failure is one that causes the component to lose its safety function in a PSA model. For example, in the case of an I&C measurement channel, failure to provide a signal is a critical failure and deviation of a set-point beyond the allowed technical specifications is also a critical failure. However, deviation of a set-point within the technical specification limits may require maintenance but it is not a critical failure. The data are also used in Appendix B2, although a few corrections were made here as described in Section B1.2.

B1.2 Preparation for Analysis

B1.2.1 Cleaning of the Data

Some of the failed components had clearly erroneous entries, which were corrected.

A few failures were recorded twice, in separate records. A systematic search was made for such pairs of records, by searching for matching failure dates within a unit, and six records were deleted.

In general, critical failures (defined above) are given a higher level of quality review, and therefore are more reliable. No additional review of the records was performed for this study, other than a general examination.

B1.2.2 Counts of Components of Any Age

To study failure behaviour as a function of age, it is necessary to know the number of components of any age in the data set. These numbers were counted as follows.

First, consider the determination of the ages of the components. The ages of nearly all of the individual components are assumed to equal the age of the unit, counting the date of commissioning as age zero. Since components are replaced only rarely, this assumption will be correct for the vast majority of all components, and will underestimate the number of aged components only slightly. In the few instances when the failure record stated that a component was replaced, the replacement component was considered new, and its true age was used for the rest of the data period. Because each unit's commissioning date is reported only by month and year, not by day, all calculated ages are approximate, to within one month.

To establish the count of components at any age, consider first the situation where no components were replaced. The age of any component on a certain date is defined as that date minus the commissioning date (the commercial start date) of the reactor. Units enter the data set either at the start of the data collection period or at the commissioning date, whichever comes later. Units leave the data set at the end of the data collection. (No units left the data set because they were decommissioned.) For each unit, calculate the age when unit enters the data set and leaves the data set.

Combine all these ages, ordered from the smallest age to the largest. At each such age, count the *change* in the number of components in the data — if a unit is entering the data set, the number of components increases by the number of components in the unit, and if a unit is leaving the data set the number of components decreases. Beginning at the youngest age, increment or decrement the number of components until the final age is reached. The number of components in the data set is typically small for very small ages, increases to a maximum in the middle, and finally drops back to zero at the final age, when the oldest unit leaves the data set.

Now consider the additional complication that a component is replaced by a new one on date dddddd. The unit changes its number of original components on that date. Suppose that the unit is named U, and that it has n components. Define an artificial unit named Ua, with n components that were installed when the unit U was commissioned. The unit Ua differs from U in that it enters the data set when unit U does but it leaves on date dddddd. Define also a unit named Ub, with $n-1$ originally installed components, which enters the data set on date dddddd+1 and leaves at the end of the data collection period. These two artificially defined units replace unit U in the data set, and contain all the originally installed components. Finally, add a third "unit" Ux with only the one new component, which enters the data set on date dddddd+1, has age 0 on that day, and leaves the data set at the end of the collection period. These three artificial "units" contain all the components, old and new, of the actual unit U. To establish the count of components of any age, follow the process of the previous paragraph, but use Ua, Ub, and Ux instead of U.

The failures in unit U must now be recoded as occurring in either Ua, Ub, or Ux. Then it is direct to calculate the age of any component at the time of its failure and the number of components of that age in the data set.

B1.2.3 Gathering the Data into Bins

It is easy to count the data in any range, such as yearly ranges. The component-years corresponding to a bin are also easy to obtain, using the work described above. For example, if one unit enters the data at the end of September in some year (suppose with exactly 1/4 of a year remaining), and it has n components, then for that year it contributes $n/4$ component years.

One use of bins is to construct a single value of the failure frequency for the bin. This is the estimate of $\lambda(t_{mid})$, where t_{mid} is an appropriately chosen value somewhere in the middle of the bin. If all the components are in the data set for the entire year, it is usual to set t_{mid} to the midpoint of the bin. However, if the number of components in the data set changes during the course of the year, it is not so obvious how to define t_{mid}. The numerical consequences of the wrong choice could be noticeable if the data are sparse so that several years must be combined into one bin.

The solution is as follows. Consider that portion of the data set corresponding to a certain bin. Suppose that we had a single component that is in the bin from age L to age U. (The letters stand for "Lower" and "Upper". If the data are generated by a nonhomogeneous Poisson process with intensity $\lambda(t)$, the expected number of failures for this component in the bin is

$$\int_L^U \lambda(t)dt \ . \qquad \text{(B1-1)}$$

We want a value of t_{mid} so that the expected count is approximated by

$$\lambda(t_{mid})\times(U-L), \qquad \text{(B1-2)}$$

because $U-L$ is the number of component-years for the component in the bin. The exact value of t_{mid} depends on the value of the integral, which depends on the unknown form of $\lambda(t)$. However, if $\lambda(t)$ is approximated by its first-order Taylor expansion,

$$\lambda(t) \approx a + bt \ ,$$

then Expression (B1-1) is approximated by

$$a(U-L) + ½\, b(U^2 - L^2) \qquad \text{(B1-3)}$$

and Expression (B1-2) is approximated by

$$a(U-L) + bt_{mid}(U-L)\ . \qquad \text{(B1-4)}$$

If these Expressions (B1-3) and (B1-4) are equated, the solution for t_{mid} is the familiar expression $½(U+L)$.

Now, however, we want to extend the situation by assuming that various components have various values L_i and U_i. The expected failure count is the sum of the expected values for the components, so we want t_{mid} to satisfy the equation

$$\Sigma_i[a(U_i - L_i) + ½\, b(U_i^2 - L_i^2)] = \Sigma_i[a(U_i - L_i) + bt_{mid}(U_i - L_i)]\ .$$

A little algebra shows that the solution is

$$t_{mid} = ½\ \Sigma_i(U_i^2 - L_i^2)\ /\ \Sigma_i b(U_i - L_i)\ \ .$$

This value of t_{mid} is used in the following analyses of the data.

B1.3 First Look at Each Data Set

B1.3.1 Crude Tabular Summary of Data

Table B1.1 shows the numbers of failures and component years for the two kinds of unit, T and U, and the two kinds of environment, A and R. Because not all the component repairs and adjustments are severe enough to be considered representative of true failures, totals are given for all events and also for only the critical failures. Many of the analyses later in this appendix assume that the data are generated by a (possibly nonhomogeneous) Poisson process; common-cause failures (CCFs) violate the assumptions of a Poisson process, and therefore are excluded from most of the work in this appendix.

Table B1.1. Summary of failure counts in the four reactor/component types.

Reactor-Component Type	Component-Years	Age Range (Yrs)[a]	All components in failure events	All non-CCF events	All critical non-CCF events
T-A	4158.7	0 – 15.1	160	156	132
U-A	4928.3	1.8 – 20.3	188	177	152
T-R	3534.9	0 – 15.1	127	110	76
U-R	3696.2	1.8 – 20.3	95	85	61
a. Only units are included here, not individual replaced components					

Table B1.2 shows a few more comparisons of possible interest, with data derived from Table B1.1.

Table B1.2. Further summary of non-CCF failure counts in the four reactor/component types.

Reactor-Component Type	Component-Years	Failures per component-year	Critical failures per component-year	Percent of non-critical failures
T-A	4158.7	0.038	0.032	15%
U-A	4928.3	0.036	0.031	14%
T-R	3534.9	0.031	0.021	31%
U-R	3696.2	0.023	0.017	28%

Table B1.2 shows that the T reactors have somewhat more failures per component-year than do the U reactors, in spite of the fact that the T reactors are younger. Table B1.2 also shows that, compared to the R components, the A components have more failures per component-year, and many more critical failures per component-year. A related comparison is that the A components have only half as many non-critical failures (as a percent of all failures) compared to the R components. Recall that the A components have more stressful pressure and temperature, and less stressful water chemistry and radiation.

B1.3.2 Cumulative Plots

A cumulative failure plot shows cumulative failures per component vs. component age. For each failure that occurs at some component age, the plot jumps by height

1/(no. of components of that age in the data) .

The number of components of a certain age may be thought of as the number of components at risk, the number that were available to fail. The slope of the cumulative plot at any part of the plot is a nonparametric estimate of

λ = frequency of failures per component per year,

for components of about that age. Figure B1.1 later in this report is an example of such a plot.

During age ranges when many components are in the data, there are relatively many failures, and the plot is stable. During age ranges with few components in the data (the very oldest and youngest component ages observed), there are relatively few failures among few components, and the plot is unstable.

Conclusions from the right and left ends of the plot may be questionable, because they are too subject to the random behaviour of a few components. In the middle, on the other hand, the slope of the plot can be quite stable.

B1.3.3 Side-by-Side Confidence Interval Plots

If the data are binned into age intervals, and the failure frequency λ is treated as approximately linear within each bin, a confidence interval can be found for $\lambda(t_{mid})$ in each bin. The meaning of t_{mid} is explained above. Such a plot can be examined for evidence of a trend. To help in this examination, a horizontal line is shown with height equal to the overall maximum likelihood estimate (MLE) if λ is assumed to be constant. This MLE is just the total number of failures divided by the total number of component-years in the data set. Figure B1.2 later in this report is an example of such a plot.

To keep the confidence intervals moderately short, the bins should not be too sparse. In the analyses below, the bins are calculated so that the expected number of failures in each bin is at least 3. This means that the bins at the ends of the plot include several years each, while the bins in the middle consist of one-year intervals. Initially, the value 5 rather than 3 was chosen. This is a conservative rule of thumb for bins that allow a chi-squared test of the hypothesis that λ is constant. However, that choice seemed overly conservative for the purposes of this study, which include a comparison of the various parametric forms for $\lambda(t)$. Such a comparison works better if the bins are not combined too much at the end of the range. Also, the calculation of expected count in a bin was based on the assumption of no ageing. If ageing occurs, the expected counts in the upper bins will be larger than calculated. The lower bins (age < 5 years) are ignored in some cases, to avoid the complication of burn-in failures.

The analyses of the various data sets are now presented, using the two types of plots described above.

B1.3.4 Preliminary Graphical Analyses of the Data Sets.

B1.3.4.1 T-A: Units of Type T, Components of Type A.

There are 20 units of type T, each with 20 components of type A. The data collection period is eleven years, so there would be 4400 component-years except for the fact that some of the units were commissioned after the start of the data collection.

Figure B1.1 shows the cumulative plot for failures that are not common-cause failures. Figure B1.2 shows the plot of confidence intervals for the same data set. Figures B1.3 and B1.4 show the same plots when the failures are restricted to critical failures only.

All four of these plots show a steady increase in λ as the components age. This appears to be a textbook example of ageing behaviour.

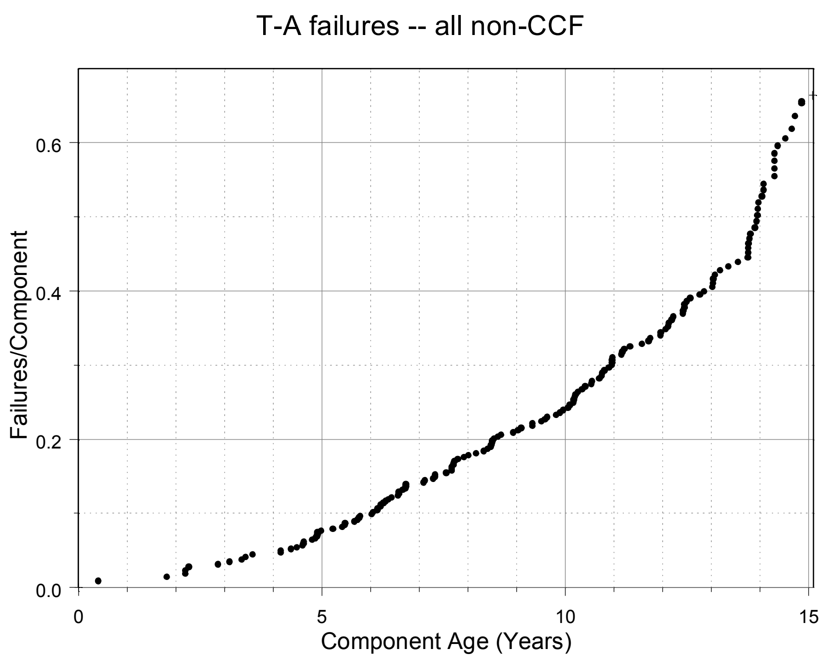

Figure B1.1. Cumulative failure plot, for T-A failures (critical and non-critical) other than common-cause failures.

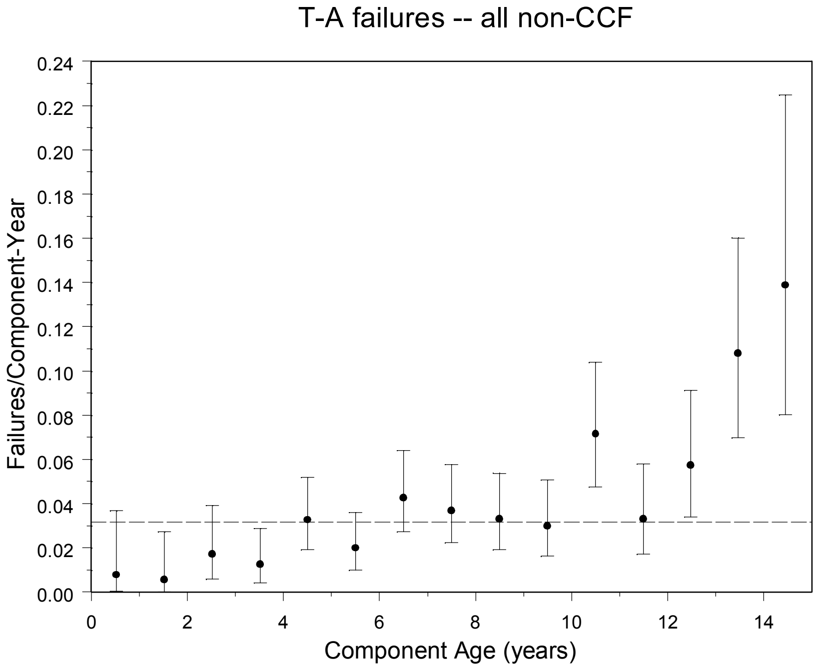

Figure B1.2. Side-by-side 90% confidence intervals for λ, for T-A failures (critical and non-critical) other than common-cause failures. The dashed line shows the MLE if λ is assumed to be constant.

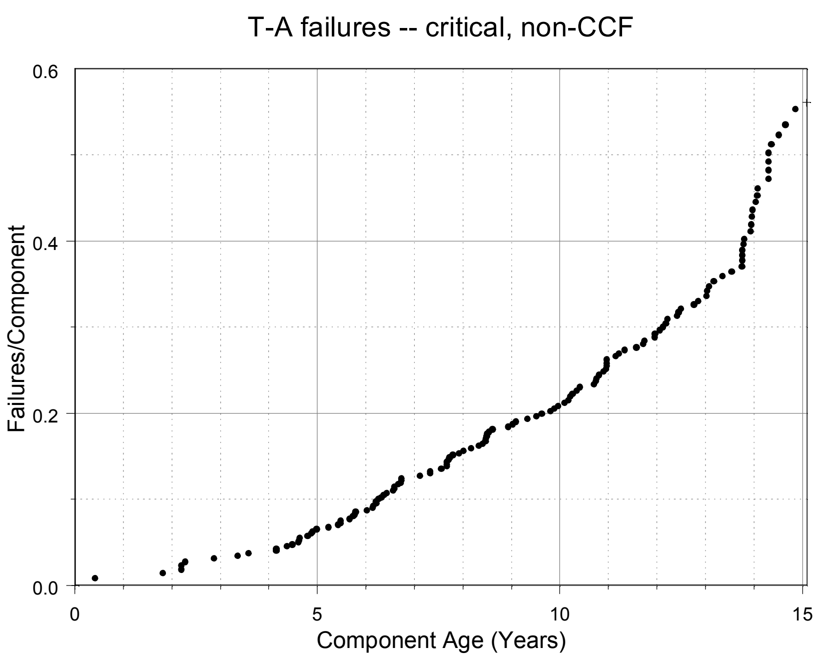

Figure B1.3. Cumulative failure plot, for T-A critical failures other than common-cause failures.

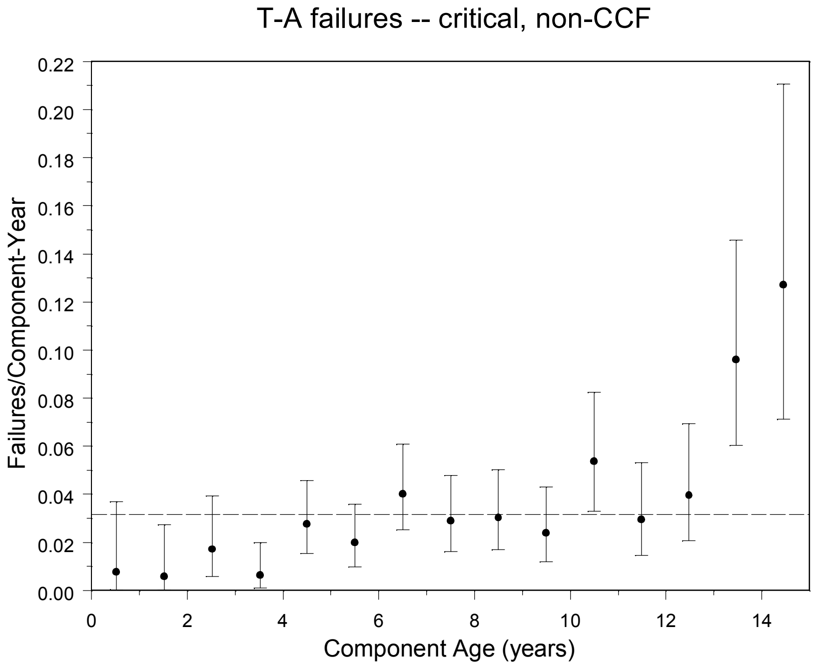

Figure B1.4. Side-by-side 90% confidence intervals for λ, for T-A critical failures other than common-cause failures.

B1.3.4.2 U-A: Units of Type U, Components of Type A.

There are 28 units of type U, each with 16 components of type A. The data collection period is eleven years, so there are 4928 component-years. The error beyond the decimal place in Table B1.1 results from approximating every year by exactly 365.25 days.

Figure B1.5 shows the cumulative plot for failures that are not common-cause failures. Figure B1.6 shows the plot of confidence intervals for the same data set. Figures B1.7 and B1.8 show the same plots with the data restricted to critical failures. All the plots show a failure rate that increases sharply at about age 12, but which drops back again to the average value at about age 17. Evidently, if ageing is affecting the failure rate, the relationship is complicated and other factors are also at work.

The left side of each plot shows a few burn-in failures. They are not relevant for an investigation of ageing.

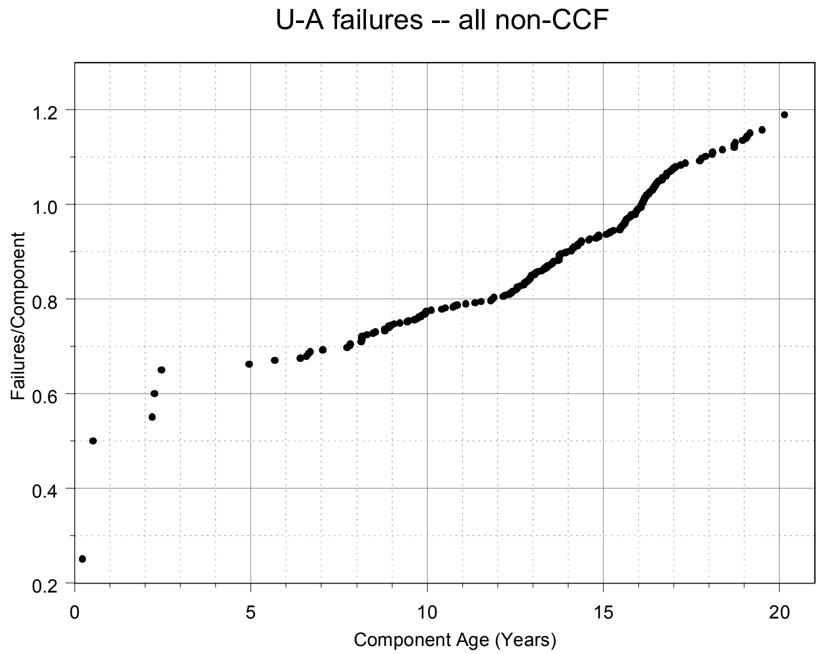

Figure B1.5. Cumulative failure plot, for U-A failures (critical and non-critical) other than common-cause failures.

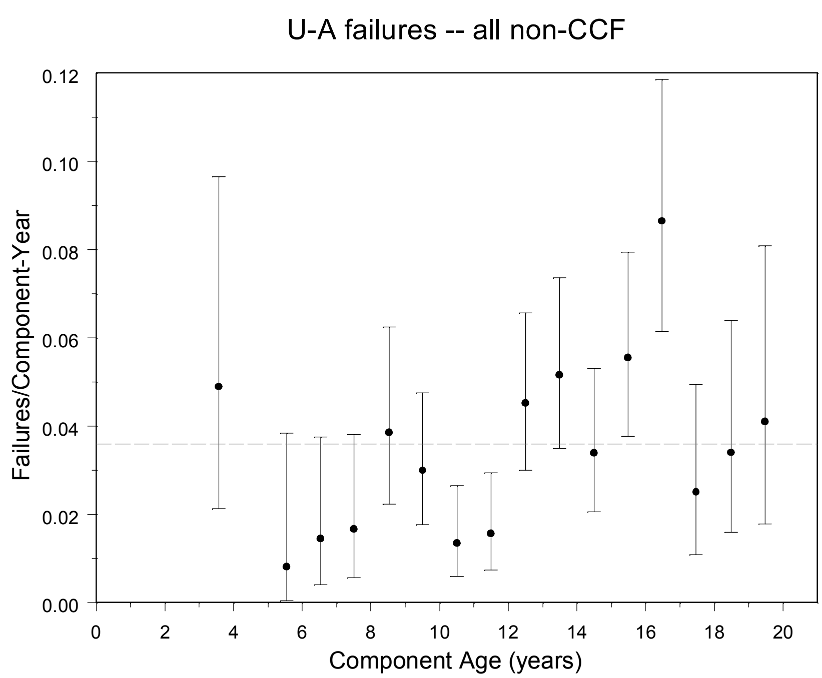

Figure B1.6. Side-by-side 90% confidence intervals for λ, for U-A failures (critical and non-critical) other than common-cause failures.

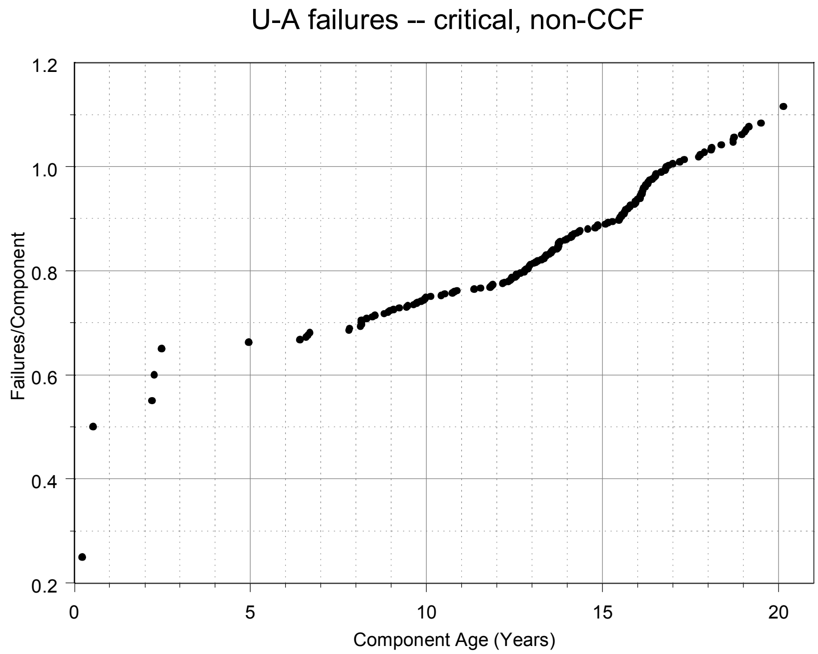

Figure B1.7. Cumulative failure plot, for U-A critical failures other than common-cause failures.

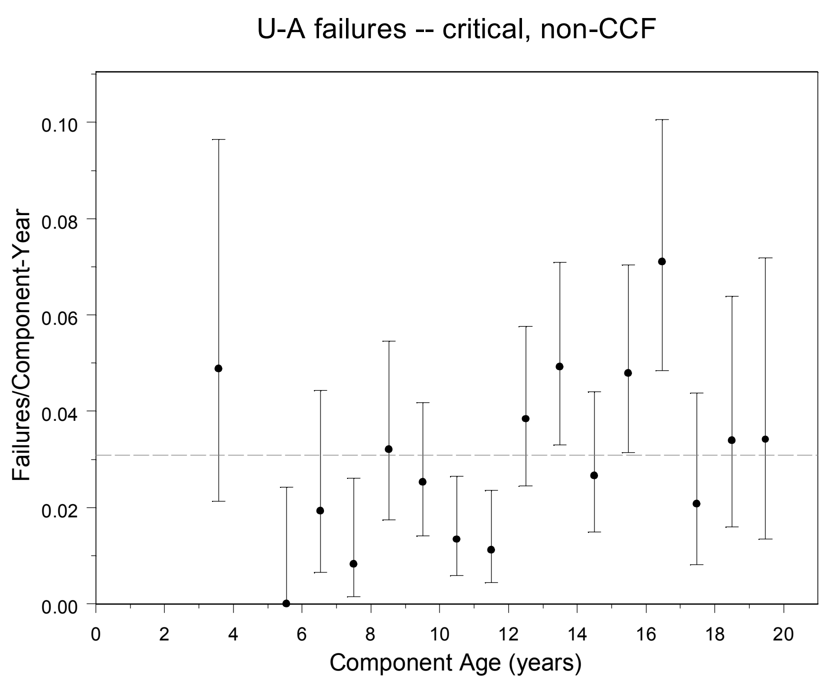

Figure B1.8. Side-by-side 90% confidence intervals for λ, for U-A critical failures other than common-cause failures.

B1.3.4.3 T-R: Units of Type T, Components of Type R.

There are 20 units of type T, each with 17 components of type R. The data collection period is eleven years, so there would be 3740 component-years except for the fact that some of the units were commissioned after the start of the data collection.

Figure B1.9 shows the cumulative plot for failures that are not common-cause failures. Figure B1.10 shows the plot of confidence intervals for the same data set.

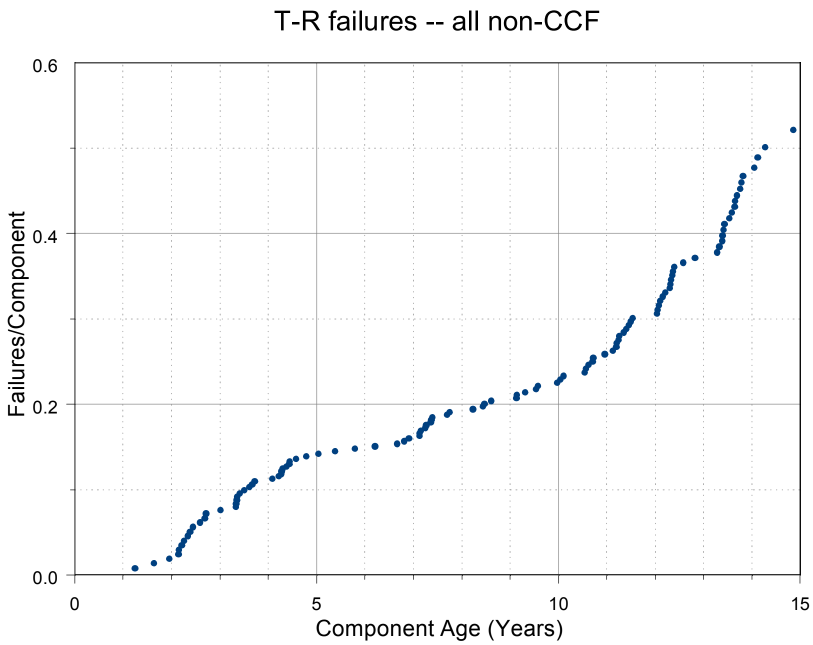

Figure B1.9. Cumulative failure plot, for T-R failures (critical and non-critical) other than common-cause failures.

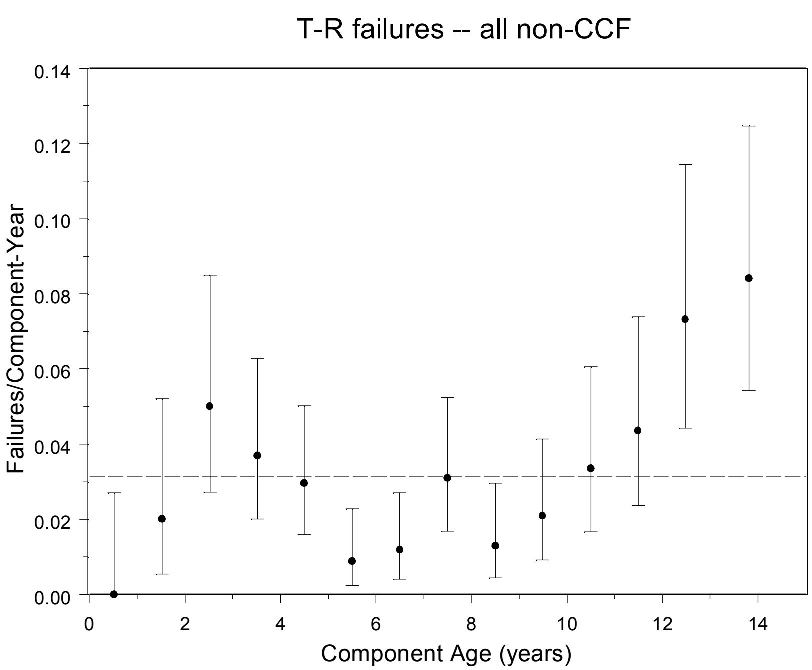

Figure B1.10. Side-by-side 90% confidence intervals for λ, for T-R failures (critical and non-critical) other than common-cause failures. The horizontal line shows the maximum likelihood estimate of constant λ.

Both of these plots show multiple changes in λ. Without the initial small value on the left of Figure B1.10, the curve would be a bathtub curve, high on the left and right and low in the middle. With the small value on the left, the curve is harder to interpret.

Figures B1.11 and B1.12 show the same plots when the non-critical failures are excluded

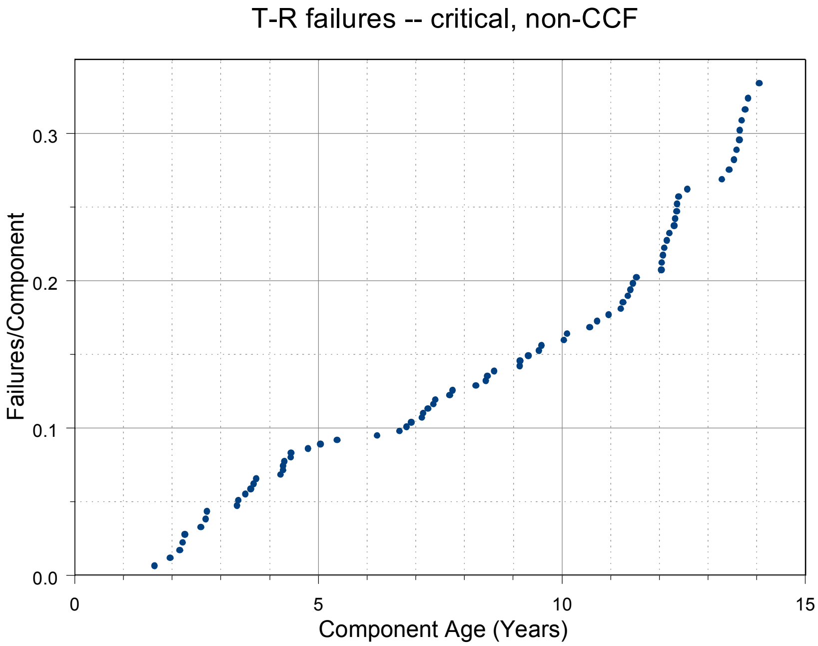

Figure B1.11. Cumulative failure plot, for T-R critical failures other than common-cause failures.

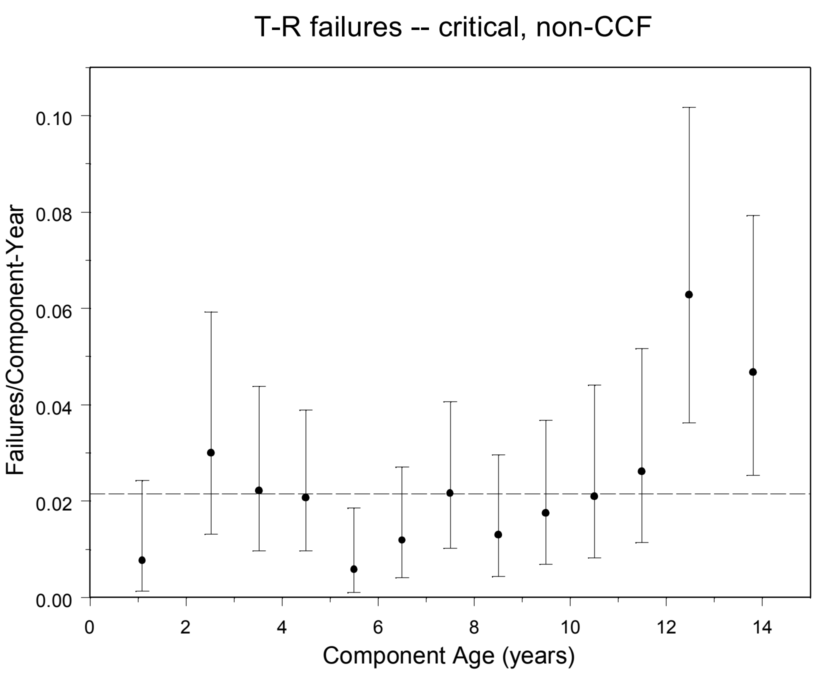

Figure B1.12. Side-by-side 90% confidence intervals for λ, for T-R critical failures other than common-cause failures.

These plots show a moderately constant λ until about age 12, and then a noticeably larger λ for the next couple of years. Nine of the twenty units are in the data set after age 12. There were 22 failures that occurred after age 12, and they are spread over eight of these nine units, with no unit having more than 7 failures. This shows that the increase in λ cannot be attributed to a few rogue units. It is possible that the increase is a result of ageing.

B1.3.4.4 U-R: Units of Type U, Components of Type R.

There are 28 units of type U, each with 12 components of type R. The data collection period is eleven years, so there are 3696 component-years. The error beyond the decimal place in Table B1.1 results from counting the ages in days and then approximating every year by exactly 365.25 days.

Figure B1.13 shows the cumulative plot for failures that are not common-cause failures. The peculiar appearance of this plot is largely explained by one outlying component. This component was installed as a new replacement, and had 10 failures in the eight months following the replacement, 8 critical failures and 2 non-critical. The entire data set had only 5 components in the age range from 0 to 3 years, so the 10 recurrent failures are highly visible.

Figure B1.14 shows the same plot with the one outlying component removed. Figure B1.15 shows the plot of side-by-side confidence intervals, for all failures except common-cause failures and failures of the one outlying component.

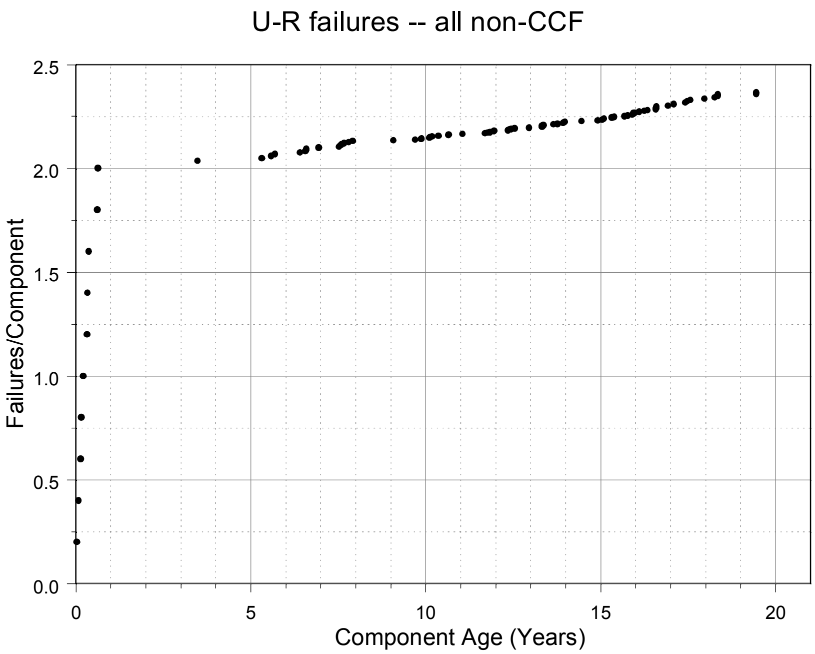

Figure B1.13. Cumulative failure plot, for U-R failures (critical and non-critical) other than common-cause failures.

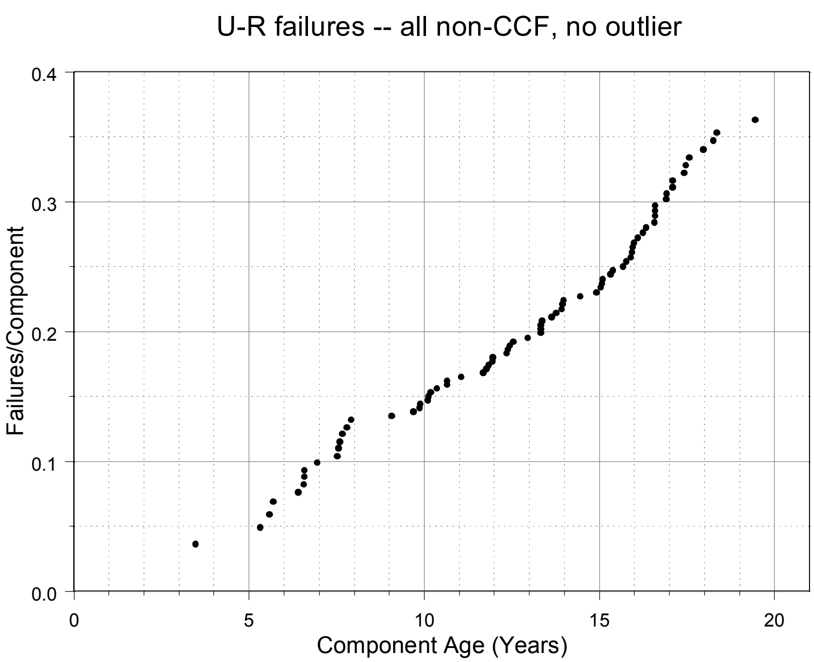

Figure B1.14. Figure B1.13 with the outlying component removed.

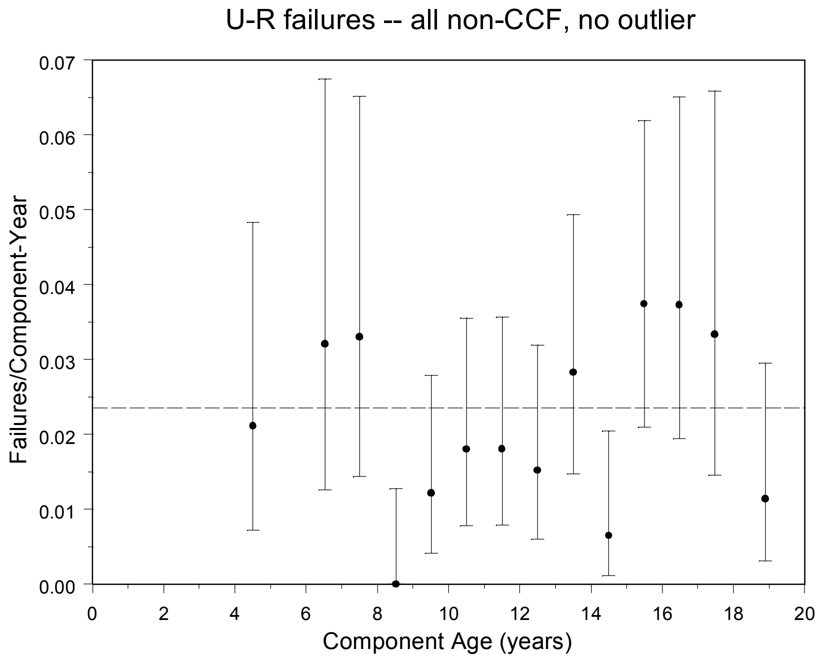

Figure B1.15. Side-by-side 90% confidence intervals for λ, for U-R failures (critical and non-critical) other than common-cause failures, and excluding the outlying component.

Figures B1.16 and B1.17 show the same plots when the failures are restricted to critical failures and the outlying component is excluded from the data. They show little or no evidence of ageing. In particular, the cumulative plot shows no failures for components over 17.6 years of age, although 166 components attained that age and then did not leave the data set for up to 2.8 years more. This is more obvious in Figure B1.17 than in Figure B1.16.

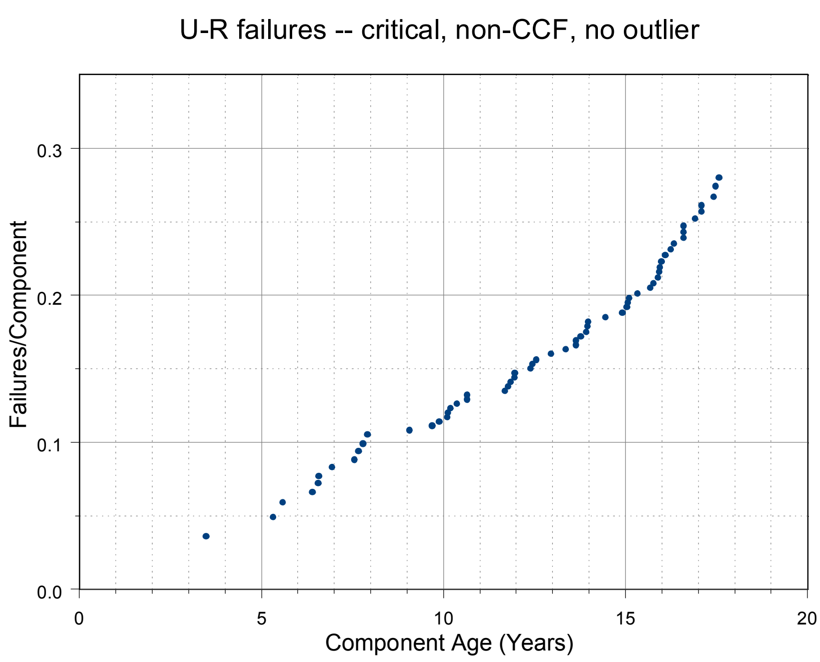

Figure B1.16. Cumulative failure plot, for U-R critical failures other than common-cause failures, and excluding the outlying component.

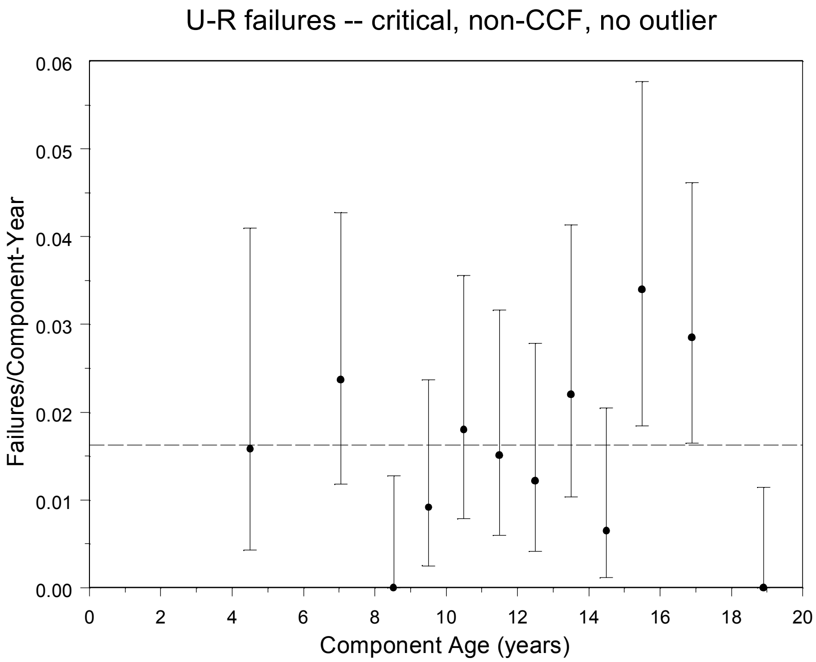

Figure B1.17. Side-by-side 90% confidence intervals for λ, for U-R critical failures other than common-cause failures, and excluding the outlying component.

B1.3.5 Summary of Conclusions from Preliminary Graphical Analyses

Table B1.3 shows conclusions that can be drawn from the above graphs. Different analysts may see different things in the displayed patterns, but this table is an attempt to list minimal conclusions, unprejudiced by preconceptions or desires.

Table B1.3. Summary of conclusions from preliminary plots.

Reactor-Component Type	Age Range (Yrs)	Apparent Range of Ageing	Comments
T-A	0 – 15.1	..-15.1	Clear upward curve throughout
U-A	1.8 – 20.3	12-17	Complex behaviour. Failure rate drops to average value or lower after 17 yrs.
T-R	0 – 15.1	12-15	Hardly any failures in first 2 years. Then bathtub shape: average on the left, then lower, then high.
U-R	1.8 – 20.3	16-17.5	After outlying component removed, slightly higher failure rate in brief range, followed by *no* failures. Little overall evidence of ageing.

The four data sets do not show any common pattern, except for a lack of frequent failures after about 17 years in the older units. This raised questions, which are partially answered in the investigation of Section B1.5.2. However, the following points appear to be true:

- There is no evidence of any unusually extensive corrective maintenance at any particular age.
- Because all the units are owned by a single utility, the maintenance philosophy appears to be the same for all the units and components. (It will be seen below that the units show great variability nevertheless.)
- There is no evidence of any incompleteness in the data at later ages. However, the data before 1994 may contain relatively more reported events than the data after 1994, because of modifications in the reporting procedure. The effect of this modification, if any, is to under-represent the extent of ageing.

Because of time limitations, not all the data sets can be analyzed in detail. We make the following choices.

- We analyze the critical failures, for two reasons: (a) the critical failures are more important, of greater concern in PSA; and (b) the data for critical failures have been scrutinized more carefully, and therefore may be of higher quality.
- We analyze the "A" data (T-A and U-A) carefully, because those data sets have more failures per component year. Any analyses of the "R" data are presented in only a cursory way.

In summary, we analyze the critical failures of the "A" data, corresponding to Figures B1.3 and B1.4 and to Figures B1.7 and B1.8.

B1.4 Fitting Models to Data

Early failures contribute noticeably to some of the data. These failures are seen for individual components in Figures B1.5, B1.7, and B1.13. They are also seen for groups of components in Figures B1.9 through B1.12. These are *burn-in* failures rather than ageing failures. The simplest parametric models for ageing do not allow modelling of both burn-in and ageing. **Therefore, whenever a model for ageing is fitted to a data set, if burn-in failures seem to be present either the early years of age are ignored or the outlying components are removed from the data.**

Several functional forms have been proposed for $\lambda(t)$. The ones that we consider are:

Linear ageing
$\lambda(t) = \lambda_0 + bt$, or equivalently
$\lambda(t) = \lambda_0(1 + \beta t)$,

Log-linear or exponential ageing,
$\ln\lambda(t) = a + \beta t$, or equivalently
$\lambda(t) = \lambda_0\exp(\beta t)$

Power-law or Weibull ageing,
$\lambda(t) = \lambda_0 t^{\beta}$, or equivalently
$\lambda(t) = \lambda_0\exp[\beta(\ln t)]$.

B1.5 Additional Analysis of Data

B1.5.1 Detailed Analysis of T-A Data

B1.5.1.1 Fitted Models

Burn-in failures do not seem to be a problem in Figures B1.3 and B1.4, so the fitting calculations are performed using all critical failures, even for young components.

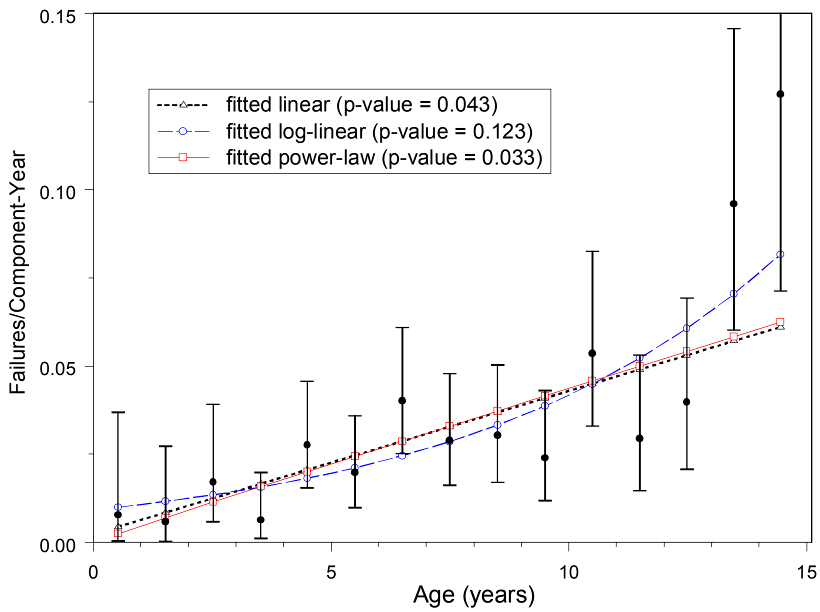

Figure B1.18. Three fitted trend lines for $\lambda(t)$. The p-values measure goodness of fit, with a small value showing poor fit.

The three fitted equations are

log-linear:	$\lambda(t) = 9.200\text{E-}3 \times \exp(0.1511t)$
power-law	$\lambda(t) = 4.617\text{E-}3 \times t^{0.9754}$
linear	$\lambda(t) = 2.250\text{E-}3 \times (1 + 1.810t)$

The Pearson chi-squared test shows that only the log-linear model has an acceptable fit, with p-value 0.123. However, even this fit is not wonderful. This lack of fit is not a result of lack of ingenuity in finding a suitable curve. Instead, it is a result of the sudden jumps in the observed failure frequencies. In particular, the failure rate appears to be roughly constant from ages 6 to 13, and to jump suddenly at about age 13.

The results are similar if only the data above age 5 are used, but then the three curves are more similar to each other. Of the three models, the log-linear model still has the best fit.

B1.5.1.2 Investigation of Correctness of Model Assumptions

An important assumption was that the data set is homogeneous, that is, each piece of the data has the same $\lambda(t)$. There were 132 critical failures, 20 units, and 400 components. The number of failures is large enough to permit a comparison of the units, since there are about 8 failures per unit on average. There are not enough failures to permit a comparison of ageing of individual components, because most of the components have no failures.

The following test was performed before it was decided to focus on critical failures only. The units were observed over different age ranges: six units were commissioned after the start of the data collection, whereas six units were already over three years old at the start of the data collection. This made it impossible to compare the units by the simple chi-squared test proposed in the body of this report. Instead, the time period was divided into "young" and "old" periods, with 7 years being defined as the dividing line between young and old. For each unit, the expected fraction of failures in the "young" column was calculated, based on the assumed log-linear model with β equal to the estimated value of 0.1544/component-yr (based on both critical and non-critical failures). The *fractions* of young and old failures were calculated because they involve only the parameter β, not the parameter λ_0. Then a 20×2 contingency table was formed, corresponding to the 20 units and 2 age periods (young and old). The expected count of young failures was estimated for each unit by the calculated fraction of young failures times the observed total number of failures. The expected count of old failures was estimated in a similar way. Some of the expected counts were quite small, with a few being zero. To improve the validity of the chi-squared test, units with 2 or fewer observed failures were dropped. This can be justified on the grounds that nothing much can be learned about ageing at a unit with only 2 observed failures. After dropping those units, the contingency table had dimensions 12×2. The chi-squared statistic was calculated in the usual way, and was equal to 26.1. The p-value, corresponding to 11 degrees of freedom, was 0.006, indicating very strong evidence that the units do not all have the same β. In particular, Units T02 and T16 had too many young failures.

The above work was not repeated after it was decided to focus on the critical failures only, because the graphical examinations below reveal so many differences among the units. The above type of work would only show the same conclusion with less detail.

To further investigate the homogeneity assumption, a cumulative plot was constructed for each unit. To examine failures at a single unit, the cumulative plot is modified slightly. First, the points are connected by a line, so that plots from several units can be distinguished if they are displayed in the same graph. More important, the components at one unit all enter and leave the data base at the same age (except in those rare cases when a component is replaced by a new component), and these starting and ending ages should be shown. To show the beginning and end of the recorded data, a dashed line is drawn from the start of the data-collection period to the first failure point and from the final failure point to the end of the data-collection period. The slopes of those lines are as if there were half a failure at the end of the data collection and half a failure at the first failure time.[1]

As mentioned before, the history is only shown after age 5, because ageing will not be seen before that age and burn-in might. In addition, Unit T13 contained a new replacement component that failed several times. This burn-in outlier was dropped from the data altogether. A graph showing all these cumulative plots is complex, and therefore is presented in two pieces. Figure B1.19 shows the plots of those units that show little or no ageing. For simplicity, units with 4 or fewer failures are not shown at all.

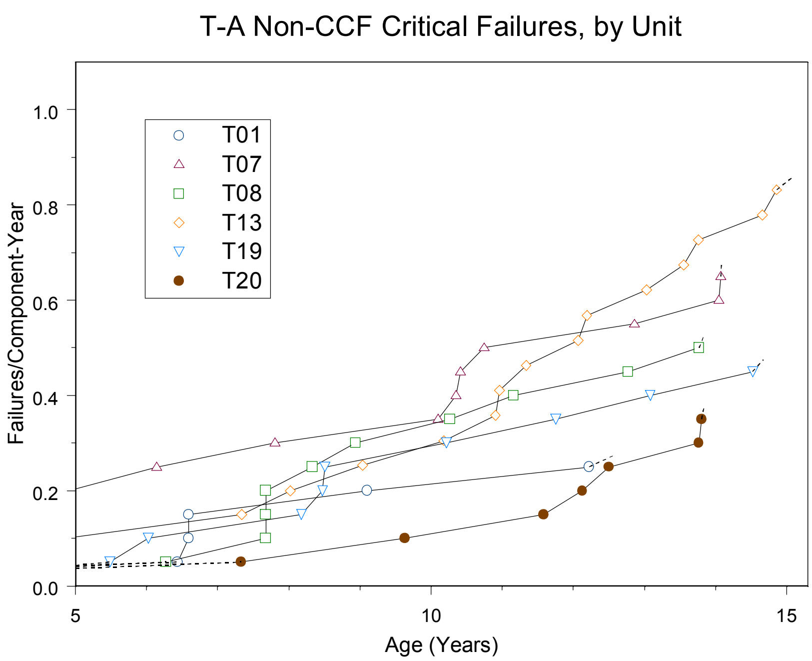

Figure B1.19. Cumulative failure plots for six selected units, counting all critical failures other than common-cause failures. At each failure, the plot rises by (number of failures)/(number of components in the unit), typically 1/20. The dashed lines indicate the beginning and end of the data-collection periods.

[1] The reason for this peculiar-seeming choice of slopes is given here. The estimated cumulative failure rate assigns a discrete probability at each observed failure. The estimated cumulative failure is therefore actually a step function, with jumps at the observed failures. However, when several step functions are shown on one plot, they become difficult to distinguish. Also, the curvature in a step function is not as visually evident as the curvature in a smoother line. Therefore, the plots shown connect the *middle* of each jump to the middle of the next jump. At the ends of the data period, the top and bottom of the step function are marked. This is accomplished (except for a slight vertical offset) by treating the first failure as half a failure, by assuming half a failure at the end of the data, and by connecting the other points as they already have been plotted.

None of the six lines in this graph seems to curve very much, with the possible exception of Unit T20. They do have different slopes. In particular, Unit T13 has a rather steep slope, but no indication of ageing. The dashed lines at the right ends of the curves are short, indicating that for each unit the final failure occurred close to the end of the data collection period. This
is consistent with ageing, but does not by itself show ageing. In summary, the plot suggests that the units have different values of λ, but each unit has roughly constant λ.

By contrast, Figure B1.20 shows the plots for three units that show much more variable failure rates.

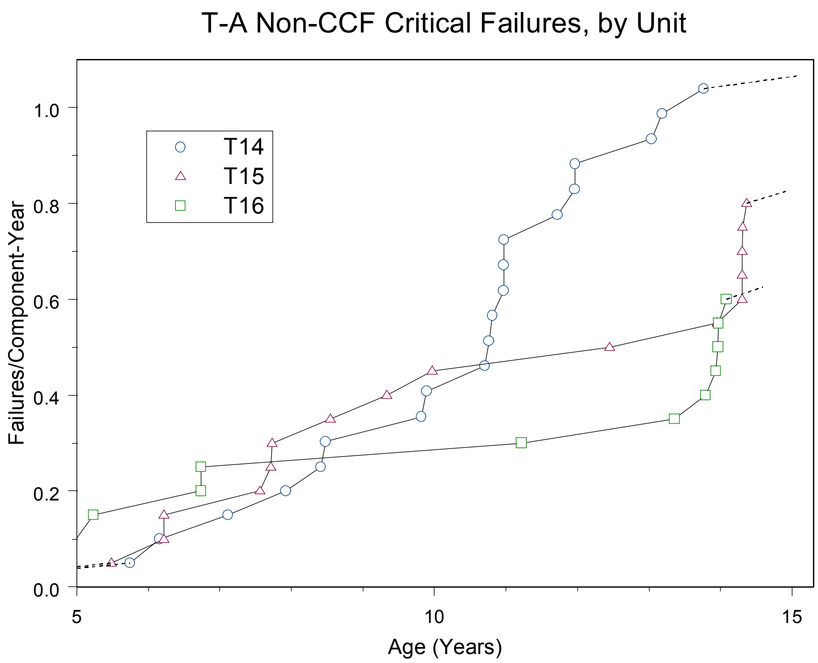

Figure B1.20. Cumulative failure plots for three selected units, counting all critical failures other than common-cause failures. At each failure, the plot rises by (number of failures)/(number of components in the unit), typically 1/20. The dashed lines indicate the beginning and end of the data-collection periods.

Units T15 and T16 both seem to start ageing suddenly at about age 13 or 14. Unit T14 has a large number of failures in its 10th year, although the failure rate then seems to taper off, with no failures at all in the final year and a half. The failure data were examined to see whether a single component was responsible for these sudden changes. The findings are summarized in Table B1.4.

Table B1.4. Components that failed during periods of frequent failure.

Unit	Age Range (Yrs)	Number of Failures	Number of Distinct Components	Highest Number of Failures by One Component
T14	10.5 – 11.0	6	5	2
T14	10.5 – 14.0	12	8	4
T15	13.5 – 14.5	6	5	2
T16	13.1 – 14.1	6	6	1

Except for one component with 4 failures at T14, the increased number of failures does not seem to be the result of a single bad component.

Units T14 through T16 are all located at a single site. The fourth unit at that site is T13, which also stands out from the other units in Figure B1.19. This single site has approximately as many failures as all sixteen other units combined. (When one newly installed component at T13 is removed from the data, because it was subject to burn-in failures, the site has exactly 64 critical failures, and the remaining sixteen units also have exactly 64 critical failures.) For this reason, we now partition the data into two groups, T13 through T16 as one group, and everything else as the other group.

B1.5.1.3 Analysis with One Site Treated Separately

B1.5.1.3.1 The One Special Site.

The four units at the one site all were commissioned within seven months of each other, and so all entered the data set at about age 4 and left the data set at about age 15. T13 had one component that was installed as a new replacement and failed four times. This outlying component was removed from the analysis below; it shows burn-in failures, but is too new to show ageing. T14 also had one new replacement component installed, but it never failed and so was left in the data; the decision to keep it or drop it makes virtually no difference in the analysis.

The four units were treated together, and their cumulative failure plot was constructed. It is shown in Figure B1.21.

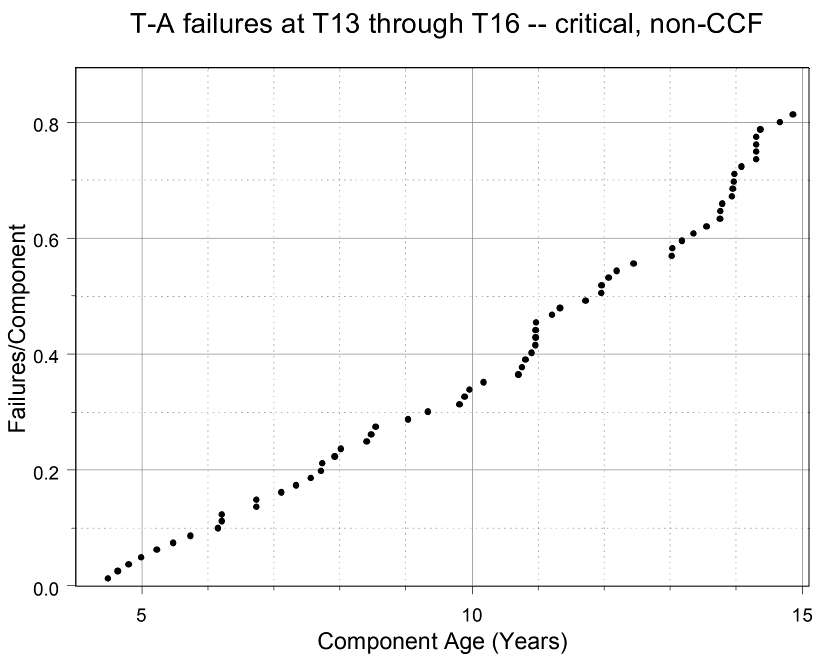

Figure B1.21. Cumulative failure plots for the site with units T13 through T16, counting all critical failures other than common-cause failures and one newly installed component with burn-in failures. At each failure, the plot rises by (number of failures)/(number of components at the site), typically about 1/80.

This plot shows a striking lack of curvature. Nevertheless, when a log-linear trend is fitted to the data, a small increase is seen, as shown in Figure B1.22. The line with long dashes is the fitted line, based on maximum likelihood estimates (MLEs) of the two unknown parameters. The short dashed lines show 90% confidence intervals on the fitted value. That is, at any particular age t, a 90% confidence interval for $\lambda(t)$ goes from the lower line to the upper one. The fitting equation is

$\lambda(t) = 2.808\text{E-}2\times\exp(0.0975t)$.

The value of β, with MLE = 0.0975, has a standard error of 0.0340. Thus, the estimate is almost three standard errors away from zero, statistically very significant. (More precisely, the estimate is 2.87 standard errors from zero, and 2.87 is the 99.8 percentile of the normal distribution. Based on the asymptotic normality of the MLE of β, the trend is statistically significant at the 0.002 significance level, based on a one-sided test.) In addition, the model fits well, with a p-value for lack of fit of 0.6.

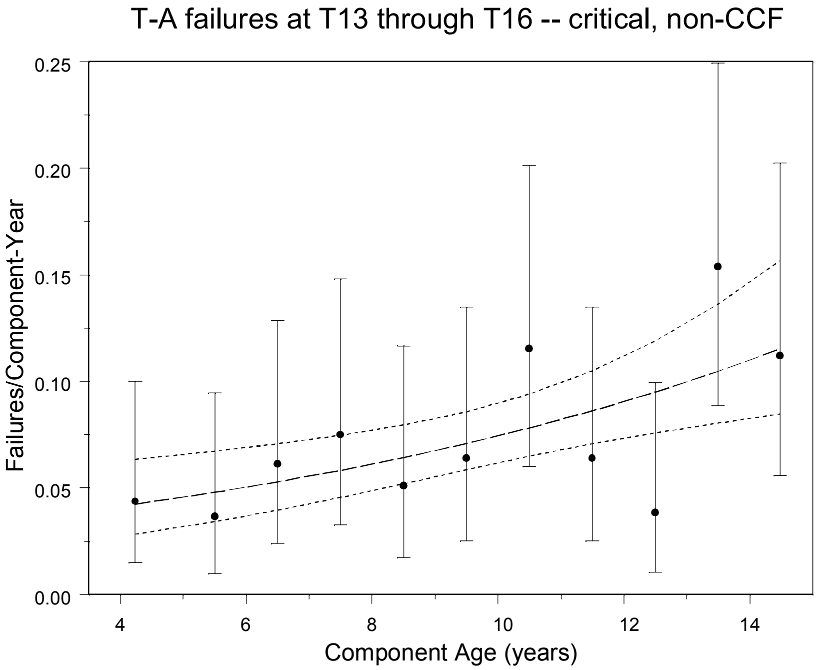

Figure B1.22. Data from Figure B1.21 with fitted log-linear trend for $\lambda(t)$.

Let us now consider nonparametric tests for trend that could also be applied. When the nonparametric test of Appendix B2 is applied, there are $M = 11$ point estimates of λ, and $A = 15.5$ inversions (counting the tie between ages 9.5 and 11.5 as half an inversion). For example, the rightmost value of $\lambda(t)$ is smaller than two other values, giving 2 of the 15.5 inversions. The one-sided test is significant at the 0.05 level, because 15.5 is less that $A_L = 17$. It is not significant at the 0.025 level, because 15.5 is not less than $A_L = 14.5$.

Section 3.2.1.3 also gives several nonparametric tests, one of which does not assume the same failure rate for different components or the same age range for the various components. It only looks to see if the failures tend to occur "late", that is, in the second half of the age ranges of the components, or "early". In the present data set, 40 of the 62 failures occurred late. (The two failures that resulted in component replacement are not included in the count of early and late failures.) The probability of 40 or more late failures out of 62 failures in all is 0.015, if early and late failures are equally likely. (This probability can be found by any software that calculates the cumulative distribution of the binomial distribution.) Therefore the null hypothesis of constant failure rate for each component is rejected at the 0.015 significance level.

When these significance levels are compared with the 0.002 from the parametric test, we see that the two nonparametric test based on early and late failures is somewhat more powerful than the inversion test, but that the parametric test is more powerful than either nonparametric test, more able to detect departures from the null hypothesis.

B1.5.1.3.2 All the Other Units. The evidence of ageing is somewhat clearer at the remainder of the units. The cumulative failure plot is shown in Figure B1.23. The gentle curvature is confirmed when the data are binned as in Figure B1.24.

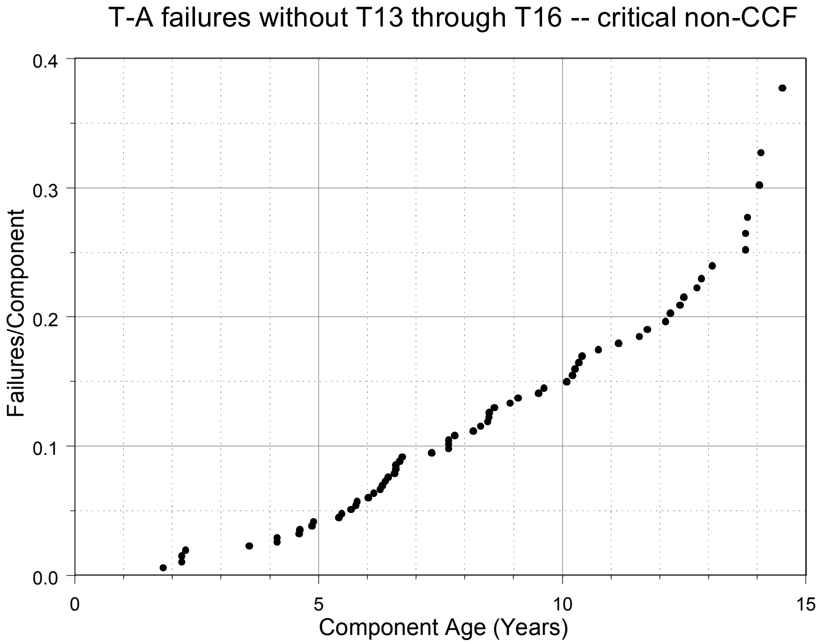

Figure B1.23. Cumulative failure plot excluding Units T13 through T16, for T-A critical failures other than common-cause failures.

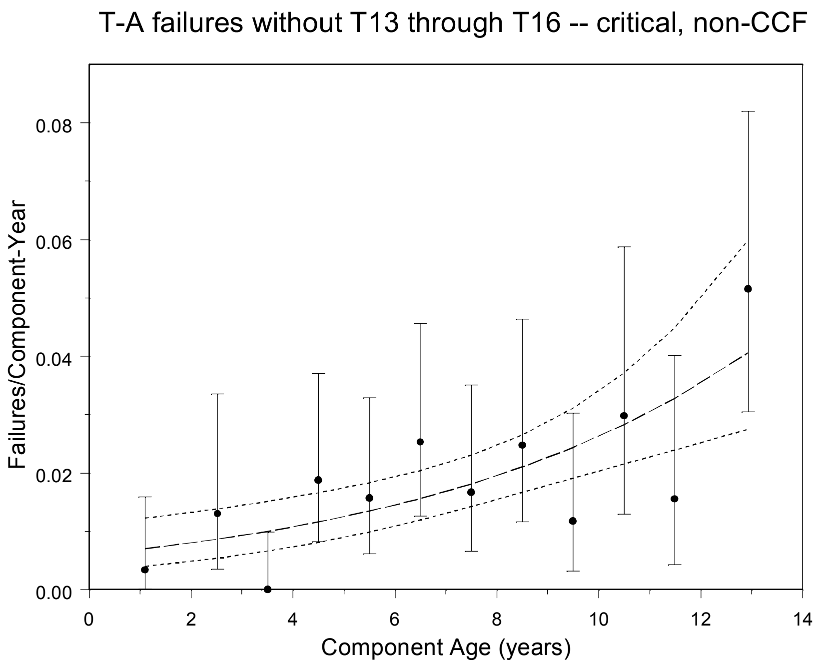

Figure B1.24. Data from Figure B1.23 with fitted log-linear trend for $\lambda(t)$.

Figure B1.24 shows the results when the data are collected into bins and a log-linear trend is fitted. The fit is acceptable, with a p-value of 0.17 for lack of fit. The dashed lines have the same interpretation as in Figure B1.22. The fitting equation is

$\lambda(t) = 7.18\text{E-}3 \times \exp(0.134t)$.

Note that the ageing parameter, 0.134, is larger than for Figure B1.22. Also, this value is 3.6 standard errors from zero, and so is statistically significant at the 0.0002 significance level.

For comparison, a power-law, or Weibull, trend was also fitted to this data set. The graph is shown as Figure B1.25. This model also fits acceptably, with a p-value of 0.23 for lack of fit. The estimated fitting equation is

$\lambda(t) = 3.88\text{E}{-3} \times t^{0.86}$

The fitted exponent is 3.44 standard errors from zero, statistically significant at the 0.0003 level. Either fitting curve, log-linear or power-law, is acceptable as the other.

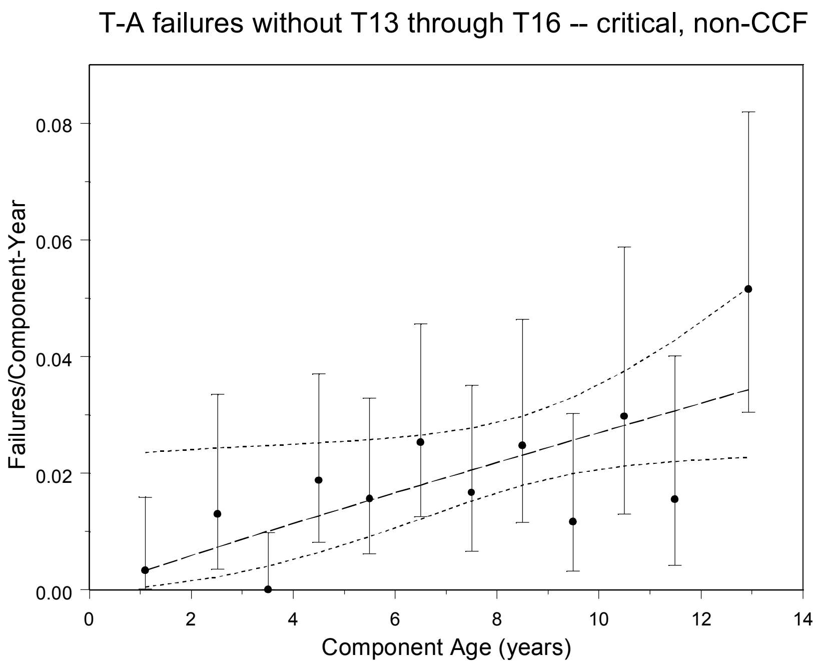

Figure B1.25. Data from Figure B1.24 with fitted power-law trend for $\lambda(t)$.

The nonparametric test of Appendix B2 counts A = 18 inversions from M = 12 data values. The one sided test is not quite significant at the 0.025 significance level but is significant at the 0.05 level. The nonparametric test of Section 3.2.1.3 counts only 35 late failures out of 64 failures in all. Therefore, the null hypothesis is rejected only at significance level 0.27.

As with the earlier comparison involving Figure B1.22, the parametric tests are both much more powerful than the nonparametric tests, that is, more sensitive to the existence of a trend.

In this example, the inversion test finds significant evidence of a trend but the test based on late and early failures does not. The different conclusions of these two nonparametric tests is largely explained by their different assumptions. The inversion test is based on the null hypothesis that all components have the same constant failure rate, whereas the test based on late failures uses the null hypothesis that each component has a constant failure rate, but that different components may have different failure rates. The fact that the two tests give such different results may give a warning that the components (or units) have different baseline failure rates, but this is issue is not pursued here.

One must realize that all the analyses corresponding to Figures B1.23 through B1.25 rely heavily on the failures after age 12. There were 13 such failures. There is no guarantee that such a short trend will persist into later years.

B1.5.1.3.3 Summary of Analysis of T-A Data. The above investigation of the individual units has shown the following for Units T13 through T16.

- The site containing Units T13 through T16 has approximately five times as many failures per component-year as the other units. The reason is not known.
- The site with T13 through T16 shows evidence of ageing, but overall it is not rapid ageing, and it is uneven at the four units.
  - T15 and T16 may show ageing in the last couple of years.
  - T14 had a run of frequent failures in the 10th year followed by a *decreasing* failure frequency.
  - T13 seems to have a constant failure frequency.

  It is not yet clear whether T15 and T16 will continue to have frequent failures, indicating a long-term increased failure rate, or whether they will improve again as T14 did.

- During the periods of more frequent failures, the failures were distributed over many components within each of the affected units, not restricted to a few bad components.

The investigation has shown the following at the rest of the units, T01 through T12 and T17 through T20.

- There is evidence that the failure frequency increases with age. However, most of the evidence is based on the failures after age 12. It is not yet clear whether the increase seen after age 12 will persist or be corrected by maintenance.
- Of the units other than T13 through T16, eight units passed 12 years of age, by amounts from 0.5 years to 2.5 years. The thirteen failures after age 12 were scattered among six of these eight units, with no unit having more than four of the failures. No component failed twice among these thirteen failures. This scattering suggests that the increasing failure frequency may be an overall ageing pattern, not just a quirk of one component or unit.

It is unwise to trust extrapolations from any model for more than a year or two into the future, for several reasons: (a) In both data sets, the evidence for ageing is based heavily on the last few years of data. (b) At one unit (T14) a temporarily high failure rate was seen to decrease markedly. Finally, (c) if one model fits well, other models probably also fit well, but may lead to different extrapolations.

B1.5.2 Detailed Analysis of U-A Data

There is no point trying to fit a smooth curve through the data of Figure B1.7 or Figure B1.8. No such curve can accommodate the sudden increase between ages 11 to 13 or the sudden drop between ages 16 and 18. Any proposed curve that is fitted to the data will fail the goodness-of-fit test. Therefore, let us try to find the causes of these large abrupt changes in the failure rate. Evidently, the model assumptions are violated somehow.

B1.5.2.1 Investigation of Correctness of Model Assumptions

There are too many units to distinguish on a single graph. Figures B1.26 through B1.28 show some of the units, organized very roughly into categories but also so that no two units have plots that overlap too much in a single graph. Units that have 4 or fewer failures are not shown at all.

Figure B1.26 shows units with the most pronounced ageing. For example Unit U04 entered the data set at age 6.25 years, and left the data set at age 17.25. It had one failure in the first 6.5 observed years, and 20 failures in the remaining 4.5 years. The failures in the latter period occurred at rather regularly spaced intervals. The best fitting model would show a step function for $\lambda(t)$, with a small value of λ before age 12.75, and a larger value after that age.

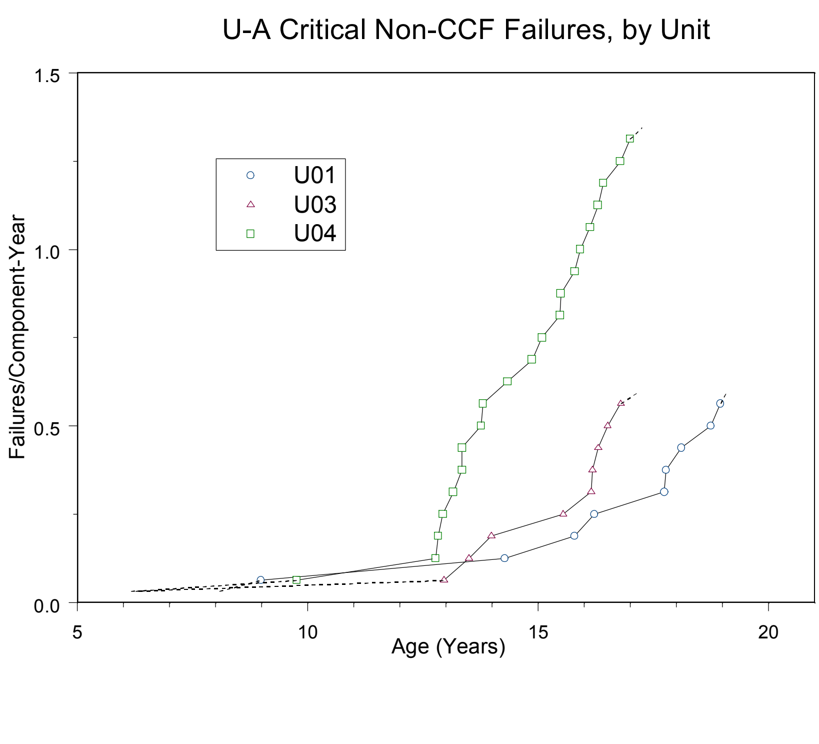

Figure B1.26. Cumulative failure plot for selected units in the U-A data set, counting all failures (critical and non-critical) other than common-cause failures.

Similar statements can be made for the other units shown in Figure B1.26, although they have different ages when $\lambda(t)$ jumps from small to large, and the size of the jumps is not necessarily as dramatic. All the units shown in Figure B1.26 were in the data set for the full eleven years.

Figure B1.27 shows selected other units, which had periods of high failure frequency followed by extended periods with no failures at all. They are units that improved in the last years of the data collection.

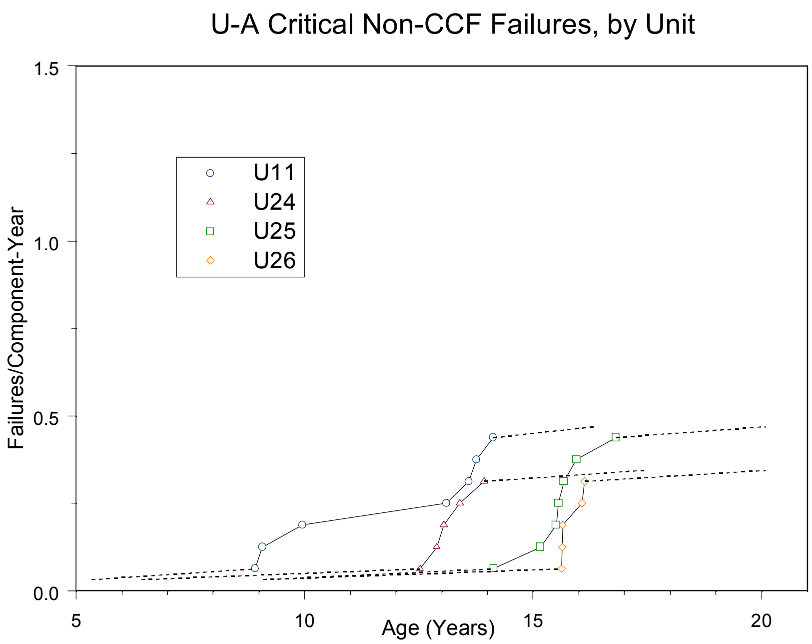

Figure B1.27. Cumulative failure plot for selected units in the U-A data set, counting all failures (critical and non-critical) other than common-cause failures.

Figure B1.28 shows some units that show relatively constant failure rates throughout the observation period.

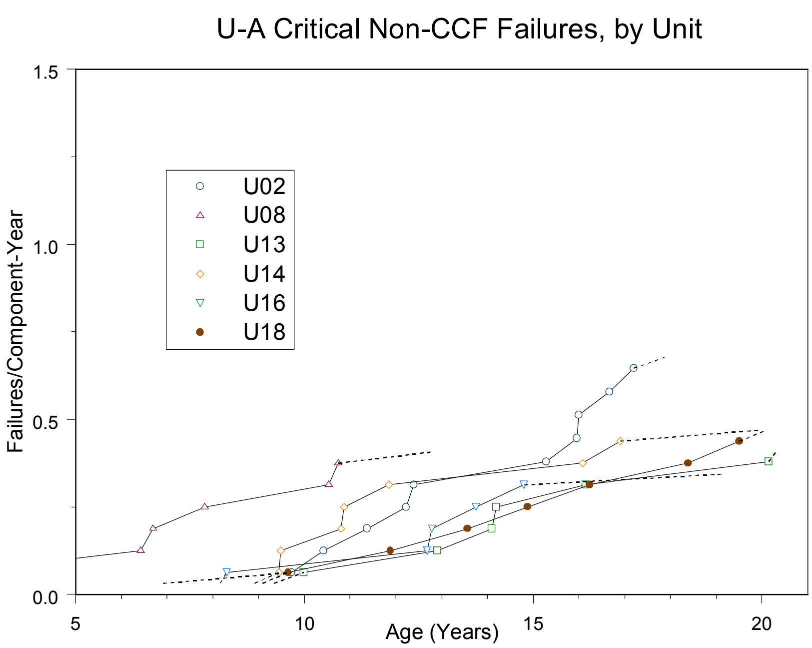

Figure B1.28. Cumulative failure plot for selected units in the U-A data set, counting all failures (critical and non-critical) other than common-cause failures.

The above three figures suggest that Units U01 through U04, which are at a single site, should be analyzed separately from the rest of the units. This site had 49 critical failures. The remaining 24 units (six times as many) had only 97 failures after burn-in failures were excluded. The separate analysis results for the two groups of units are presented next.

B1.5.2.2 Analysis with One Site Treated Separately

It turns out that separating the data into two groups allows each data subset to be fitted with a trend model, although this was not possible with the combined data.

B1.5.2.2.1 The One Special Site. Units U01 through U04 are all located at a single site. Unit U01 was commissioned at the end of 1981, and the other three units were all commissioned during 1983. As a result, they entered the data set with minimum ages of 6 to 8 years, and they each left the data set with ages 17 to 19 years. The cumulative plot for the site is shown in Figure B1.29. An increasing failure rate is evident.

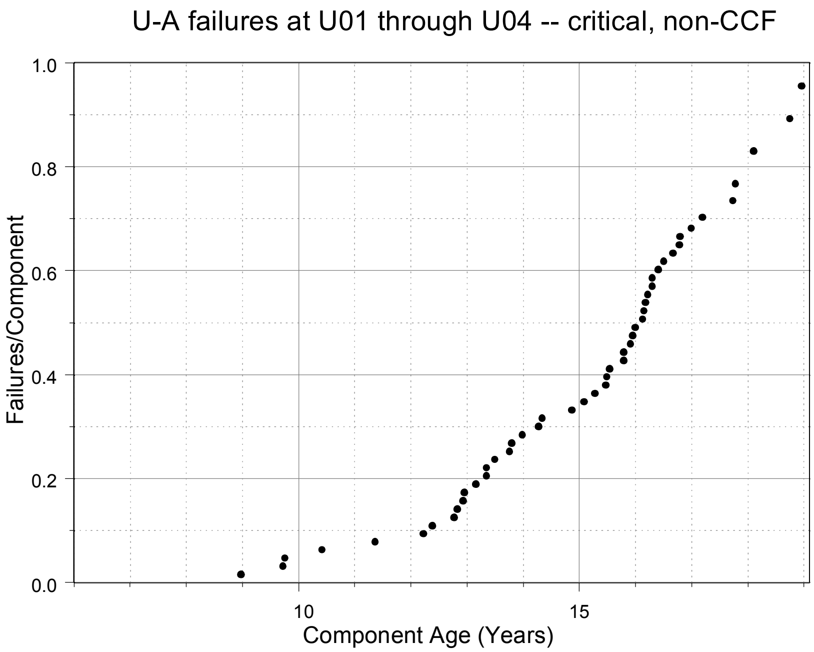

Figure B1.29. Cumulative failure plot for site consisting of Units U01 through U04, counting critical failures other than common-cause failures.

The failures were gathered into bins and a log-linear trend for $\lambda(t)$ was fitted. The result is shown in Figure B1.30.

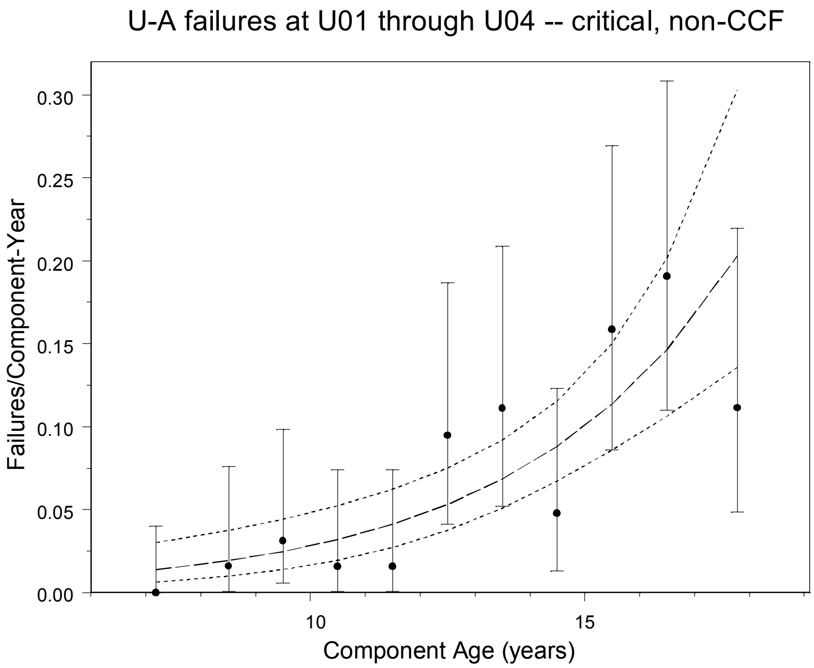

Figure B1.30. Data from Figure B1.29 with fitted log-linear trend for $\lambda(t)$.

The fit is acceptable, with a p-value of 0.29 for lack of fit. The dashed lines have the same interpretation as in the earlier figures, marking the 90% confidence limits on $\lambda(t)$. The fitting equation is
$\lambda(t) = 2.216\text{E-}3\times\exp(0.2540t)$.
The ageing parameter, estimated as 0.2540, is 4.9 standard errors from zero, and so is statistically extremely significant (at the 5E-7 significance level!).

The nonparametric inversion test presented elsewhere has 8 inversions, which is significant at the 0.01 level. The nonparametric test based on late and early failures counts 42 late failures out of 48 non-replacement failures in all. Therefore, the hypothesis that every component has a constant failure rate is rejected at the significance level 5E-8.

In summary, all three tests clearly identify the trend, but the inversion test has less power than the other two.

However, before the trend is interpreted as ageing, one must investigate the causes of the increasing failure rates. Recurrent failures appear to play a role. This is shown in Table B1.5. The rightmost column of the table is sometimes vague because the identity of the failed component is not always clearly recorded.

Table B1.5. Components that failed at U01 through U04.

Unit	Number of Critical Failures	Number of Distinct Failed Components	Highest Number of Failures by One Component
U01	9	5	3 (two such cases)
U02	10	7	3 or 4
U03	9	5	3
U04	20	4	7 (possibly two such cases)

B1.5.2.2.2 All the Other Units. The 24 units other than U01 through U04 show a different picture. There were three new replacement components and several burn-in failures. The cumulative failure plot is shown in Figure B1.30, with failures before age 5 removed from the data.

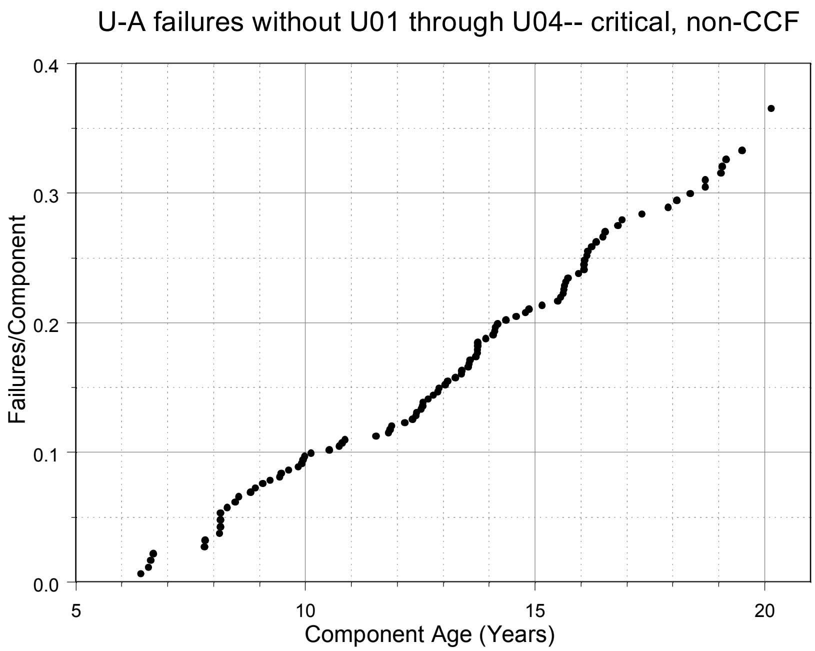

Figure B1.31. Cumulative failure plot for all U-A units except Units U01 through U04, counting critical failures other than common-cause failures, and excluding failure before age 5.

This figure is remarkably straight. The failures were gathered into bins and a log-linear trend was fitted, as shown in Figure B1.32. The failures before age 5 are shown, but only the data after age 5 were used to calculate the fitted trend. If the outlying early failures in Figure B1.32 seem bothersome, the left part of the graph may be manually covered.

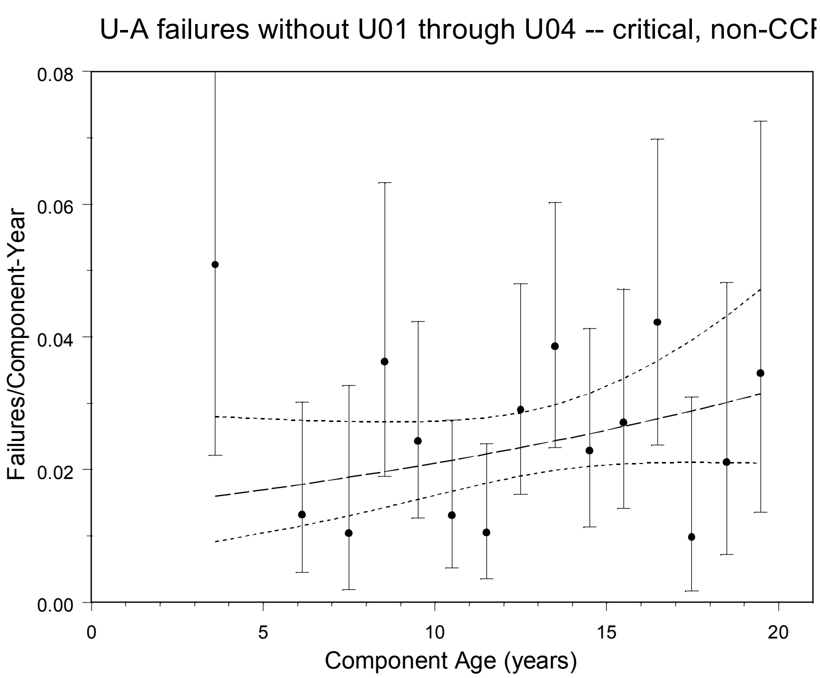

Figure B1.32. Critical U-A failures at all units except U01 through U04, with fitted log-linear trend for $\lambda(t)$. The fitting calculations were based only on the failures after age 5.

The fit is acceptable (after age 5!), with a p-value of 0.14 for lack of fit. The dashed lines have the same interpretation as in the earlier figures, marking the 90% confidence limits on $\lambda(t)$. The fitting equation is
$\lambda(t) = 1.366\text{E-}2\times\exp(0.0427t)$.
The ageing parameter, estimated as 0.0427, is markedly smaller than for the Units U01 through U04. Also, it is only 1.5 standard errors from zero, not statistically significant at the 0.05 level. The significance level is 0.13.

The nonparametric test of Appendix B2 also does not see a trend. With M = 14 data values and A = 38 inversions, the trend is not significant at the 0.05 level. The table in that appendix does not show the significance level at which the hypothesis of constancy would be rejected, but it is greater than 0.05.

The nonparametric test based on late and early failures also does not see a statistically significant trend. When the age ranges are all restricted to exclude the period before age 5 years, there are 54 late failures out of 95 non-replacement failures. The corresponding significance level at which the null hypothesis is rejected is 0.11.

In summary, the three tests agree that the trend is not statistically significant. The power of the test based on late and early failures is similar to that of the parametric test. The table in Appendix B2 is not detailed enough to give more exact information for the inversion test.

B1.5.2.2.3 Summary of Analysis of U-A Data. The above investigations have shown that the individual units have great diversity, and in particular the site containing Units U01 through U04 has both more failures and more ageing. At the site with Units U01 through U04, we find

- Three of the units showed apparent step increases in their failure rates. Because the times of the jumps varied, they led to a gradual rise in the overall site rate, as shown in Figure B1.29. Recurrent failures of certain failures contributed to the periods of high failure frequency.
- The four units behave differently enough — indeed, individual components behave differently enough — that a single estimated failure frequency should not automatically be used for the entire site.

At the remaining 24 units, we find the following.

- Several units showed high failure rates in portions of the range from ages 12 to 17, but then they showed hardly any failures for years afterwards. They showed increasing step changes followed by decreasing step changes. Thus, they contributed to sudden jumps seen at ages 12 and 17 in Figure B1.29. In particular, Units U25 and U26 had very high failure rates between ages 15 and 17, but no failures at all between ages 17 and 20.
- When an ageing trend is fitted to the data from the 24 units, the trend is small and not statistically significant.

B1.5.3 Cursory Analysis of T-R Data

The T-R data show the most early failures. Any evidence of ageing will be seen only in the later failures. Therefore, we drop the period before age 5 from the data. When this is done, the data set contains 55 critical failures, distributed among 20 units. The units with the most failures overlap somewhat with the units that had the most failures in the T-A data: T01, T13, T14, T16, and T20. Each unit other than these has fewer than five critical failures. As with the T-A data, the site containing Units T13 through T16 contains about half the failure data, 25 failures out of the total 55.

Figures B1.11 and B1.12 show clear evidence of an increasing failure rate after age 5, but with fewer failures to analyze than in the other data sets. Because of lack of time, this data set is not analyzed in detail.

B1.5.4 Cursory Analysis of U-R Data

The U-R data seems to show the least ageing. We dropped the outlying component and common-cause failures and examined the data set with all other critical failures.

When a log-linear trend model was fitted, the fitted trend line was nearly flat, almost the same as the constant MLE shown in Figure B1.17. More exactly, the fitted model was
$\lambda(t) = 1.310\text{E-}2\times\exp(0.0341t)$.

The trend parameter, estimated as 0.0341, is only 0.51 standard errors away from 0, statistically not at all significant. Also, neither the fitted model nor the model with a constant λ fits the data acceptably. The p-values for lack of fit are 0.02 in each case. The outlying values are shown in Figure B1.17 as age ranges 8-9, 15-16, and 18-20.

When the failures were examined by unit, the following facts were found.

- The failures are quite sparse, and nearly uniformly scattered among the units. There are 59 critical failures at 28 units, for an average of 2.1 per unit. In fact, no unit has more than four failures.
- Units U01 through U04 appear similar to the other units. These four units reported 8 failures, and the remaining 24 units reported 51 failures. This consistency differs from what was seen in the U-A data.

If the U-R data set followed the pattern of the T-A data, some of the units would reveal their ageing by experiencing more than one failure every few years. The rarity of failures per unit contributes to the fact that no ageing is seen in the U-R data. It is not clear whether the credit
for the low failure frequency should go to particularly reliable equipment, to superior maintenance, or to non-reporting of some failures.

B1.6 Overall Conclusions from Demonstration Study

There are enough unexplained questions that any conclusions must be tentative. However, the following observations can be made.

- The sites show very different behaviours. For the "A" data, two sites have reported many more failures per component-year than the other sites. It is not known whether these differences reflect actual differences in failure counts or differences in reporting standards.
- Even if a group of units shows an overall trend that can be fitted by a gradually increasing failure rate, the individual units may not exhibit this smooth behaviour. Instead, the units may appear to have a failure rate that changes suddenly from one constant to another. This change may be an increase or a decrease.
- Some components have had recurrent failures, which contribute to high observed failure rates for the affected units. It is not known whether these recurrences represent misdiagnosed root causes.
- We do not have access to any analyses of the failures from an engineering point of view. Engineering insight could be very useful in reaching a decision as to whether ageing is occurring.

In the light of this, what is a PSA modeller to do? What estimate should be used for the failure rate of a component? The answers suggested below are those of one analyst, C. Atwood. They are not to be treated as authoritative.

1. Because of the diverse behaviour of the various units, and indeed of components within the units, a strong reliance on simple models seems unwise. It is more trustworthy to base estimates primarily on the recent history of the unit of interest.
2. A Bayesian analysis quantifies belief about $\lambda(t)$ as a probability distribution. To obtain such a distribution, fit a model to the data from units resembling the unit of interest. Any of the proposed models for ageing might be good enough. Either use Bayesian software such as WinBUGS®, or use a non-Bayesian method, as was done in this appendix. (In Section 3.1.1.5, the beginning of the subsection "Non-Bayesian Analysis" gives a justification for using frequentist calculations to obtain a Bayesian distribution.) Based on the fit, obtain a Bayesian distribution for $\lambda(t)$ at some representative t, where t is not much larger than observed ages in the data. The approach in this appendix yields a lognormal distribution for $\lambda(t)$, but the analyst may replace this by a more convenient distribution if desired.
3. Then consider making the distribution more diffuse, to account for differences among the units and components. Also, if several models are consistent with the data but give different extrapolations, the distribution should be widened to account for this model uncertainty.
4. It is then tempting to treat the above distribution as a prior, and to update it with the most **recent** unit-specific data. However, one must beware of double counting of the data. If the recent data from the unit of interest was influential in determining the prior, it should not be used again in a Bayesian update.

5. In any case, once a trend has been observed the corresponding values in the PSA should be reassessed frequently, as new data become available.

APSA in risk informed applications

Appendix B2

Application of Statistical Methods for Identification of Ageing Trends

A. Rodionov - IRSN

October 2005

A case study on "Application of Statistical Methods for Identification of Aging Trends"

SUMMARY

This document presents the results of a case study on "Application of Statistical Methods for Identification of Aging Trends". It was prepared by IRSN for the Institute for Energy, EC Joint Research Center, Petten, NL in the frame of the JRC purchase order B100732 signed 15/06/05.

The report discusses a non-parametric statistical test that permit to identify an aging trend using operating experience failure data. The method uncertainty and sensitivity are also presented.

CONTENTS

Introduction

One of the tasks of reliability and operating feedback analysis is an identification of evolution in time of reliability and performance characteristics of System, Structure or Component (SSC). Such assessment is necessary to predict and avoid unacceptable degradations related to the aging of SSC.

In case of large population of the SSCs and well doing operating experience data collection the statistical methods could be applied to identify the appearance of aging effect to SSC reliability.

In simplest way, the task of statistical analysis consists to verify the hypotheses that SSC failure rate is constant.

The various statistical tests could be used to validate or to refuse this assumption. Some of them are discussed in NUREG/CR-6823 [1]. According to the statistical model construction they can be divided into two groups : parametrical and non-parametrical.

The basic feature of parametrical methods is that for their application the law of random value distribution is assumed. Then the accepted hypothesis is checked on the basis of the received data. To make the assumption on the distribution law and to inspect the accepted hypothesis it is necessary to have certain set and volume of the initial data. But it is not always available.

In some cases, this difficulty can be bypassed using non-parametrical tests, which don't apply any assumptions concerning the type of random value distribution. *Bendat and Piersol* [2] propose two criteria for evaluation of random processes data, which do not depend on distribution form : series criterion and inversion criterion.

IRSN has some experience with application of inversion criterion test. The advantages of this method are the following :

- the method is rather simple,
- it can be applied by the limited set of an initial data,
- the method essence consists of revealing presence or absence of random value trend, which is usually enough to make a conclusion.

It is necessary to mention that presently most of Nuclear Utilities have a good reliability data collection system and a large amount of data elaborated for the safety important components in the frame of a Probabilistic Safety Assessment (PSA).

These data also could be used for the aging analysis.

However, some deficiencies to use a failure statistic considered in PSA could relate to the following issues :

- component reliability parameters usually estimated on the basis of recent period of NPP operation (3–5 years) and do not cover component history from the beginning of operation,
- for some types of safety components (as for example, HPSI pumps, safety valves, diesel generators, etc.) the population installed on considered unit or NPP is not large enough to have sufficient failure statistic,

- information about component commissioning, replacement and maintenance usually do not considered in the frame of PSA reliability data elaboration,
- many of safety components are very reliable and, as a result, there are only few (sometimes nothing) critical failures occurred during the data collection period.

In those cases some additional efforts to enlarge available statistic usually required.

Case study

Description of initial data set

To demonstrate the method applicability and compare the results with other case studies IRSN proposed to use the same data set presented in Annex 1.

This statistic represents the "virtual" failure and replacement dates of "virtual" electrical or I&C components. It is quite close to the real operating experience data collected on the French NPPs. In particular, it is the large sample that represents one technological group of components. The data is censored by interval, e.g. the times in operation are truncated by right and by left ends. The components in the sample haven't the same date of putting in service, and as a consequence haven't the same age on the date of the beginning and of the end of observation.

Initial data contains :

- list of equipment of the same type observed during certain period of NPPs operation (by a number of the same type of components per reactor),
- period of observation (data collection) given by calendar dates (from 1/01/90 to 31/12/2000),
- dates of the equipment commissioning (age = 0), that are not the same for all components,
- list of critical (criticality factor >0) and non critical (criticality factor 0) failures "occurred" during the observation period (for some components no failures occurred),
- information about eventual equipment "replacements". (It could be supposed that installed (replaced) equipment is new after equipment replacement).

Annex 1 provides the description of data structure, coding and the data itself.

During the study the data was cleaned up from few duplications and imprecise information. Consequently, the data used for the trend analysis is not exactly the same as provided in Annex 1.

Method

As it was mentioned, the inversion criteria test was proposed by *Bendat and Piersol* [2] and it represents the case of Kendall test [3], that don't require knowledge of the random value distribution law.

The test could be applied for the statistical samples of identical from design and operation point of view repairable components installed at one or several units.

It could be used for investigation of particular failure modes or to analyze the total failure intensity behavior in time.

It is supposed that n observations of variable λ_i are distributed continuously, independently and identically. The test verifies if the null hypothesis H_0 that λ is constant, is true.

So, the method consists to analyze the sequence of age-ordered values of failure rates $\{\lambda_i\}$ calculated for reasonably small, equal times intervals (Δt) belonged to the observation period.

For that, an "age window" is defined as a period of operation for wich statistical information about failure events and component mission times is available. This "age window" is divided in M intervals (t_i , $t_i + \Delta t$). For each i-th interval the failure rate λ_i is calculated as

$$\lambda_I = n_i / \left(\sum_{k=1}^{N_i} \Delta t_k^i \right)$$

where:

n_i – total number of failures observed within the i-th interval,

N_i – number of components been in operation during the i-th interval,

Δt_k^i – time in operation of k-th component at i-th interval.

If all (N_i) components were in operation during whole interval duration the formula could be re-wrought as

$$\lambda_I = n_i / (N_i \, \Delta t).$$

The inversions number A_i for each i-member of the sequence is a number of cases, when $\lambda_i > \lambda_j$ for $i < j$ ($j = i+1, i+2, ..., M$).

$$A_i = \sum_{j=i+1}^{M} h_{ij} \text{ , where : } h_{ij} = \begin{cases} 1 \ \ for \ \lambda_i > \lambda_j; \\ 0 \ \ for \ \lambda_i \le \lambda_j. \end{cases}$$

Then the total number of inversions could be defined as

$$A = \sum_{i=1}^{M-1} A_i \, .$$

H_0 hypotheses of absent of trend is accepted if :

$A_l < A < A_u$,

here the lower (A_l) and the upper (A_u) inversion limits depend on supposed confidence level α. The values of A_l and A_u as a function of M and α are given in table 1.

M	$(1-\alpha/2) = 0.99$	$(1-\alpha/2) = 0.975$	$(1-\alpha/2) = 0.95$	$\alpha/2 = 0.05$	$\alpha/2 = 0.025$	$\alpha/2 = 0.01$
10	9	11	13	31	33	35
12	16	18	21	44	47	49
14	24	27	30	60	63	66
16	34	38	41	78	81	85
18	45	50	54	98	102	107
20	59	64	69	120	125	130
30	152	162	171	263	272	282
40	290	305	319	460	474	489
50	473	495	514	710	729	751
60	702	731	756	1013	1038	1067
70	977	1014	1045	1369	1400	1437
80	1299	1344	1382	1777	1815	1860
90	1668	1721	1766	2238	2283	2336

100	2083	2145	2198	2751	2804	2866

Table 1.

The case of $A < A_l$ corresponds to the increasing trend of failure rate and as a consequence it could be supposed that aging impacts to the components reliability. If $A_u < A$ the trend is decreasing and it means that reliability is improved with time.

Results of the trend analysis

The analysis includes the following cases :

- analysis for each statistical sample :
  - A-type of components for unit type U (U-A group),
  - R-type of components for unit type U (U-R group),
  - A-type of components for unit type T (T-A group),
  - R-type of components for unit type T (T-R group),
- In addition data were regrouped by environment types :
  - A-type of components for both types of unit (A group),
  - R-type of components for both types of unit (R group).

Only critical failures, both single and CCF were considered.

The data were rearranged by age of the equipments and then values of failure rates were calculated for each one-year interval. It was done for all age's intervals where the data about components failures and operating times were available (covered by observation period).

Annex 2 provides the results of data treatment for every component group.

The following notations were used in the tables of Annex 2 :

- column "Unit" contents unit code,
- column "Start up" contents the dates of commissioning,
- column "L_TAIL" provides a estimated times between the date of start of observation period and date when unit reach first integer number of years in operation after beginning of observation,
- column "R_TAIL" provides a estimated times between date when unit reach the last integer number of years in operation and date of the end of observation,
- column "EQP" gives a number of components per unit,
- column "# of failures, n" contents the total number of critical failures occurred at the corresponded unit (row) during the observation period,
- "age" rows (grey, green, white and blue cells) represents the observation period with regards to unit (component) age,
  - grey-colored cells represent the years of operation outside the observation period,
  - white-colored cells represent the years of operation within the observation period,

  - green-colored cells represent the left incomplete intervals Δt (where component were in operation only part of the time Δt), they correspond to the durations "L_TAIL",
  - blue-colored cells represent the right incomplete intervals Δt (where component were in operation only part of the time Δt), they correspond to the durations "R_TAIL",

- the numbers given in the "age" cells correspond to the number of critical failures occurred at the corresponded unit (row) during given age interval Δt (column),
- row "failure count, n" contents the total number of critical failures occurred at the corresponded age interval Δt,
- row "operating time" contents the information about total cumulated operating time (all units, all components) at the corresponded age interval Δt,
- row "λ" provides the values of failure rates λ_I,
- rows "$\lambda_{\_up}$" and "$\lambda_{\_low}$" provide the upper and lower boundaries of λ_i confidence interval.

To obtain more credible results of the trend analysis each group were analysed by several iterations. First, for every considered age-interval the lower and upper boundaries of λ_i were estimated. Then, the age-intervals, for which the uncertainties of failure rate were considerably higher, were excluded from the analysis. As it is shown on the figures 1-6, those cases correspond to the beginning and to the end of covered "age window".

For example, for group A failure statistic is available for the ages from 0 to 21 years. What means that during the observation period from 01/01/90 to 31/12/00 there are certain components that were put into operation (as for the units T05, T06, T09, T10, T17, T18) as well as some components which reach 20 years old on the date of the end of observation (as for the units U13, U17, U18, U25, U26). In accordance with the plot on the figure 1 the most uncertain estimation of λ_I corresponds to the 21th age-interval. (This interval represents the components that were in the age range from 20 to 21 years on the moment of the end of observation.) So, as a conclusion, this interval was escaped and the following evaluation was performed for only M = 1,…, 20.

At the same logic, for the groups U-A and U-R, see figures 3, 4, the available statistics correspond to the ages from second to twenty first years, but for the trend analysis only 16 intervals were considered, from 5th to 20th years.

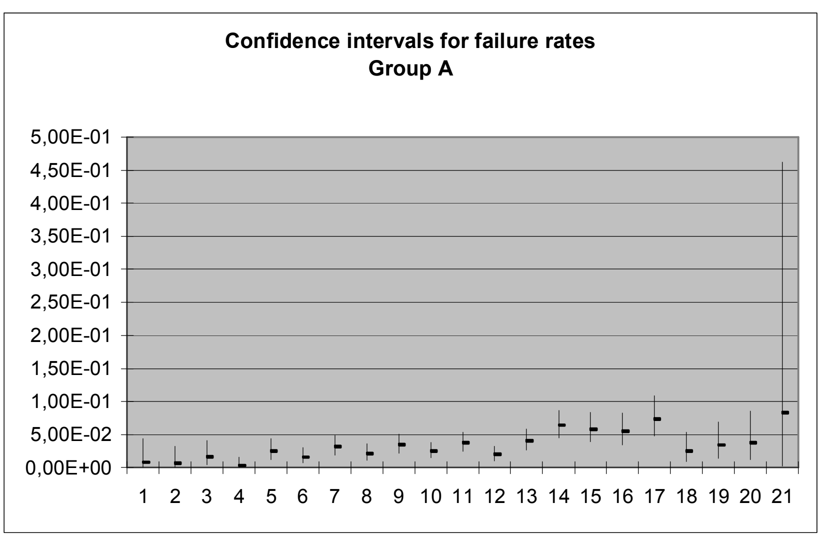

Figure 1. Distribution of failure rates and their confidence bounds, as a function of component age. Group A.

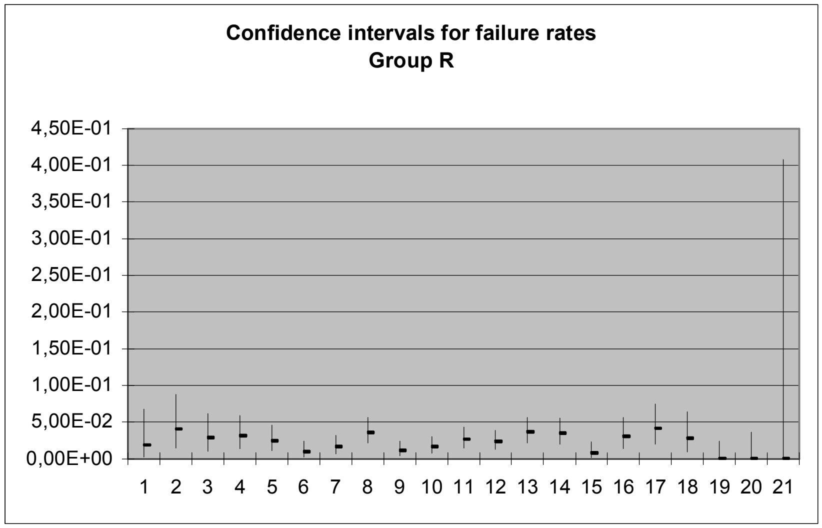

Figure 2. Distribution of failure rates and their confidence bounds, as a function of component age. Group R.

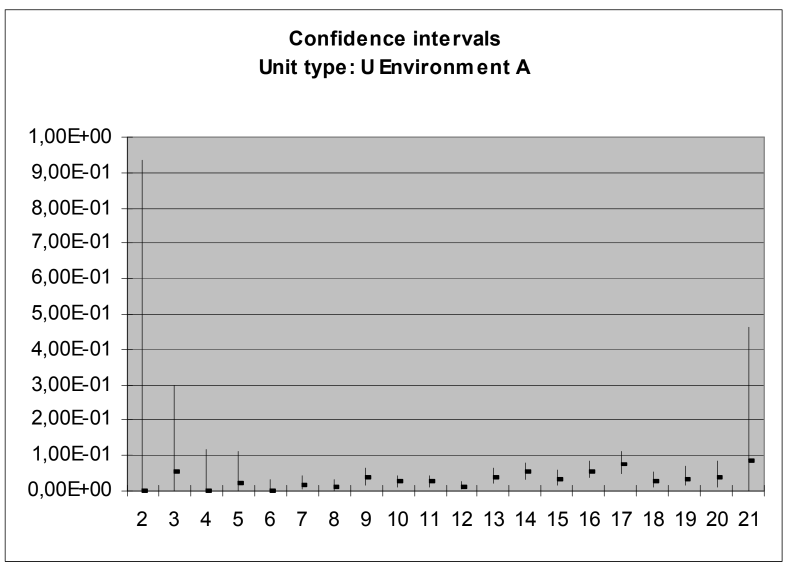

Figure 3. Distribution of failure rates and their confidence bounds, as a function of component age. GroupU-A.

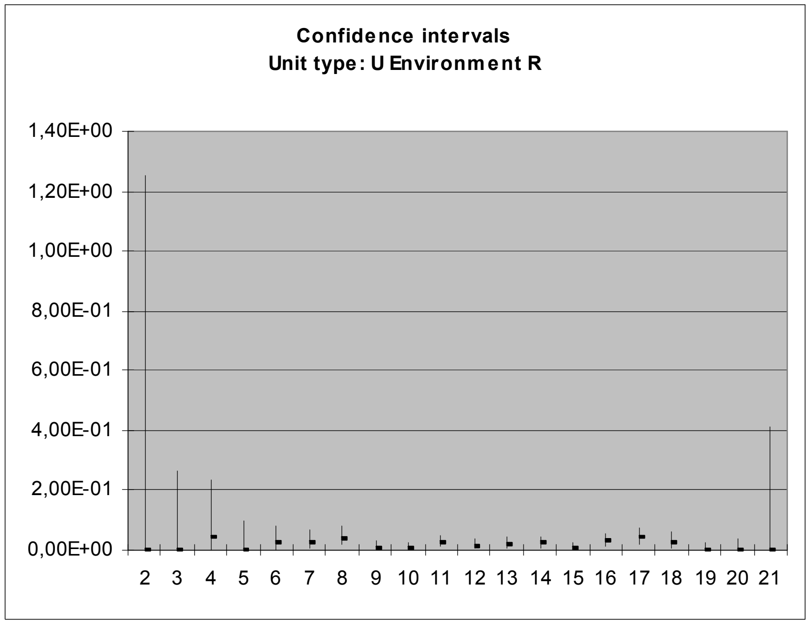

Figure 4. Distribution of failure rates and their confidence bounds, as a function of component age. Group U-R.

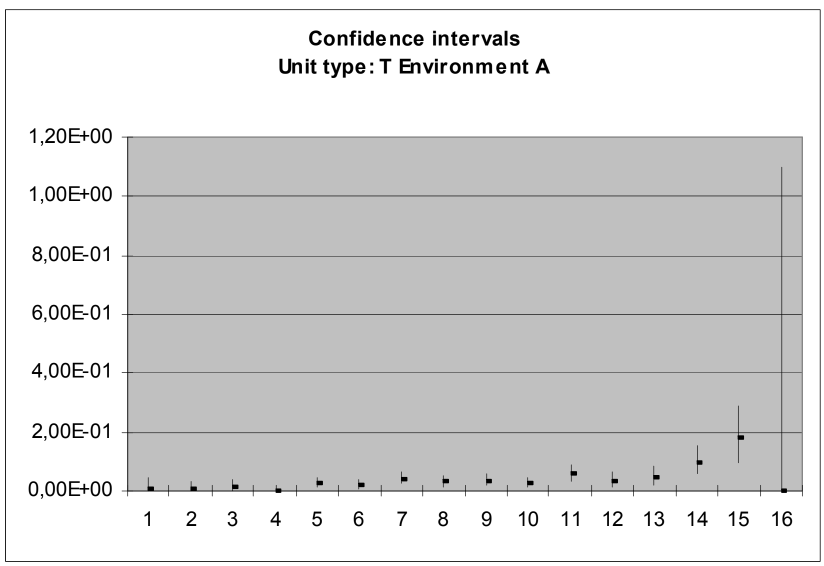

Figure 5. Distribution of failure rates and their confidence bounds, as a function of component age. Group T-A.

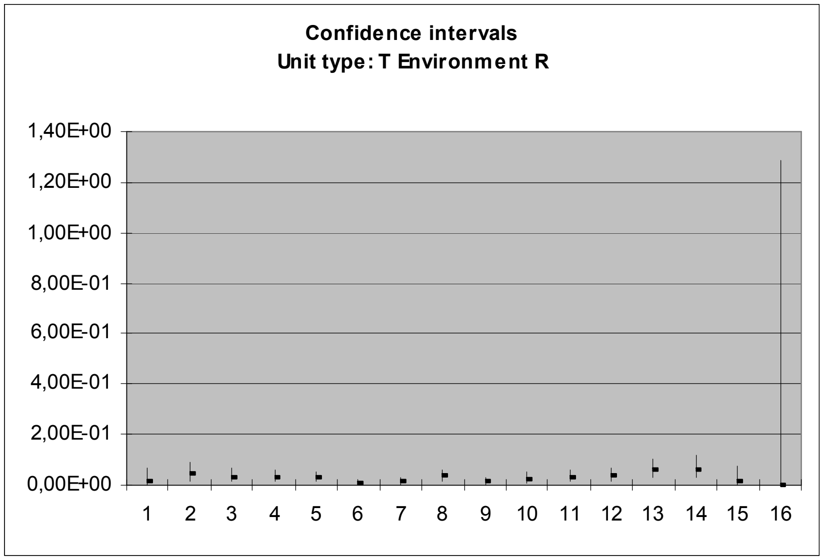

Figure 6. Distribution of failure rates and their confidence bounds, as a function of component age. Group T-R.

The inversion test was done taking into account 95% confidence level. The results of analysis are presented in Table 2.

Group code	Covered age intervals	Considered intervals, M	Total number of failures, n	Inversions number, A	A_L	A_U	Conclusions
A	1-21	1-20	300	41	64	125	Increasing trend
R	1-21	1-20	168	106	64	125	No trend
U-A	2-21	5-20	163	31	38	81	Increasing trend
U-R	2-21	5-20	72	59	38	81	No trend
T-A	1-16	1-15	137	15	33	72	Increasing trend
T-R	1-16	1-15	96	44	33	72	No trend

Table 2.

The results show the increasing trend for the groups U-A and T-A. This conclusion is obtained also for an enlarged sample, which regroups the components of type A from two types of units, U and T.

Increasing trend of λ for T-A statistical group could be identified by qualitative assessment of distribution of mean values for the failure rates versus the component age, as shown on the figure 7. The inversion criteria test confirms the intuitive conclusion of analyst and justifies it from the statistical point of view.

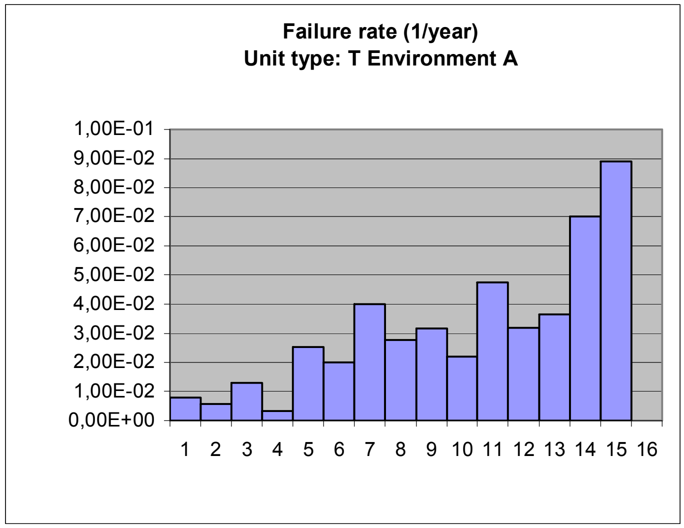

Figure 7. Failure rate distribution. Group T-A.

Method uncertainty and limitations

Uncertainties and impact to results

This statistical approach requires to consider the different kinds of uncertainties on each stage of analysis :

- uncertainties related to the initial data quality (failures data, operation times, failures' types, equipment replacement, dates of commissioning),
- uncertainties of failure rates estimation (characterized by confidence intervals),
- uncertainties in acceptance of the hypothesis of trend.

Initial data uncertainty

Initial data uncertainties relates to the data collection and treatment procedure, and in particular :

- established criteria for data collection and processing,
- quality of plant procedures;
- level of plant's personnel qualification and their accuracy,
- definition of failure criteria, etc.

It has to be recognized that even with well-defined and transparent reporting criteria not all failures and abnormal events will be registered, and exhaustiveness of data relates to the technical, organizational and human aspects. This consideration is important to understand the uncertainty in the final conclusion about the trend, which cannot be evaluated by statistical techniques.

The data set used for this case study is quite similar with data usually used for reliability parameters estimation for the PSA. It could be considered as a good quality data : a very few failures events with missing or imprecise information. Also, the data structure is sufficient to apply inversion criteria test.

Uncertainties of failure rates estimation

The confidence interval limits of failure rates λ_i were calculated by applying χ^2 – distribution. The width of the interval depends from assumed confidence level α, number of failures and cumulated operating time.

The confidence intervals were used to except from statistic the age intervals with most uncertain information.

This kind of uncertainty have to be taken into account because of the results are sensitive.

For example, for the group U-A, 20 intervals were initially defined (from 2 to 21). From table A2.3 of Annex 2, the cumulated operating time for interval which corresponds to the second year in operation, is 3,94 component x years. Then this parameter increases to the value of 448 component x years for 11th and 12th intervals, and after came down again. Finally, for 21th interval it is only 12,05 years of cumulated operating time. Of cause, the failure rate parameters corresponded to the 2nd, 3rd, 4th and 21th intervals couldn't be considered as a representative in comparison with all others λ_i . But, if we will take into account failure rates λ_2, λ_3, λ_4 and λ_{21} for inversion criteria test the conclusion will be different : in this case with confidence level α = 0,05 the total number of inversions is A = 77, when A_L = 64 and A_U = 125. So, A_L< A <A_U, and the hypothesis of increasing trend cannot be accepted.

Uncertainties of inversion criteria test

These kinds of uncertainties are the statistical ones and relate to the assumed confidence level. In general, for the engineering evaluations, a confidence level is supposed as α = 0,05 or 0,1.

Of cause, in some cases the choice of α can impact to the final result of the trend analysis.

Limitations and main factors with impact to results

The conclusions and recommendations provided below based on the practical experience of method application.

The following factors could impact the results of analysis :

- total number of failures (n). The method could not be applied if the number of failures is less than 10 and in general it is recommended to have more then 20 failures. This recommendation comes from experience of application and common sense considerations ;
- number (M) and length (Δt) of considered intervals. The table 1 covers the range of M from 10 to 100. In practice the choice of M depends from the length of interval and period of data collection. It is recommended to adjust the values of M and Δt to avoid a large number of intervals with zero failure statistic (not more then 10% of M). From theoretical point of view it is necessary to satisfy the assumption about continuous distribution ;
- uncertainties in failure rate estimation (see section 3.1) ;
- quantity of components been in operation at time interval Δt. It is recommended to exclude from the analysis the intervals where less then 10 components were in operation. Again, it relates to the assumption about continuous distribution ;
- intervals with repeated values of failure rates. In case if the number of such intervals more then 10% of M it is recommended to use Sean's correction [3] for the inversions formula :

$$A = \sum_{i=1}^{M-1} A_i + \operatorname{int} 0{,}5 \sum_{i=1}^{M-1} S_i \ ,$$

where $\operatorname{int} 0{,}5 \sum_{i=1}^{M-1} S_i$ is an integral part of value $0{,}5 \sum_{i=1}^{M-1} S_i$ and

$$S_i = \sum_{j=i+1}^{M} q_{ij} \text{ when } \mathrm{q_{ij}} = \begin{cases} 1 \ \mathit{if} \ \ \mathrm{n_i} = \mathrm{n_j}; \\ 0 \ \mathit{if} \ \ \mathrm{n_i} \neq \mathrm{n_j}. \end{cases}$$

- non-monotone failure rate behavior within the age. In case of "bathtub" - type distribution of failure rate the method cannot provide the valuable results. For example, for the component X, see figure 8, it is concluded after the analysis by inversion criteria that there is no trend (A = 87 when M = 20 and α = 0,1). But, the failure rate distribution for this component is decreased after the first eight years and then rise-up from 9^{th} to 19 years. In this case more precise analysis was performed for the period from 9 to 19 years of operating and the conclusions were revised (A = 16 < A_L(=17), when M = 11 and α =

0,1). So in such a case it is recommended to exclude the statistic, which corresponds to the "burning-in" period of operation ;

- number of component replacements. Component replacements have to be taken into account during the initial data treatment. So, after the replacement a new component with age 0 has to be added to the statistic for failure rates estimation. But for the reliable reparable components, in case of only few replacements (less then 3-5% from total number of components) their impact to the trend analysis results is negligible ;
- counting of repeated, critical and non critical failures and CCF. All these factors relate to the failure rates estimation and as a consequence could modify a final conclusion. So, dependent to the follow-up application of the results the decision concerning the processing of these types of failures has to be taken before the analysis.

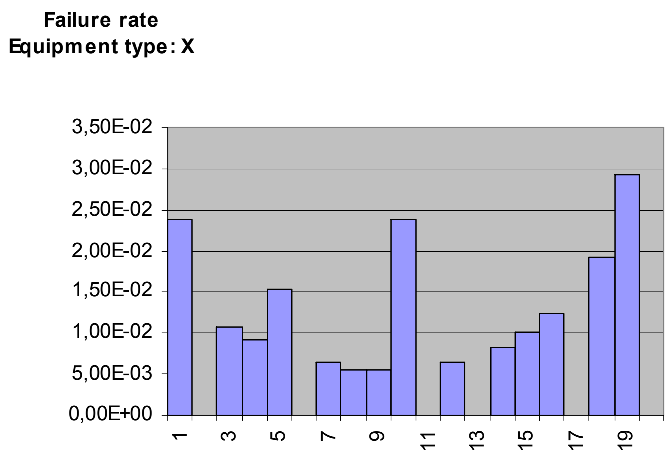

Figure 8. Example of failure rate distribution versus age for component type X.

Conclusions

The case study demonstrates an application of one non-parametrical method to verify of aging trend. The demonstration is done by examination of initial data, which has the same structure and quality as a component reliability data collected in the frame of PSA development for the French NPP. Presented method could be applied for preliminary data analysis in Aging PSA to identify the component groups with aging trend and, as a consequence, to select the components for further age-dependent models construction.

As it was discussed before this method has the following advantages :

- it's simple to apply,
- it can be applied by the limited set of an initial data,
- structure of raw data used for PSA component reliability parameters estimation is enough for method application,
- it permits to use the statistics from different units.

The methods disadvantages relate to :

- it provides only qualitative indication about of presence or absence of aging trend,
- limitations and uncertainties discussed in chapter 3.

Finally, It has to be mentioned that, in practical cases, the results of trend evaluations shall be accompanied with a comparison of actual component or system reliability level with a required one. That means that a conclusion about absence or presence of aging trend is always relative and the final design should be taken by use both acceptable reliability level and aging trend characteristics.

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Annex 1 :

Initial data set for the case study on "Application of Statistical Methods for Identification of Aging Trends"

Introduction

To demonstrate the method applicability and compare the results with other case studies IRSN proposes to use the same data set. All data in the data set are "virtual". However, the statistic, which is provided for the case study is quite close to the real operating experience data collected on the French NPPs. In particular, it is a large sample that represents one technological group of components. The data are censored by interval, e.g. the times in operation are truncated by right and by left ends. The components in the sample haven't the same date of putting in service, and as a consequence haven't the same age on the date of the beginning and of the end of observation.

Initial data structure

Units and components

The sample of equipments for which the failure data were collected represents 1524 components. The equipments are installed on two types of units U and T and operate in different environments (type A and type R).

Each individual component could be identified by Unit code and Equipment code.

Unit code includes 3 symbols xyy, where

x = {T ; U} – type of unit,

yy – digital number of particular unit.

There are 20 units of type T and 28 units of type U.

Equipment code has a mask x*szz, where

x = {T ; U} – type of unit,

* - unknown unit number,

s = {A ; R} – environment,

zz – digital number of component.

For example : T10; T*A01 is an identification of component with ID 01, installed on unit T10, operated in A type of environment.

So, on each unit of type T there are 20 components which operate in A type environment and 17 components operate in R environment. Correspondently, there are 16 and 12 components on A and R environments on the unit type U. The list of components are provided in tables A1.1, A1.2, A1.3 and A1.4.

Installation dates

Dates of equipment commissioning (age = 0), correspond to the dates of unit commissioning. Unit commissioning dates are presented in table A1.5.

Failure data

The data is collected on each unit for the period between 1/01/1990 and 31/12/2000.

The data contents : unit and component ID, date of failure, criticity factor, replacement info (OUI – in case of replacement). It could be supposed that installed (replaced) equipment is new after replacement.

In total 468 critical failures were registered. The failure data is presented in tables A1.6 to A1.9.

Imprecise information

In case of imprecise information concerning component ID or relation between failure and component the following masks are used :

? x*szz/? x*szz – this means that it is not clear to which component the failure is associated with,

x*s?? – this means that the component ID is not clear.

Table A1.1.

Unit type	Environment	Component
U	R	U*R01
U	R	U*R02
U	R	U*R03
U	R	U*R04
U	R	U*R05
U	R	U*R06
U	R	U*R07
U	R	U*R08
U	R	U*R09
U	R	U*R10
U	R	U*R11
U	R	U*R12

Table A1.2.

Unit type	Environment	Component
T	R	T*R01
T	R	T*R02
T	R	T*R03
T	R	T*R04
T	R	T*R05
T	R	T*R06
T	R	T*R07
T	R	T*R08

T	R	T*R09
T	R	T*R10
T	R	T*R11
T	R	T*R12
T	R	T*R13
T	R	T*R14
T	R	T*R15
T	R	T*R16
T	R	T*R17

Table A1.3.

Unit type	Environment	Component
U	A	U*A01
U	A	U*A02
U	A	U*A03
U	A	U*A04
U	A	U*A05
U	A	U*A06
U	A	U*A07
U	A	U*A08
U	A	U*A09
U	A	U*A10
U	A	U*A11
U	A	U*A12
U	A	U*A13
U	A	U*A14
U	A	U*A15
U	A	U*A16

Table A1.4.

Unit type	Environment	Component
T	A	T*A01
T	A	T*A02
T	A	T*A03
T	A	T*A04
T	A	T*A05
T	A	T*A06
T	A	T*A07
T	A	T*A08
T	A	T*A09
T	A	T*A10
T	A	T*A11
T	A	T*A12
T	A	T*A13
T	A	T*A14
T	A	T*A15
T	A	T*A16
T	A	T*A17

T	A	T*A18
T	A	T*A19
T	A	T*A20

Table A1.5.

Unit	Comm. Date
T01	juin-88
T02	janv-89
T03	avr-87
T04	févr-88
T05	févr-91
T06	janv-92
T07	déc-86
T08	mars-87
T09	févr-91
T10	mars-94
T11	févr-88
T12	mai-89
T13	déc-85
T14	déc-85
T15	févr-86
T16	juin-86
T17	déc-90
T18	nov-92
T19	mai-86
T20	mars-87
U01	déc-81
U02	févr-83
U03	nov-83
U04	oct-83
U05	févr-84
U06	août-84
U07	mars-87
U08	avr-88
U09	avr-84
U10	avr-85
U11	sept-84
U12	févr-85
U13	sept-80
U14	févr-81
U15	mai-81
U16	nov-81
U17	nov-80
U18	déc-80
U19	juin-81
U20	oct-81
U21	janv-85
U22	oct-85
U23	août-83
U24	août-83
U25	déc-80

U26	déc-80
U27	mai-81
U28	nov-81

Table A1.6.

Unit	Environment	Component	Failure date	Criticity factor	Remplacement
U01	R	U*R01	15/10/1991	0	
U01	R	U*R02	09/07/1998	1	
U02	R	U*R01	27/09/1993	1	
U02	R	U*R01	13/10/1994	1	
U02	R	U*R08	08/03/1999	1	
U03	R	U*R08	31/05/2000	0	
U04	R	U*R01	25/08/1999	1	
U04	R	U*R01	14/09/1997	1	
U04	R	U*R01	01/09/1998	1	
U04	R	U*R08	08/06/1999	1	
U05	R	U*R01/U*R??	09/05/1994	2	
U05	R	U*R03	13/08/1991	0	
U05	R	U*R03	08/09/1991	0	
U05	R	U*R03	04/10/1991	1	
U07	R	U*R02	17/09/1999	1	
U07	R	U*R08	12/08/1999	1	
U07	R	U*R11	10/07/1999	0	
U07	R	U*R11	30/06/2000	0	
U07	R	U*R11	30/06/2000	0	
U07	R	U*R03	30/09/1993	0	
U07	R	U*R03	30/09/1993	1	
U07	R	U*R05	27/07/1993	1	
U07	R	U*R??	29/06/2000	0	
U08	R	U*R03	27/11/1998	1	
U08	R	U*R05	25/09/1991	1	
U08	R	U*R05	27/07/1993	1	
U09	R	U*R04	08/03/2000	1	
U09	R	U*R02	17/01/1992	1	OUI
U09	R	U*R02	29/01/1992	0	
U09	R	U*R02	16/02/1992	0	
U09	R	U*R02	11/03/1992	0	
U09	R	U*R02	16/03/1992	0	
U09	R	U*R02	05/04/1992	0	
U09	R	U*R02	14/05/1992	0	
U09	R	U*R02	18/05/1992	0	
U09	R	U*R02	01/06/1992	1	
U09	R	U*R02	30/08/1992	0	
U09	R	U*R02	05/09/1992	1	
U09	R	U*R05	28/04/1993	1	
U10	R	U*R08	21/08/2000	0	
U11	R	U*R01/U*R02/U*R??	05/06/1992	3	
U11	R	U*R05	26/03/1991	1	

U11	R	U*R05	24/03/1992	1	
U11	R	U*R12	04/04/1990	1	
U12	R	U*R05	12/01/1992	1	
U12	R	U*R12	15/06/1995	1	OUI
U13	R	U*R01	17/10/1990	1	
U13	R	U*R01	10/11/1990	1	
U13	R	U*R02	23/07/1990	1	OUI
U13	R	U*R03	11/10/1990	1	OUI
U14	R	U*R01	23/06/1993	1	
U14	R	U*R05	12/11/1992	1	
U14	R	U*R05	11/11/1994	1	
U15	R	U*R08	21/04/1999	0	
U15	R	U*R05	13/09/1994	1	
U16	R	U*R04	30/09/1998	0	
U16	R	U*R11/U*R04	30/09/1998	2	
U17	R	U*R01	26/06/1994	1	
U17	R	U*R01	26/06/1994	1	
U18	R	U*R03	07/10/1992	1	
U18	R	U*R03	13/11/1992	1	
U19	R	U*R01	16/06/1996	1	
U19	R	U*R08	05/09/1999	0	
U19	R	U*R08	11/10/1999	0	
U19	R	U*R??	10/02/1991	1	
U20	R	U*R08	28/04/1999	1	
U20	R	U*R08	06/05/1998	1	
U20	R	U*R11	05/05/1998	1	
U21	R	U*R03	01/05/2000	1	
U21	R	U*R04	14/12/2000	1	
U21	R	U*R02	14/09/1990	0	
U21	R	U*R03	18/12/1996	1	
U22	R	U*R11	16/09/1998	1	
U23	R	U*R01	01/11/1999	1	
U23	R	U*R01	02/07/1991	1	
U23	R	U*R04	14/01/1998	1	OUI
U23	R	U*R??/U*R??/U*R??	15/01/1996	3	
U24	R	U*R04	28/07/1999	1	
U24	R	U*R03	07/09/1998	1	
U24	R	U*R11	24/07/1997	1	
U24	R	U*R??	27/08/1998	1	
U25	R	U*R02	06/01/1998	1	
U25	R	U*R03	22/12/1991	0	
U25	R	U*R03	23/05/1998	1	
U25	R	U*R12	06/05/1998	1	
U26	R	U*R02	02/11/1997	1	
U26	R	U*R02	06/01/1998	1	
U27	R	U*R03	05/04/1995	1	
U27	R	U*R08	13/10/2000	0	
U28	R	U*R02	11/08/1997	1	
U28	R	U*R04	03/03/1998	1	

Table A1.7.

Unit	Environment	Component	Failure date	Criticity factor	Remplacement
T10	R	T*R01	22/07/1999	1	
T14	R	T*R02	10/10/2000	0	
T04	R	T*R04	30/11/2000	0	
T13	R	T*R04	15/06/1999	1	
T13	R	T*R04	13/08/1999	1	
T16	R	T*R04	26/10/1999	0	
T16	R	T*R05	30/10/1997	1	
T16	R	T*R05	26/01/2000	1	
T20	R	T*R05	14/06/2000	1	
T20	R	T*R05	21/07/2000	0	
T04	R	T*R08/T*R??	26/09/1995	2	
T12	R	T*R08	13/07/2000	0	
T12	R	T*R08	17/07/2000	1	
T12	R	T*R08	01/08/2000	0	
T01	R	T*R09	29/07/2000	1	
T03	R	T*R09	31/07/2000	0	
T03	R	T*R09	01/11/2000	1	
T20	R	T*R09	13/12/2000	0	
T06	R	T*R11	10/06/1996	1	
T13	R	T*R11	18/01/2000	0	
T14	R	T*R11	22/12/1999	1	
T04	R	T*R??	12/05/1992	1	
T11	R	T*R??	19/06/1992	0	
T20	R	T*R??	23/05/1991	1	
T20	R	T*R??	09/08/1995	1	
T03	R	?T*R??/?T*R17	22/12/1990	1	
T02	R	117MN	06/08/1991	1	
T16	R	T*R12	02/02/1990	1	OUI
T02	R	T*R01	26/02/1991	0	
T02	R	T*R01	02/03/1991	1	
T02	R	T*R01	12/09/1991	1	
T02	R	T*R01	21/09/1991	1	
T08	R	T*R01	06/03/1990	0	
T12	R	T*R01	11/10/1993	1	
T13	R	T*R01	23/08/1996	1	
T13	R	T*R01	15/04/1998	1	
T14	R	T*R01	19/12/1990	1	
T16	R	T*R01	17/08/1992	1	
T16	R	T*R01	18/11/1997	1	
T06	R	T*R01/T*R02/T*R03/ T*R04	08/10/1993	4	
T01	R	T*R02	06/03/1996	1	
T02	R	T*R02	02/12/1995	1	
T02	R	T*R02	14/08/1997	1	
T03	R	T*R02	29/10/1997	1	
T12	R	T*R02	21/12/1990	1	
T12	R	T*R02	17/04/1991	1	
T13	R	T*R02	24/09/1992	1	

T16	R	T*R02/T*R03	06/06/1997	2	
T01	R	T*R03	19/07/1995	1	
T05	R	T*R03	04/08/1994	1	
T14	R	T*R03	02/07/1998	1	
T16	R	T*R03	21/07/1995	1	
T20	R	T*R03	22/08/1995	1	
T20	R	T*R03	09/07/1998	1	
T01	R	T*R04	14/11/1990	0	
T04	R	T*R04	29/04/1996	1	
T07	R	T*R04	22/03/1991	1	
T13	R	T*R04	13/04/1998	1	
T15	R	T*R04	28/06/1998	1	
T16	R	T*R04	13/01/1990	1	
T16	R	T*R04	24/07/1995	1	
T17	R	T*R04	05/04/1993	0	
T20	R	T*R04	12/07/1994	1	
T15	R	T*R05	25/05/1998	1	
T03	R	T*R16	10/05/1999	1	
T06	R	T*R16	22/03/1994	1	
T11	R	T*R16	18/04/2000	1	
T12	R	T*R16	13/11/2000	1	
T13	R	T*R16	02/05/1999	0	
T13	R	T*R16	10/05/1999	1	
T16	R	T*R16	25/01/2000	1	
T19	R	T*R16	10/08/2000	0	
T20	R	T*R16	18/03/1999	1	
T20	R	T*R16	05/12/2000	1	
T20	R	T*R16	26/12/2000	1	
T10	R	T*R16/T*R05	04/07/1997	0	
T10	R	T*R16/T*R05	05/07/1997	2	
T10	R	?T*R16/?T*R08	03/07/1997	1	
T01	R	T*R08	19/07/1995	0	
T01	R	T*R08	19/10/1995	0	
T01	R	T*R08	27/10/1995	1	
T10	R	T*R08	08/03/1993	0	
T10	R	T*R08	01/06/1995	0	
T10	R	T*R08	05/06/1996	1	
T13	R	T*R08	20/12/1997	1	
T19	R	T*R08	10/06/1996	1	
T05	R	T*R08/T*R10	25/08/1995	2	
T14	R	T*R08/T*R10	16/01/1993	2	
T03	R	T*R09	24/07/1996	1	
T04	R	T*R09	03/10/1994	1	
T08	R	T*R09	02/04/1991	0	
T08	R	T*R09	12/09/1996	1	
T10	R	T*R09	22/04/1993	1	
T10	R	T*R09	11/07/1997	1	
T11	R	T*R09	14/10/1995	1	
T14	R	T*R09	28/01/1993	1	
T15	R	T*R09	03/06/1998	0	
T15	R	T*R09	03/06/1998	1	
T17	R	T*R09	02/05/1994	0	

T19	R	T*R09	01/11/1997	0	
T14	R	T*R10	18/11/1996	1	OUI
T06	R	T*R11	11/05/1995	0	
T07	R	T*R11	01/07/1996	1	OUI
T13	R	T*R11	06/03/1997	1	
T13	R	T*R11	31/12/1997	1	
T01	R	T*R17	18/03/1993	1	
T02	R	T*R17	03/04/1996	1	
T04	R	T*R17	14/05/1992	1	
T06	R	T*R17	27/11/1991	1	
T02	R	T*R??	20/09/1999	0	
T03	R	T*R??/T*R??	18/08/1996	2	
T04	R	T*R??/T*R??	14/08/1998	2	
T05	R	T*R??	02/09/1995	0	
T12	R	T*R??	23/04/1999	0	
T15	R	T*R??	21/03/1997	0	
T16	R	T*R??	28/09/1998	0	
T18	R	T*R??	10/02/2000	0	
T13	R	T*R??	19/09/1991	0	
T02	R	T*R??	24/05/1991	0	
T11	R	T*R??	19/08/1998	0	
T11	R	T*R??	16/09/1998	0	
T01	R	T*R??	19/06/1998	1	

Table A1.8.

Unit	Environment	Component	Failure date	Criticity factor	Remplacement
U01	A	U*A08	13/09/1999	1	
U01	A	U*A08	01/09/2000	1	
U01	A	U*A08	16/11/2000	1	
U01	A	U*A12	28/08/1999	1	
U01	A	U*A12	10/01/2000	1	
U01	A	?U*A03/?U*A12	11/03/1996	1	
U01	A	U*A05/U*A06/U*A07	01/07/1998	0	
U01	A	U*A06	20/02/1998	1	
U01	A	U*A11	16/09/1997	1	
U01	A	U*A12	24/11/1990	1	
U01	A	U*A12	11/11/1998	0	
U01	A	U*A13	15/11/1994	0	
U02	A	U*A03	03/10/1999	1	
U02	A	U*A06	14/01/1999	1	
U02	A	U*A09	13/04/2000	1	
U02	A	U*A12	30/01/1999	1	
U02	A	U*A04	24/04/1995	1	
U02	A	U*A05	22/06/1995	1	OUI
U02	A	U*A06	29/11/1992	0	
U02	A	U*A09	23/10/1992	1	
U02	A	U*A09	05/07/1993	1	
U02	A	?U*A09/?U*A03	15/05/1998	1	
U02	A	U*A14	15/06/1994	1	
U03	A	U*A02	19/05/1999	1	

U03	A	U*A06	04/05/2000	1	
U03	A	U*A08	20/02/2000	1	
U03	A	U*A09	28/12/1999	1	
U03	A	U*A11	07/01/2000	1	
U03	A	U*A11	17/08/2000	1	
U03	A	U*A02	02/05/1997	1	
U03	A	U*A05	15/10/1996	1	
U03	A	U*A05/U*A11/U*A13	29/07/1998	2	
U03	A	U*A11	28/10/1997	1	
U04	A	U*A03	29/03/1999	1	
U04	A	U*A03	18/01/2000	1	
U04	A	U*A04	23/03/1999	1	
U04	A	U*A09	18/07/1999	1	
U04	A	U*A10	31/08/1999	1	
U04	A	U*A10	17/11/1999	1	
U04	A	U*A10	29/02/2000	1	
U04	A	U*A10	13/07/2000	1	
U04	A	U*A10	28/09/2000	1	
U04	A	U*A03	31/07/1996	1	
U04	A	U*A03	06/09/1996	1	
U04	A	U*A03	05/02/1997	1	
U04	A	U*A03	01/02/1998	1	
U04	A	?U*A03/?U*A04	10/07/1996	1	
U04	A	U*A04	05/07/1997	1	
U04	A	U*A04	14/08/1998	1	
U04	A	U*A09	28/11/1996	1	
U04	A	U*A09	05/02/1997	1	
U04	A	U*A09	20/07/1997	1	
U04	A	U*A09/U*A03	05/05/1997	2	
U04	A	U*A10	04/07/1993	1	
U04	A	U*A10	02/11/1998	1	
U04	A	U*A10	13/12/1998	0	
U04	A	U*A??	02/08/1999	2	
U05	A	U*A07	14/08/2000	1	
U05	A	U*A07	01/06/1996	1	
U06	A	U*A01	04/01/1997	1	
U06	A	U*A05	27/08/2000	1	
U06	A	U*A06	06/07/1994	1	
U07	A	U*A05	21/08/1995	1	
U07	A	U*A11	20/12/1995	1	
U07	A	U*A03	13/02/1992	1	
U07	A	U*A15	17/03/1994	0	
U08	A	U*A06	01/09/1994	1	
U08	A	U*A07	27/01/1996	1	
U08	A	U*A07	11/10/1998	1	
U08	A	U*A10	29/12/1998	1	
U08	A	U*A11	10/07/1990	1	
U08	A	U*A13	10/12/1994	1	
U09	A	U*A07	17/05/1994	1	
U10	A	U*A03	20/01/1993	1	
U10	A	U*A03	20/05/1993	1	OUI

U10	A	U*A03	11/08/1993	1	
U10	A	U*A07	16/10/1996	1	
U11	A	U*A05	01/08/1993	1	
U11	A	U*A05	03/08/1993	0	
U11	A	U*A07	23/08/1994	0	
U11	A	U*A08	29/09/1993	1	
U11	A	U*A08	16/08/1994	1	
U11	A	U*A08	10/10/1997	1	
U11	A	U*A08	06/04/1998	1	
U11	A	U*A08	06/06/1998	1	
U11	A	U*A08	18/10/1998	1	
U12	A	U*A02	20/08/1993	1	
U12	A	U*A06	01/11/1998	1	
U12	A	U*A13	29/10/1992	0	
U12	A	U*A14	09/12/1994	1	
U13	A	U*A03	25/10/2000	1	
U13	A	U*A02	26/10/1996	1	OUI
U13	A	U*A02	10/05/1997	1	
U13	A	U*A03	13/02/1997	0	
U13	A	U*A08	29/08/1990	1	
U13	A	U*A09	06/10/1994	1	
U13	A	U*A09	09/11/1994	1	
U13	A	U*A11	31/07/1993	1	
U14	A	U*A02	14/12/1991	1	
U14	A	U*A02	08/12/1992	1	
U14	A	U*A03	21/11/1991	1	
U14	A	U*A04	03/03/1997	1	
U14	A	U*A04	26/12/1997	1	
U14	A	U*A09	13/07/1990	1	
U14	A	U*A09	25/07/1990	1	
U15	A	U*A03	26/07/1990	1	
U15	A	U*A07	22/02/1993	1	
U15	A	U*A07	17/11/1994	1	
U15	A	U*A07	02/02/1995	1	
U16	A	U*A06	06/07/1994	1	
U16	A	U*A07	16/08/1994	1	
U16	A	U*A11	18/08/1996	1	
U16	A	U*A12	19/02/1990	1	
U16	A	U*A12	02/08/1995	1	
U17	A	U*A11	21/07/1999	1	
U17	A	U*A14	21/07/1999	1	
U17	A	U*A02	27/09/1998	1	
U17	A	U*A05	08/07/1997	0	
U18	A	U*A04	22/04/1999	1	
U18	A	U*A09	05/06/2000	1	
U18	A	U*A03	19/10/1992	1	
U18	A	U*A03	17/10/1995	1	
U18	A	U*A04	26/06/1994	1	
U18	A	U*A05	25/02/1997	1	
U18	A	U*A06	23/07/1990	1	
U18	A	U*A10	20/07/1995	0	
U19	A	U*A02	30/09/1998	1	

U19	A	?U*A02/?U*A05	16/10/1995	1	
U19	A	U*A07	04/01/1996	1	
U19	A	U*A08	18/02/1995	1	
U19	A	U*A12	08/07/1992	0	
U19	A	U*A13	12/09/1995	0	
U20	A	U*A13	05/11/1999	1	
U20	A	U*A02	13/05/1997	0	
U21	A	U*A14	24/10/1993	0	
U21	A	U*A15	03/03/1997	1	
U22	A	U*A04	26/11/1993	1	
U22	A	U*A04/U*A05	13/05/1996	2	
U22	A	U*???/U*A05/U*A07	22/12/1995	3	
U22	A	U*A05	21/05/1992	1	
U22	A	U*A08	26/11/1993	1	
U22	A	U*A12	26/11/1993	1	
U22	A	U*A16	10/06/1991	0	
U23	A	U*A06	01/12/1999	1	
U23	A	U*A12	22/04/1999	1	
U23	A	U*A02	23/02/1996	1	
U23	A	U*A02	24/02/1996	0	
U23	A	U*A06	22/02/1996	1	
U23	A	U*A06	29/04/1996	0	
U24	A	U*A06	25/12/1996	1	
U24	A	U*A06	07/07/1997	1	
U24	A	U*A02	08/02/1996	1	
U24	A	U*A03	18/08/1996	1	
U24	A	U*A06	20/06/1996	1	
U24	A	U*A06	20/12/1997	0	
U25	A	U*A11	21/01/1995	1	
U25	A	U*???	23/09/1997	1	
U25	A	U*A04	03/06/1996	1	
U25	A	U*A04	13/11/1996	1	
U25	A	U*A11	28/01/1996	1	
U25	A	U*A11	23/06/1996	1	
U25	A	U*A11	04/08/1996	1	
U26	A	U*A05	14/07/1996	1	
U26	A	U*A02/U*???	28/10/1996	0	
U26	A	U*A03	20/07/1996	1	
U26	A	U*A09	27/12/1996	1	
U26	A	U*A11	18/01/1997	1	
U26	A	U*A13	24/07/1996	1	
U27	A	U*A08	20/12/2000	1	
U27	A	U*???	23/09/1997	0	
U27	A	U*A03	28/09/1993	1	
U27	A	U*???	19/05/1998	0	
U27	A	U*A08	20/05/1994	0	OUI
U27	A	U*A08	05/08/1996	1	
U27	A	U*A08	10/11/1996	1	
U27	A	U*A11	08/08/1994	1	
U27	A	U*A11	28/09/1994	1	
U28	A	U*A02	20/11/2000	1	

U28	A	U*A08	01/12/2000	1	
U28	A	U*A11	31/12/2000	1	
U28	A	U*A03	28/09/1993	0	
U28	A	U*A06	26/04/1998	1	

Table A1.9.

Unit	Environment	Component	Failure date	Criticity	Remplacement
T01	A	T*A05	21/08/2000	1	
T01	A	T*A06	07/11/1994	1	
T01	A	T*A06	03/01/1995	1	
T01	A	T*A08	03/01/1995	1	
T01	A	T*A10	08/07/1997	1	
T01	A	T*A10	22/12/1998	0	
T01	A	T*A14	13/08/1998	0	
T01	A	T*A20	04/08/1998	0	
T02	A	T*A05	09/07/1998	1	
T02	A	T*A10	27/10/1990	1	
T02	A	T*A10	12/04/1991	1	
T02	A	T*A10	03/09/1995	1	
T02	A	T*A??	11/06/1992	0	
T03	A	T*A19	03/09/1992	1	
T03	A	T*A19	26/07/1993	1	
T04	A	T*A19	13/09/1996	1	
T05	A	T*A09	02/09/1994	1	
T05	A	T*A13	02/08/1999	1	
T07	A	T*A01	30/08/1997	1	
T07	A	T*A02	15/10/1991	1	
T07	A	T*A06	11/10/1999	1	
T07	A	T*A09	30/04/1997	1	
T07	A	T*A10	19/03/1994	0	
T07	A	T*A10	06/01/1997	1	
T07	A	T*A11	28/10/1991	1	
T07	A	T*A11	07/04/1997	1	
T07	A	T*A11	29/12/2000	1	
T07	A	T*A12	19/09/1994	1	
T07	A	T*A16	28/01/1991	1	
T07	A	T*A17	28/01/1991	1	
T07	A	T*A19	21/01/1993	1	
T07	A	T*A19	18/12/2000	1	
T08	A	T*A01	08/12/1999	1	
T08	A	T*A05	07/06/1993	1	
T08	A	T*A06	02/11/1994	1	
T08	A	T*A07	02/11/1994	1	
T08	A	T*A08	02/11/1994	1	
T08	A	T*A08	30/06/1995	1	
T08	A	T*A08	06/06/1997	1	
T08	A	T*A11	28/04/1998	1	
T08	A	T*A12	07/12/2000	1	
T08	A	T*A15	06/05/1998	0	
T08	A	T*A17	07/02/1996	1	

T09	A	T*A02	14/04/1993	1	
T09	A	T*A17	14/04/1993	1	
T09	A	T*A19	03/03/1990	0	
T10	A	T*A10	09/04/1997	0	
T10	A	T*A13	19/11/2000	1	
T10	A	T*A??	23/03/1993	0	
T11	A	T*A05	05/07/2000	1	
T13	A	T*A01	17/11/1996	1	
T13	A	T*A03	29/05/1990	1	
T13	A	T*A06	03/04/1997	1	
T13	A	T*A07	24/12/1995	0	
T13	A	T*A08	15/08/1993	0	
T13	A	T*A08	09/02/1998	1	
T13	A	T*A09	04/09/1999	1	
T13	A	T*A10	04/07/1995	0	
T13	A	T*A10	21/06/1999	1	
T13	A	T*A11	10/08/1994	0	
T13	A	T*A11	27/12/1997	1	
T13	A	T*A11	30/07/2000	1	
T13	A	T*A12	21/09/1990	1	
T13	A	T*A12	14/12/1994	1	
T13	A	T*A13	12/12/1998	1	
T13	A	T*A13	12/10/2000	1	
T13	A	T*A17	02/04/1993	1	
T13	A	T*A17	27/10/1996	1	
T13	A	T*A19	07/12/1993	1	OUI
T13	A	T*A19	08/05/1994	1	
T13	A	T*A19	23/10/1996	1	
T13	A	T*A19	17/04/1997	1	
T13	A	T*A19	23/04/1998	1	
T13	A	T*A20	05/02/1996	1	
T14	A	T*A03	12/01/1993	1	
T14	A	T*A03	19/11/1996	1	
T14	A	T*A04	04/11/1993	1	
T14	A	T*A04	25/05/1994	1	
T14	A	T*A05	23/09/1996	1	
T14	A	T*A05	06/05/1998	0	
T14	A	T*A05	07/09/1999	1	
T14	A	T*A06	15/06/1996	0	
T14	A	T*A08	15/12/1998	1	
T14	A	T*A09	25/09/1995	1	
T14	A	T*A09	15/08/1996	1	
T14	A	T*A09	20/11/1996	1	
T14	A	T*A09	21/08/1997	1	
T14	A	T*A09	19/11/1997	1	
T14	A	T*A10	17/11/1997	1	
T14	A	T*A10	16/05/1998	0	
T14	A	T*A10	29/06/1998	0	
T14	A	T*A13	27/01/1992	1	
T14	A	T*A13	05/09/1996	1	
T14	A	T*A14	30/04/1994	1	OUI
T14	A	T*A18	19/11/1996	1	

T14	A	T*A19	29/08/1991	1	
T14	A	T*A19	23/10/1995	1	
T14	A	T*A20	06/02/1999	1	
T15	A	T*A??	02/06/1995	0	
T15	A	T*A02	23/05/2000	1	
T15	A	T*A03	20/10/1993	1	
T15	A	T*A03	16/07/1998	1	
T15	A	T*A03	18/02/1999	0	
T15	A	T*A07	27/07/1991	1	
T15	A	T*A07	23/05/2000	1	
T15	A	T*A08	15/01/2000	1	
T15	A	T*A08	24/05/2000	1	
T15	A	T*A09	07/03/1993	0	
T15	A	T*A11	20/04/1992	1	
T15	A	T*A11	28/12/1999	0	
T15	A	T*A11	23/05/2000	1	
T15	A	T*A12	02/06/1995	1	
T15	A	T*A13	20/01/1996	1	
T15	A	T*A13	15/06/2000	1	
T15	A	T*A14	03/01/1991	0	
T15	A	T*A18	19/08/1994	1	
T15	A	T*A19	03/01/1991	0	
T15	A	T*A19	20/04/1992	1	
T15	A	T*A19	25/08/1993	1	
T15	A	T*A19	27/10/1993	1	
T15	A	T*A??	22/10/2000	0	
T16	A	T*A02	24/02/1993	1	
T16	A	T*A02	19/05/2000	1	
T16	A	T*A03	25/08/1991	1	
T16	A	T*A07	24/02/1993	1	
T16	A	T*A07	22/05/2000	1	
T16	A	T*A09	01/07/2000	1	
T16	A	T*A14	10/10/1999	1	
T16	A	T*A18	20/01/1991	1	
T16	A	T*A18	08/05/2000	1	
T16	A	T*A19	29/05/1991	1	
T16	A	T*A19	19/08/1997	1	
T16	A	T*A19	17/03/2000	1	
T17	A	T*A01	08/09/1996	1	
T17	A	T*A01	17/09/1996	1	
T17	A	T*A12	17/07/1995	1	
T17	A	T*A18	12/07/1995	1	
T18	A	T*A11	04/07/1998	1	
T18	A	T*A11	18/03/1999	1	
T18	A	T*A11	28/05/1999	0	
T18	A	T*A11	28/05/1999	1	
T18	A	T*A14	14/08/1992	1	
T19	A	T*A02	08/11/2000	1	
T19	A	T*A03	30/01/1998	1	
T19	A	T*A06	21/10/1994	1	
T19	A	T*A09	25/10/1991	1	
T19	A	T*A09	05/07/1994	1	

T19	A	T*A11	01/06/1999	1	
T19	A	T*A13	18/07/1996	1	
T19	A	T*A14	03/11/1994	1	
T19	A	T*A18	10/05/1992	1	
T19	A	T*A??	29/09/2000	4	
T20	A	T*A02	20/03/1993	0	
T20	A	T*A02	05/12/2000	1	
T20	A	T*A07	29/06/1994	1	
T20	A	T*A12	14/04/1999	0	
T20	A	T*A12	17/04/1999	1	
T20	A	T*A15	20/12/2000	1	
T20	A	T*A17	30/08/1999	1	
T20	A	T*A19	17/10/1996	1	
T20	A	T*A19	30/09/1998	1	

Annex 2 : Assessment of initial data

Group A														AGE												
UNIT	**START UP**	**L_TAIL**	**R_TAIL**	**EQP**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	# of failures
U01	01/12/1981	0,915	0,084	16									1	0	0	0	0	0	1	1	1	2	3	0		9
U02	01/02/1983	0,084	0,917	16							0	0	0	1	1	1	2	0	0	2	2	1				10
U03	01/11/1983	0,832	0,167	16							0	0	0	0	0	0	1	1	3	1	5	0				11
U04	01/10/1983	0,747	0,252	16							0	0	0	1	0	0	3	7	2	7	4	1				25
U05	01/02/1984	0,084	0,917	16						0	0	0	0	0	0	0	1	0	0	0	1					2
U06	01/08/1984	0,58	0,419	16						0	0	0	0	1	0	0	1	0	0	0	1					3
U07	01/03/1987	0,161	0,838	16			0	0	1	0	0	0	2	0	0	0	0	0								3
U08	01/04/1988	0,246	0,753	16		0	1	0	0	0	2	1	0	0	2	0	0									6
U09	01/04/1984	0,246	0,753	16						0	0	0	0	0	1	0	0	0	0	0	0					1
U10	01/04/1985	0,246	0,753	16					0	0	0	1	2	0	0	1	0	0	0	0						4
U11	01/09/1984	0,665	0,334	16						0	0	0	1	2	0	0	0	3	1	0	0					7
U12	01/02/1985	0,084	0,917	16					0	0	0	0	1	1	0	0	0	1	0	0						3
U13	01/09/1980	0,665	0,334	16										1	0	0	1	0	2	0	2	0	0	0	1	7
U14	01/02/1981	0,084	0,917	16									0	2	2	1	0	0	0	0	2	0	0	0		7
U15	01/05/1981	0,328	0,671	16									0	1	0	1	0	2	0	0	0	0	0	0		4
U16	01/11/1981	0,832	0,167	16									1	0	0	0	2	1	1	0	0	0	0	0		5
U17	01/11/1980	0,832	0,167	16										0	0	0	0	0	0	0	0	1	2	0	0	3
U18	01/12/1980	0,915	0,084	16										1	0	1	0	1	1	0	1	0	1	1	0	7
U19	01/06/1981	0,413	0,586	16									0	0	0	0	0	1	2	0	0	1	0	0		4
U20	01/10/1981	0,747	0,252	16									0	0	0	0	0	0	0	0	0	0	1	0		1
U21	01/01/1985	1	0,002	16						0	0	0	0	0	0	0	1	0	0	0	0					1
U22	01/10/1985	0,747	0,252	16					0	0	1	0	3	0	5	0	0	0	0	0						9
U23	01/08/1983	0,58	0,419	16							0	0	0	0	0	0	2	0	0	1	1	0				4
U24	01/08/1983	0,58	0,419	16							0	0	0	0	0	0	2	3	0	0	0	0				5
U25	01/12/1980	0,915	0,084	16										0	0	0	0	0	1	5	1	0	0	0	0	7
U26	01/12/1980	0,915	0,084	16										0	0	0	0	0	0	3	2	0	0	0	0	5
U27	01/05/1981	0,328	0,671	16									0	0	0	0	1	2	0	2	0	0	0	1		6
U28	01/11/1981	0,832	0,167	16									0	0	0	0	0	0	0	0	1	0	0	3		4
T01	01/06/1988	0,413	0,586	20		0	0	0	0	0	3	0	0	1	0	0	1									5
T02	01/01/1989	1	0,002	20		1	1	0	0	0	1	0	0	1	0	0	0									4
T03	01/04/1987	0,246	0,753	20			0	0	0	1	1	0	0	0	0	0	0	0								2
T04	01/02/1988	0,084	0,917	20		0	0	0	0	0	0	0	1	0	0	0	0									1
T05	01/02/1991	1	0,917	20	0	0	0	1	0	0	0	0	1	0												2
T06	01/01/1992	1	0,002	20	0	0	0	0	0	0	0	0	0	0												0
T07	01/12/1986	0,915	0,084	20				0	4	0	1	1	0	0	4	0	1	0	2							13
T08	01/03/1987	0,161	0,838	20			0	0	0	0	1	3	2	0	1	1	1	1								10
T09	01/02/1991	1	0,917	20	0	0	2	0	0	0	0	0	0	0												2
T10	01/03/1994	1	0,838	20	0	0	0	0	0	0	1															1
T11	01/02/1988	0,084	0,917	20		0	0	0	0	0	0	0	0	0	0	0	1									1
T12	01/05/1989	0,328	0,671	20	0	0	0	0	0	0	0	0	0	0	0	0										0
T13	01/12/1985	0,915	0,084	20					2	0	0	1	2	1	4	2	3	3	2	0						20
T14	01/12/1985	0,915	0,084	20					0	1	1	2	2	2	6	3	0	3	0	0						20
T15	01/02/1986	0,084	0,917	20				0	0	1	2	3	1	2	0	0	1	1	5							16
T16	01/06/1986	0,413	0,586	20				0	2	1	2	0	0	0	0	1	0	5	1							12
T17	01/12/1990	1	0,084	20	0	0	0	0	2	2	0	0	0	0	0											4
T18	01/11/1992	1	0,167	20	1	0	0	0	0	1	2	0	0													4
T19	01/05/1986	0,328	0,671	20				0	0	1	1	0	3	0	1	1	0	1	5							13
T20	01/03/1987	0,161	0,838	20			0	0	0	0	0	1	0	1	0	1	2	2								7
failure count,n					1	1	4	1	11	8	19	13	23	19	27	14	27	38	29	22	24	6	7	5	1	300
operating time				848	126,56	175,556	249,936	346,8	445,832	521,2	601,928	620	675,004	772,592	729,68	721,42	672,488	597,988	501,16	402,112	326,8	242,784	208	136,24	12,048	9086,128
λ					7,90E-03	5,70E-03	1,60E-02	2,88E-03	2,47E-02	1,53E-02	3,16E-02	2,10E-02	3,41E-02	2,46E-02	3,70E-02	1,94E-02	4,01E-02	6,35E-02	5,79E-02	5,47E-02	7,34E-02	2,47E-02	3,37E-02	3,67E-02	8,30E-02	
λ up					4,40E-02	3,17E-02	4,10E-02	1,61E-02	4,41E-02	3,02E-02	4,93E-02	3,59E-02	5,11E-02	3,84E-02	5,38E-02	3,26E-02	5,84E-02	8,69E-02	8,31E-02	8,27E-02	1,09E-01	5,38E-02	6,94E-02	8,57E-02	4,62E-01	
λ low					2,00E-04	1,44E-04	4,36E-03	7,30E-05	1,23E-02	6,63E-03	1,90E-02	1,12E-02	2,17E-02	1,48E-02	2,44E-02	1,06E-02	2,65E-02	4,52E-02	3,88E-02	3,44E-02	4,72E-02	9,06E-03	1,35E-02	1,19E-02	2,10E-03	

Table A2.1. Data for group A

Group R															AGE											
UNIT	START UP	L_TAIL	R_TAIL	EQP	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	# of failures
U01	01/12/1981	0,915	0,084	12									0	0	0	0	0	0	0	0	1	0	0	0		1
U02	01/02/1983	0,084	0,917	12							0	0	0	0	1	1	0	0	0	0	1	0				3
U03	01/11/1983	0,832	0,167	12							0	0	0	0	0	0	0	0	0	0	0	0				0
U04	01/10/1983	0,747	0,252	12							0	0	0	0	0	0	0	1	1	2	0	0				4
U05	01/02/1984	0,084	0,917	12						0	0	1	0	0	2	0	0	0	0	0	0					3
U06	01/08/1984	0,58	0,419	12						0	0	0	0	0	0	0	0	0	0	0	0					0
U07	01/03/1987	0,161	0,838	12			0	0	0	0	2	0	0	0	0	0	2	0								4
U08	01/04/1988	0,246	0,753	12		0	0	1	0	1	0	0	0	0	1	0	0									3
U09	01/04/1984	0,246	0,753	12						0	0	1	2	1	0	0	0	0	0	1	0					5
U10	01/04/1985	0,246	0,753	12					0	0	0	0	0	0	0	0	0	0	0	0						0
U11	01/09/1984	0,665	0,334	12						1	1	4	0	0	0	0	0	0	0	0	0					6
U12	01/02/1985	0,084	0,917	12					0	0	1	0	0	0	1	0	0	0	0	0						2
U13	01/09/1980	0,665	0,334	12										1	3	0	0	0	0	0	0	0	0	0	0	4
U14	01/02/1981	0,084	0,917	12									0	0	0	1	1	1	0	0	0	0	0	0		3
U15	01/05/1981	0,328	0,671	12									0	0	0	0	0	1	0	0	0	0	0	0		1
U16	01/11/1981	0,832	0,167	12									0	0	0	0	0	0	0	0	2	0	0	0		2
U17	01/11/1980	0,832	0,167	12										0	0	0	0	2	0	0	0	0	0	0	0	2
U18	01/12/1980	0,915	0,084	12										0	0	2	0	0	0	0	0	0	0	0	0	2
U19	01/06/1981	0,413	0,586	12									0	1	0	0	0	0	0	1	0	0	0	0		2
U20	01/10/1981	0,747	0,252	12									0	0	0	0	0	0	0	0	2	1	0	0		3
U21	01/01/1985	1	0,002	12						0	0	0	0	0	0	1	0	0	0	2	0					3
U22	01/10/1985	0,747	0,252	12					0	0	0	0	0	0	0	0	1	0	0	0						1
U23	01/08/1983	0,58	0,419	12							0	1	0	0	0	0	3	0	1	0	1	0				6
U24	01/08/1983	0,58	0,419	12							0	0	0	0	0	0	0	1	0	2	1	0				4
U25	01/12/1980	0,915	0,084	12										0	0	0	0	0	0	0	0	3	0	0	0	3
U26	01/12/1980	0,915	0,084	12										0	0	0	0	0	0	0	1	1	0	0	0	2
U27	01/05/1981	0,328	0,671	12									0	0	0	0	0	1	0	0	0	0	0	0		1
U28	01/11/1981	0,832	0,167	12									0	0	0	0	0	0	0	1	1	0	0	0		2
T01	01/06/1988	0,413	0,586	17		0	0	0	1	0	0	3	0	0	1	0	1									6
T02	01/01/1989	1	0,002	17		0	4	0	0	0	1	1	1	0	0	0	0									7
T03	01/04/1987	0,246	0,753	17			0	1	0	0	0	0	0	3	1	0	1	1								7
T04	01/02/1988	0,084	0,917	17		0	0	0	2	0	1	2	1	0	2	0	0									8
T05	01/02/1991	1	0,917	17	0	0	0	1	2	0	0	0	0	0												3
T06	01/01/1992	1	0,002	17	1	4	1	0	1	0	0	0	0	0												7
T07	01/12/1986	0,915	0,084	17				0	1	0	0	0	0	1	0	0	0	0	0							2
T08	01/03/1987	0,161	0,838	17			0	0	0	0	0	0	0	1	0	0	0	0								1
T09	01/02/1991	1	0,917	17	0	0	0	0	0	0	0	0	0	0												0
T10	01/03/1994	1	0,838	17	1	0	1	4	0	1	0															7
T11	01/02/1988	0,084	0,917	17		0	0	0	0	0	0	1	0	0	0	0	1									2
T12	01/05/1989	0,328	0,671	17	0	2	0	0	1	0	0	0	0	0	0	2										5
T13	01/12/1985	0,915	0,084	17					0	0	1	0	0	0	1	1	4	3	0	0						10
T14	01/12/1985	0,915	0,084	17					0	1	0	3	0	0	1	0	1	0	1	0						7
T15	01/02/1986	0,084	0,917	17				0	0	0	0	0	0	0	0	0	3	0	0							3
T16	01/06/1986	0,413	0,586	17				2	0	0	1	0	0	2	0	4	0	2	0							11
T17	01/12/1990	1	0,084	17	0	0	0	0	0	0	0	0	0	0	0											0
T18	01/11/1992	1	0,167	17	0	0	0	0	0	0	0	0	0													0
T19	01/05/1986	0,328	0,671	17				0	0	0	0	0	0	0	1	0	0	0	0							1
T20	01/03/1987	0,161	0,838	17			0	0	1	0	0	1	2	0	0	1	1	3								9
# of failures, n					2	6	6	9	9	4	8	18	6	10	15	13	19	16	3	9	10	5	0	0	0	168
operating time				676	107,576	148,829	210,588	291,58	374,034	430,9	491,122	503	542,587	613,116	575,428	568,407	527,21	465,349	384,386	301,92	245,1	182,088	156	102,18	9,036	7230,436
λ					1,86E-02	4,03E-02	2,85E-02	3,09E-02	2,41E-02	9,28E-03	1,63E-02	3,58E-02	1,11E-02	1,63E-02	2,61E-02	2,29E-02	3,60E-02	3,44E-02	7,80E-03	2,98E-02	4,08E-02	2,75E-02	0,00E+00	0,00E+00	0,00E+00	
λ up					6,72E-02	8,78E-02	6,20E-02	5,86E-02	4,57E-02	2,38E-02	3,21E-02	5,65E-02	2,41E-02	3,00E-02	4,30E-02	3,91E-02	5,63E-02	5,58E-02	2,28E-02	5,66E-02	7,50E-02	6,41E-02	2,37E-02	3,61E-02	4,08E-01	
λ low					2,25E-03	1,48E-02	1,04E-02	1,41E-02	1,10E-02	2,53E-03	7,03E-03	2,12E-02	4,05E-03	7,82E-03	1,46E-02	1,22E-02	2,17E-02	1,97E-02	1,61E-03	1,36E-02	1,96E-02	8,92E-03	0,00E+00	0,00E+00	0,00E+00	

Table A2.2. Data for group R

Group UA														AGE											
UNIT	START UP	L_TAIL	R_TAIL	EQP	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	# of failures
U01	01/12/1981	0,915	0,084	16								1	0	0	0	0	0	1	1	1	2	3	0		9
U02	01/02/1983	0,084	0,917	16						0	0	0	1	1	1	2	0	0	2	2	1				10
U03	01/11/1983	0,832	0,167	16						0	0	0	0	0	0	1	1	3	1	5	0				11
U04	01/10/1983	0,747	0,252	16						0	0	0	1	0	0	3	7	2	7	4	1				25
U05	01/02/1984	0,084	0,917	16					0	0	0	0	0	0	0	1	0	0	0	1					2
U06	01/08/1984	0,58	0,419	16					0	0	0	0	1	0	0	1	0	0	0	1					3
U07	01/03/1987	0,161	0,838	16		0	0	1	0	0	0	2	0	0	0	0	0								3
U08	01/04/1988	0,246	0,753	16	0	1	0	0	0	2	1	0	0	2	0	0									6
U09	01/04/1984	0,246	0,753	16					0	0	0	0	0	1	0	0	0	0	0	0					1
U10	01/04/1985	0,246	0,753	16				0	0	0	1	2	0	0	1	0	0	0	0						4
U11	01/09/1984	0,665	0,334	16					0	0	0	1	2	0	0	0	3	1	0	0					7
U12	01/02/1985	0,084	0,917	16				0	0	0	0	1	1	0	0	0	1	0	0						3
U13	01/09/1980	0,665	0,334	16									1	0	0	1	0	2	0	2	0	0	0	1	7
U14	01/02/1981	0,084	0,917	16								0	2	2	1	0	0	0	0	2	0	0	0		7
U15	01/05/1981	0,328	0,671	16								0	1	0	1	0	2	0	0	0	0	0	0		4
U16	01/11/1981	0,832	0,167	16								1	0	0	0	2	1	1	0	0	0	0	0		5
U17	01/11/1980	0,832	0,167	16									0	0	0	0	0	0	0	0	1	2	0	0	3
U18	01/12/1980	0,915	0,084	16									1	0	1	0	1	1	0	1	0	1	1	0	7
U19	01/06/1981	0,413	0,586	16								0	0	0	0	0	1	2	0	0	1	0	0		4
U20	01/10/1981	0,747	0,252	16								0	0	0	0	0	0	0	0	0	0	1	0		1
U21	01/01/1985	1	0,002	16					0	0	0	0	0	0	0	1	0	0	0	0					1
U22	01/10/1985	0,747	0,252	16				0	0	1	0	3	0	5	0	0	0	0	0						9
U23	01/08/1983	0,58	0,419	16						0	0	0	0	0	0	2	0	0	1	1	0				4
U24	01/08/1983	0,58	0,419	16						0	0	0	0	0	0	2	3	0	0	0	0				5
U25	01/12/1980	0,915	0,084	16									0	0	0	0	0	1	5	1	0	0	0	0	7
U26	01/12/1980	0,915	0,084	16									0	0	0	0	0	0	3	2	0	0	0	0	5
U27	01/05/1981	0,328	0,671	16								0	0	0	0	1	2	0	2	0	0	0	1		6
U28	01/11/1981	0,832	0,167	16								0	0	0	0	0	0	0	0	1	0	0	3		4
# of failures, n					0	1	0	1	0	3	2	11	11	11	5	17	22	14	22	24	6	7	5	1	163
operating time				448	3,936	18,576	32	49,232	121,2	205,168	240	311,664	435,872	448	448	444,048	429,408	416	398,752	326,8	242,784	208	136,24	12,048	4927,728
λ					0,00E+00	5,38E-02	0,00E+00	2,03E-02	0,00E+00	1,46E-02	8,33E-03	3,53E-02	2,52E-02	2,46E-02	1,12E-02	3,83E-02	5,12E-02	3,37E-02	5,52E-02	7,34E-02	2,47E-02	3,37E-02	3,67E-02	8,30E-02	
λ up					9,38E-01	3,00E-01	1,15E-01	1,13E-01	3,04E-02	4,27E-02	3,01E-02	6,31E-02	4,52E-02	4,39E-02	2,60E-02	6,13E-02	7,75E-02	5,65E-02	8,34E-02	1,09E-01	5,38E-02	6,94E-02	8,57E-02	4,62E-01	
λ low					0,00E+00	1,36E-03	0,00E+00	5,14E-04	0,00E+00	3,02E-03	1,01E-03	1,76E-02	1,26E-02	1,23E-02	3,63E-03	2,23E-02	3,22E-02	1,84E-02	3,47E-02	4,72E-02	9,06E-03	1,35E-02	1,19E-02	2,10E-03	

Table A2.3. Data for group U-A

Group U-R											AGE										
UNIT	START UP	L_TAIL	R_TAIL	EQP	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	# of failures
U01	01/12/1981	0,915	0,084	12								0	0	0	0	0	0	0	0	1	0	0	0		1
U02	01/02/1983	0,084	0,917	12						0	0	0	0	1	1	0	0	0	0	1	0				3
U03	01/11/1983	0,832	0,167	12						0	0	0	0	0	0	0	0	0	0	0	0				0
U04	01/10/1983	0,747	0,252	12						0	0	0	0	0	0	0	1	1	2	0	0				4
U05	01/02/1984	0,084	0,917	12					0	0	1	0	0	2	0	0	0	0	0	0					3
U06	01/08/1984	0,58	0,419	12					0	0	0	0	0	0	0	0	0	0	0	0					0
U07	01/03/1987	0,161	0,838	12		0	0	0	0	2	0	0	0	0	0	2	0								4
U08	01/04/1988	0,246	0,753	12	0	0	1	0	1	0	0	0	0	1	0	0									3
U09	01/04/1984	0,246	0,753	12					0	0	1	2	1	0	0	0	0	0	1	0					5
U10	01/04/1985	0,246	0,753	12				0	0	0	0	0	0	0	0	0	0	0	0						0
U11	01/09/1984	0,665	0,334	12					1	1	4	0	0	0	0	0	0	0	0	0					6
U12	01/02/1985	0,084	0,917	12				0	0	1	0	0	0	1	0	0	0	0	0						2
U13	01/09/1980	0,665	0,334	12									1	3	0	0	0	0	0	0	0	0	0	0	4
U14	01/02/1981	0,084	0,917	12								0	0	0	1	1	1	0	0	0	0	0	0		3
U15	01/05/1981	0,328	0,671	12								0	0	0	0	0	1	0	0	0	0	0	0		1
U16	01/11/1981	0,832	0,167	12								0	0	0	0	0	0	0	0	2	0	0	0		2
U17	01/11/1980	0,832	0,167	12									0	0	0	0	2	0	0	0	0	0	0	0	2
U18	01/12/1980	0,915	0,084	12									0	0	2	0	0	0	0	0	0	0	0	0	2
U19	01/06/1981	0,413	0,586	12								0	1	0	0	0	0	0	1	0	0	0	0		2
U20	01/10/1981	0,747	0,252	12								0	0	0	0	0	0	0	0	2	1	0	0		3
U21	01/01/1985	1	0,002	12					0	0	0	0	0	0	1	0	0	0	2	0					3
U22	01/10/1985	0,747	0,252	12				0	0	0	0	0	0	0	0	1	0	0	0						1
U23	01/08/1983	0,58	0,419	12						0	1	0	0	0	0	3	0	1	0	1	0				6
U24	01/08/1983	0,58	0,419	12						0	0	0	0	0	0	0	1	0	2	1	0				4
U25	01/12/1980	0,915	0,084	12									0	0	0	0	0	0	0	0	3	0	0	0	3
U26	01/12/1980	0,915	0,084	12									0	0	0	0	0	0	0	1	1	0	0	0	2
U27	01/05/1981	0,328	0,671	12								0	0	0	0	0	1	0	0	0	0	0	0		1
U28	01/11/1981	0,832	0,167	12								0	0	0	0	0	0	0	1	1	0	0	0		2
# of failures, n					0	0	1	0	2	4	7	2	3	8	5	7	7	2	9	10	5	0	0	0	72
operating time				336	2,952	13,932	24	36,924	90,9	153,876	180	233,748	326,904	336	336	333,036	322,056	312	299,064	245,1	182,088	156	102,18	9,036	3695,796
λ					0,00E+00	0,00E+00	4,17E-02	0,00E+00	2,20E-02	2,60E-02	3,89E-02	8,56E-03	9,18E-03	2,38E-02	1,49E-02	2,10E-02	2,17E-02	6,41E-03	3,01E-02	4,08E-02	2,75E-02	0,00E+00	0,00E+00	0,00E+00	
λ up					1,25E+00	2,65E-01	2,32E-01	9,99E-02	7,95E-02	6,65E-02	8,01E-02	3,09E-02	2,68E-02	4,69E-02	3,47E-02	4,33E-02	4,48E-02	2,32E-02	5,71E-02	7,50E-02	6,41E-02	2,37E-02	3,61E-02	4,08E-01	
λ low					0,00E+00	0,00E+00	1,05E-03	0,00E+00	2,66E-03	7,08E-03	1,56E-02	1,04E-03	1,90E-03	1,03E-02	4,84E-03	8,45E-03	8,74E-03	7,76E-04	1,38E-02	1,96E-02	8,92E-03	0,00E+00	0,00E+00	0,00E+00	

Table A2.4. Data for group U-R.

Group T-A												AGE									
UNIT	START UP	L_TAIL	R_TAIL	EQP	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	# of failures
T01	01/06/1988	0,413	0,586	20		0	0	0	0	0	3	0	0	1	0	0	1				5
T02	01/01/1989	1	0,002	20		1	1	0	0	0	1	0	0	1	0	0	0				4
T03	01/04/1987	0,246	0,753	20			0	0	0	1	1	0	0	0	0	0	0	0			2
T04	01/02/1988	0,084	0,917	20		0	0	0	0	0	0	0	1	0	0	0	0				1
T05	01/02/1991	1	0,917	20	0	0	0	1	0	0	0	0	1	0							2
T06	01/01/1992	1	0,002	20	0	0	0	0	0	0	0	0	0	0							0
T07	01/12/1986	0,915	0,084	20				0	4	0	1	1	0	0	4	0	1	0	2		13
T08	01/03/1987	0,161	0,838	20			0	0	0	0	1	3	2	0	1	1	1	1			10
T09	01/02/1991	1	0,917	20	0	0	2	0	0	0	0	0	0	0							2
T10	01/03/1994	1	0,838	20	0	0	0	0	0	0	1										1
T11	01/02/1988	0,084	0,917	20		0	0	0	0	0	0	0	0	0	0	0	1				1
T12	01/05/1989	0,328	0,671	20	0	0	0	0	0	0	0	0	0	0	0	0					0
T13	01/12/1985	0,915	0,084	20					2	0	0	1	2	1	4	2	3	3	2	0	20
T14	01/12/1985	0,915	0,084	20					0	1	1	2	2	2	6	3	0	3	0	0	20
T15	01/02/1986	0,084	0,917	20				0	0	1	2	3	1	2	0	0	1	1	5		16
T16	01/06/1986	0,413	0,586	20				0	2	1	2	0	0	0	0	1	0	5	1		12
T17	01/12/1990	1	0,084	20	0	0	0	0	2	2	0	0	0	0	0						4
T18	01/11/1992	1	0,167	20	1	0	0	0	0	1	2	0	0								4
T19	01/05/1986	0,328	0,671	20				0	0	1	1	0	3	0	1	1	0	1	5		13
T20	01/03/1987	0,161	0,838	20			0	0	0	0	0	1	0	1	0	1	2	2			7
# of failures, n					1	1	3	1	10	8	16	11	12	8	16	9	10	16	15	0	137
operating time				400	126,56	171,62	231,36	314,8	396,6	400	396,76	380	363,34	336,72	281,68	273,42	228,44	168,58	85,16	3,36	4158,4
λ					7,90E-03	5,83E-03	1,30E-02	3,18E-03	2,52E-02	2,00E-02	4,03E-02	2,89E-02	3,30E-02	2,38E-02	5,68E-02	3,29E-02	4,38E-02	9,49E-02	1,76E-01	0,00E+00	
λ up					4,40E-02	3,25E-02	3,79E-02	1,77E-02	4,64E-02	3,94E-02	6,54E-02	5,18E-02	5,77E-02	4,68E-02	9,22E-02	6,25E-02	8,05E-02	1,54E-01	2,90E-01	1,10E+00	
λ low					2,00E-04	1,47E-04	2,68E-03	8,04E-05	1,21E-02	8,64E-03	2,31E-02	1,44E-02	1,71E-02	1,03E-02	3,25E-02	1,51E-02	2,10E-02	5,43E-02	9,86E-02	0,00E+00	

Table A2.5. Data for group T-A

Group T-R												AGE									
UNIT	START UP	L_TAIL	R_TAIL	EQP	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	# of failures
T01	01/06/1988	0,413	0,586	17		0	0	0	1	0	0	3	0	0	1	0	1				6
T02	01/01/1989	1	0,002	17		0	4	0	0	0	1	1	1	0	0	0	0				7
T03	01/04/1987	0,246	0,753	17			0	1	0	0	0	0	0	3	1	0	1	1			7
T04	01/02/1988	0,084	0,917	17		0	0	0	2	0	1	2	1	0	2	0	0				8
T05	01/02/1991	1	0,917	17	0	0	0	1	2	0	0	0	0	0							3
T06	01/01/1992	1	0,002	17	1	4	1	0	1	0	0	0	0	0							7
T07	01/12/1986	0,915	0,084	17				0	1	0	0	0	0	1	0	0	0	0	0		2
T08	01/03/1987	0,161	0,838	17			0	0	0	0	0	0	0	1	0	0	0	0			1
T09	01/02/1991	1	0,917	17	0	0	0	0	0	0	0	0	0	0							0
T10	01/03/1994	1	0,838	17	1	0	1	4	0	1	0										7
T11	01/02/1988	0,084	0,917	17		0	0	0	0	0	0	1	0	0	0	0	1				2
T12	01/05/1989	0,328	0,671	17	0	2	0	0	1	0	0	0	0	0	0	2					5
T13	01/12/1985	0,915	0,084	17					0	0	1	0	0	0	1	1	4	3	0	0	10
T14	01/12/1985	0,915	0,084	17					0	1	0	3	0	0	1	0	1	0	1	0	7
T15	01/02/1986	0,084	0,917	17				0	0	0	0	0	0	0	0	0	3	0	0		3
T16	01/06/1986	0,413	0,586	17				2	0	0	1	0	0	2	0	4	0	2	0		11
T17	01/12/1990	1	0,084	17	0	0	0	0	0	0	0	0	0	0	0						0
T18	01/11/1992	1	0,167	17	0	0	0	0	0	0	0	0	0								0
T19	01/05/1986	0,328	0,671	17				0	0	0	0	0	0	0	1	0	0	0	0		1
T20	01/03/1987	0,161	0,838	17			0	0	1	0	0	1	2	0	0	1	1	3			9
# of failures, n					2	6	6	8	9	2	4	11	4	7	7	8	12	9	1	0	96
operating time				340	107,576	145,877	196,656	267,58	337,11	340	337,246	323	308,839	286,212	239,428	232,407	194,174	143,293	72,386	2,856	3534,64
λ					1,86E-02	4,11E-02	3,05E-02	2,99E-02	2,67E-02	5,88E-03	1,19E-02	3,41E-02	1,30E-02	2,45E-02	2,92E-02	3,44E-02	6,18E-02	6,28E-02	1,38E-02	0,00E+00	
λ up					6,72E-02	8,95E-02	6,64E-02	5,89E-02	5,07E-02	2,13E-02	3,04E-02	6,09E-02	3,32E-02	5,04E-02	6,02E-02	6,78E-02	1,08E-01	1,19E-01	7,69E-02	1,29E+00	
λ low					2,25E-03	1,51E-02	1,12E-02	1,29E-02	1,22E-02	7,12E-04	3,23E-03	1,70E-02	3,53E-03	9,84E-03	1,18E-02	1,49E-02	3,19E-02	2,87E-02	3,50E-04	0,00E+00	

Table A2.6. Data for group T-R

European Commission

EUR 22483 EN – DG JRC – Institute for Energy
Models and data used for assessing the ageing of systems, structures and components (European Network on Use of Probabilistic Safety Assessment (PSA) for Evaluation of Ageing Effects to the Safety of Energy Facilities)

Author(s) :
C.Atwood, O.Cronval, M.Patrik, A. Rodionov

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Abstract
This report summarizes and presents the results of the studies conducted in the frame of European Network on Use of Probabilistic Safety Assessment (PSA) for Evaluation of Ageing Effects to the Safety of Energy Facilities (EC JRC IE Ageing PSA Network). The Network was initiated and will be operated within the framework of the JRC FP-6/7 Institutional Action "Analysis and Management of Nuclear Accidents" (AMA).
Report is focussed on the reliability models and data could be used for assessing the ageing of systems, structures and components including statistical and physical ones. The results of the case study on demonstration of possible application of statistical evaluation of ageing trend in case of I&C and electrical components presented in Appendix B.