EC JRO NETWORK ON USE OF PSA FOR EVALUATION OF AGING EFFECTS TO THE SAFETY OF ENERGY FACILITIES, ACTIVITIES, AND RESULTS

A. Rodionov\textsuperscript{a}, D. Serbanescu\textsuperscript{a}, M. Patrick\textsuperscript{b}
\textsuperscript{a} – Nuclear Safety Unit, European Commission Joint Research Center Institute for Energy, Netherlands.
\textsuperscript{b} – Nuclear Research Institute Rez, Czech Republic.

Email address of main author: andrei.rodionov@jrc.nl

Abstract

This paper summarises some research study results and discussions followed on the use of PSA for evaluating the SSC ageing effect on overall plant safety carried out in the framework of the EC's JRC Network on the Use of Probabilistic Safety Assessment (PSA) for the Evaluation of Ageing Effects on the Safety of Energy Facilities (Ageing PSA) [1].

1. Introduction

IAEA PRIS data on the ageing profile of nuclear generation [2] shows that currently (as of 26 June 2007) 114 units have been in operation between 30 and 40 years and 213 between 20 and 30 years, which adds up to about three quarters of the 438 reactors operated worldwide.

More and more utilities, nowadays, are moving to a policy of long-term operation. In the US, for example, as of July 2006, approximately one half of the licensed plants had either received or were under review for license renewal [3].

This means that, in the next decade, ageing management and life extension issues will become one of the key points of nuclear safety.

The basic interest in using PSA to evaluate ageing stems from the requirement to meet safety goals over the whole lifecycle of the nuclear installation (including its extended lifetime). In probabilistic terms, INSAG-12 [4] specifies the safety goal as follow:

"The target for existing nuclear power plants consistent with the technical safety objective is a frequency of occurrence of severe core damage that is below about $10^{-4}$ events per plant operating year. Severe accident management and mitigation measures could reduce by a factor of at least ten the probability of large off-site releases requiring short term off-site response."

Another motive for ageing PSA development is a worldwide tendency to apply risk-informed regulation, in which the PSA approach and results play a key role (see figure 1) [5].
The possible impact of ageing phenomena on System, Structure and Components (SSC) reliability and on overall plant safety is illustrated in the risk-barrier-target diagram, Figure 2. Each of the “barriers” that utilities use to decrease or to avoid the impact of ageing is covered in some way by the risk-informed regulation approach.

Presently, ageing evaluation-related activities have been or are being carried out as part of the following programmes:

- Periodic safety review,
- Ageing management,
- Maintenance optimisation,
- Lifetime extension.

There are number of national and international standards and guidelines available [6], but all of them in general are based on the deterministic approach and describe very limited PSA application.

The PSA could be incorporated more into these programmes as a safety evaluation tool to help identify and prioritise ageing issues and optimise ageing management activities.

In general, to apply PSA in a risk-informed approach, PSA should be as realistic as practical and appropriate support data should be available for the review. This is also true if PSA should be applied to characterize potential risks associated with ageing effects.

Could PSA be applied to ageing assessments? How realistically do PSA models reflect important ageing issues? Are any modifications or revisions of PSA assumptions needed to apply a PSA approach to risk-informed decision making with regard to ageing evaluation? What data are available and how representative are they with regard to important ageing issues?
All these and others related questions prompted the setting up of the EC JRC Ageing PSA Network.

2. Presentation of EC JRC Ageing PSA network

The initial motivation behind the Network on the Use of Probabilistic Safety Assessment (PSA) for the Evaluation of Ageing Effects on the Safety of Energy Facilities (Ageing PSA) was the fact that current standard PSA tools do not adequately address important ageing issues, which could have a significant impact on the conclusions drawn from PSA studies and applications where plants are operated at an advanced age or long term.

For instance:
- reliability models for components are based on the "component constant failure rate" assumption, which may not be valid in the long term;
- the reliability data used in the PSAs may not even adequately represent the current status of the plants, because the data was mostly collected during PSA development; it might reflect the situation at the beginning of operation, but equipment reliability could deteriorate with time;
- existing PSAs traditionally overlook some components (e.g. cables, structures, etc.) as having a very low probability of failure, but they may have increasing weight due to ageing effects.

The problem with applying the PSA approach to evaluating ageing effects is that experience in this area is limited worldwide; there are no commonly accepted methods, all the studies are performed by relatively isolated organisations, and publications on the subject are scarce.

The knowledge resulting from the Ageing PSA Network should help PSA developers and users:
- to incorporate the effects of equipment ageing into current PSA tools and models to perform engineering analysis,
- where PSA cannot be applied (where there are no or inadequate probabilistic ageing models or a lack of data, etc.), to specify and prioritise reliability monitoring actions/approaches to ensure that any decrease in the reliability of SSC is identified and corrected in time,
- to promote the use of PSA for ageing management and risk-informed applications for nuclear power plants.

The Ageing PSA Network is under development as part of JRC FP-7 institutional Project No 52101 "Analysis and Management of Nuclear Accidents" (AMA) [1].

So far, 14 organisations have joined:
- NRSC, Armenia,
- TU of Sofia, Bulgaria,
- NRI Rez, Czech Republic,
- JRC IE, European Commission,
- IRSN, France,
- VEIKI, Hungary,
- ENEA, Italy,
- KAERI, South Korea,
- LEI, Lithuania,
- JSI, Slovenia,
- KKG, Swiss,
- INR, Romania,
- CNE-prod, Romania,
- IATE, Russian Federation.

The main tasks to be covered by Network activities are as follows:
- Task 1. Organisation and coordination of network activities.
- Task 2. Analysis of main PSA tasks with regard to Ageing PSA.
• Task 3. Selection of the SSC to be considered in Ageing PSA.
• Task 4. Reliability and data analysis for active components.
• Task 5. Reliability and data analysis for active components II. Common Cause Failures.
• Task 6. Reliability and data analysis for passive components.
• Task 7. Incorporation of age-dependent reliability parameters and data into PSA model. Interpretation of quantification results.
• Task 8. Ageing PSA development and applications.

Presently, Tasks 2-4 and 7 are under development.
The Network operates via joint case studies and benchmarking exercises, expert meetings and workshops. More information about Network activities can be found on the following web site: http://www.energyrisks.jrc.nl/APS/.
The following chapters provide brief summaries and discuss some outputs of Tasks 2 and 4.

3. Analysis of main PSA tasks with regard to Ageing PSA

Broadly speaking, PSA could be applied to ageing management and risk-informed decision-making in two ways:
• as a tool to demonstrate and monitor the current level of safety, and
• in predictive risk evaluation.

Using PSA to demonstrate the current safety level involves:
• analysing ageing trends for safety important components,
• identifying components susceptible to ageing, but not modelled in PSA,
• updating reliability parameters (□=const) for PSA components with recent operating experience and inputting them into PSA,
• estimating reliability parameters for components identified as susceptible to ageing but not modelled in PSA, and introducing them into the PSA model,
• performing sensitivity analysis of ageing issues.

For predictive risk assessment the following steps could be taken:
• reviewing the scope and assumptions of PSA,
• reviewing initiating events,
• analysing ageing trends for safety-important components,
• identifying components susceptible to ageing, but not modelled in PSA,
• devising age-dependent reliability models (statistic and physic),
• introducing them into PSA (considering, where necessary, test and maintenance effectiveness and periodicity),
• performing time-dependent quantifications and sensitivity analysis.

Table 1 presents the expert opinions concerning the modifications or revisions of PSA assumptions and models that could be needed to consider ageing issues in PSA.
The table was drafted using the list of main PSA tasks as defined in the IAEA guideline on PSA level 1 [7] and insights from different US NRC and EC JRC studies concerning the incorporation of ageing effects into PSA models [8].
Table 1.

<table>
<thead>
<tr>
<th>PSA task / issue</th>
<th>Possible modifications in PSA</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>1. Definition of scope, objective of the study</strong></td>
<td></td>
</tr>
<tr>
<td>Level of detail</td>
<td>Depending on the specific application the level of detail could be revised.</td>
</tr>
<tr>
<td></td>
<td>For example, for a risk-informing application, PSA has to be sufficient to characterise or/and model the impact of the relevant ageing issue. The specification of the problem should include establishing a cause-and-effect relationship to identify portions of the PSA affected by the issue being evaluated.</td>
</tr>
<tr>
<td>Scope of SSCs to address ageing effects</td>
<td>The selection of SSC to be modelled in Ageing PSA is not easy. The starting points could be the results of deterministic analysis performed under the Ageing Management programme, reliability trend assessments and the risk importance of SSC evaluated using the existing PSA model.</td>
</tr>
<tr>
<td><strong>2. Initiating events analysis</strong></td>
<td></td>
</tr>
<tr>
<td>New initiators</td>
<td>“New” initiators may become important that may previously have been excluded due to low likelihood. Examples could include pipe breaks or flooding scenarios that were thought to be unlikely.</td>
</tr>
<tr>
<td>Initiator assumptions</td>
<td>Since ageing could entails failure modes or mechanisms not previously addressed, it is important to review the existing PSA initiator assumptions. Initiators that have been grouped (e.g., transients, main steam line breaks) may need to be broken out. New groups could be built up based on new common assumptions.</td>
</tr>
<tr>
<td><strong>3. Accident sequence analysis</strong></td>
<td></td>
</tr>
<tr>
<td>Sequence timing issues</td>
<td>Ageing affects on batteries, seals, etc., could affect multiple basic events that rely on timing considerations (e.g., recovery actions) as part of an accident sequence.</td>
</tr>
<tr>
<td>Sequence ordering and end state criteria</td>
<td>The accident sequence events will need to be reviewed to ensure that ageing affects do not change the attributes of the sequence.</td>
</tr>
<tr>
<td>Intersystem dependencies</td>
<td>Intersystem dependencies may need to be added to the PSA model to better treat the ageing effect. For example, poor water chemistry control may affect multiple piping segments in more than one location.</td>
</tr>
<tr>
<td>Consequential events</td>
<td>Consequential events could be important given the potential for safety system degradation in conjunction with internal flooding. For example, rupture of piping may cause localised flooding that impacts on other important systems.</td>
</tr>
<tr>
<td>Success criteria and supporting analysis</td>
<td>Safety system success criteria could be modified. For instance, a radiation embrittlement of RPV could require the minimum allowed ECCS water temperature to be increased.</td>
</tr>
<tr>
<td>PSA task / issue</td>
<td>Possible modifications in PSA</td>
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<td>------------------</td>
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</tr>
<tr>
<td><strong>4. Systems analysis</strong></td>
<td></td>
</tr>
<tr>
<td>Incorporating components neglected in standard PSA</td>
<td>The fault tree logic should be changed to represent new basic events (e.g., passive components or neglected active components) important to the functioning of specific systems. Examples could include tanks, vessels and piping events.</td>
</tr>
<tr>
<td>Changes to logic structure</td>
<td>Changes to the fault tree logic (e.g., change in success criteria due to heat transfer capacity or pressure capacity changes) should be made to incorporate the physical ageing models that are used. Ageing-related CCF could be considered not only at redundant component level, but also in safety function redundancy (CCFs of identical sensors installed in different systems which fulfil the same safety function).</td>
</tr>
<tr>
<td>Additional maintenance/testing</td>
<td>Component ageing may result in changes to maintenance and testing practices. Analysis should take into account maintenance or testing on passive components before potential failures.</td>
</tr>
<tr>
<td>New common cause failure mechanisms</td>
<td>Dependent failures may be modelled as part of the fault tree adjustment to incorporate the passive components. For example, failure of a piping header may defeat the redundant trains of a safety system.</td>
</tr>
<tr>
<td>Previsouly ignored failure mechanisms</td>
<td>If ignored failure mechanisms become evident during the analysis, they should be added. Ageing mechanisms are, in general, not accounted for in current PSA models. Therefore, in some cases, the relationship between the ageing mechanism and failure modes has to be identified and evaluated.</td>
</tr>
<tr>
<td>Level of detail, boundary of components</td>
<td>In relation to some applications, failure modes due to specific degradation mechanisms should be modelled in fault trees with the appropriate level of detail. On the other hand, a lack of statistical data could require several failure modes which have the same failure/ageing mechanisms to be grouped together.</td>
</tr>
<tr>
<td><strong>5. Human reliability analysis</strong></td>
<td></td>
</tr>
<tr>
<td>Conditions for human interventions</td>
<td>Ageing may have an impact on the time window needed for specific manipulation/recovery etc., and consequently on the failure probability of specific interventions. Conditions for operators within particular interventions should be revised in connection with ageing.</td>
</tr>
<tr>
<td>Support information for the operator</td>
<td>Ageing may have an impact on the availability of information from the plant unit that the operator needs in order to take a decision. If the availability of such information is included within the boundary of the operator failure event, it should be revised. (In some studies availability of information is modelled outside the boundary of human failure and therefore it is not necessary to revise it.)</td>
</tr>
<tr>
<td><strong>6. Data analysis</strong></td>
<td></td>
</tr>
<tr>
<td>PSA task / issue</td>
<td>Possible modifications in PSA</td>
</tr>
<tr>
<td>-----------------------------------------------------</td>
<td>--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>Time-dependent failure rates, initiator frequencies</td>
<td>Standard PSA is based on the use of constant failure rates. In Ageing PSA, especially in predictive evaluation, time dependent models should be implemented and used. Predictive evaluation of risk, based on extrapolation of the component reliability function over time, is important for example to identify operational weaknesses and priorities for ageing management in unit LTO. The uncertainties of such extrapolation could be an important issue in choosing the model.</td>
</tr>
<tr>
<td>Failure rates</td>
<td>A physical ageing model (e.g., corrosion, fatigue, stress corrosion cracking), can affect component failure rates. The possibility of conditional ageing-related failures also needs to be investigated (e.g. failure given initiator, etc.). Constructing time-dependent failure rates for active components requires more data than is usually available in PSA reliability data collection, especially in considering inspection and maintenance impact or lifetime.</td>
</tr>
<tr>
<td>Mission times</td>
<td>The basic event mission times are determined by decay heat removal times, recovery and isolation times, arrival rates of offsite resources, etc. Ageing could affect some of these parameters, but it is expected to be a secondary impact on core damage frequency.</td>
</tr>
<tr>
<td>Repair times and maintenance duration</td>
<td>Repair times and maintenance duration could be affected by ageing. Assumed plant operational practices for repair and maintenance should be incorporated into the plant PSA model where appropriate. In many cases, an increase in the component failure rate may not be observed due to increased preventive maintenance, which may entail increased downtime for the component.</td>
</tr>
<tr>
<td>Testing intervals</td>
<td>Test intervals and duration could be affected by ageing. Assumed operational testing practices should be incorporated into the plant PSA model where appropriate. Another factor related to testing intervals is the positive benefit from inspections. Many ageing mechanisms may be managed (i.e. reducing the risk) by proper inspections. These inspections should be credited in the analysis when possible.</td>
</tr>
</tbody>
</table>

**7. Dependent failures analysis**

Dependent failures

Ageing could cause new dependent failures to arise due to a common ageing mechanism such as FAC. It is assumed that the total failure rate for a component could be affected by ageing impacts. The ageing effect on the allocation of failures (e.g., the beta, gamma, delta parameters for the Multiple Greek Letter model) should also be evaluated.

**8. LERF Calculation**

Treatment of non-dominant sequences

If non-dominant sequences become more important, the applicability of existing recovery rules and logic modelling will have to be evaluated.
### PSA task / issue | Possible modifications in PSA
--- | ---
**9. Model calculation, interpretation of results, etc.**
Prediction of risk level | Time-dependent models needed for extrapolation have to be integrated into the model. Depending on the type of modelling, more calculations will be required to evaluate the risk profile over time.

**10. Others**
Computer codes | The treatment of input parameters for basic events and uncertainty calculation could prompt some changes or adjustments to computer codes.

### 4. Reliability and data analysis for active components

#### 4.1. Background

Drafting time-dependent component reliability models and estimating parameters could be two tasks of the Ageing PSA for application to predictive risk evaluation. Where statistical data is available, this task could be performed in several steps:

I. perform ageing trend analysis to identify the component groups sensitive to ageing,

II. for the selected component groups, fit one of the parametrical models and calculate the model parameters,

III. if necessary, improve the results of estimations by applying a Bayesian approach and generic data,

IV. evaluate the unavailability factors for given age values, taking into account model parameters, periodical tests and maintenance data.

Note that reliability analysis itself could help a utility in identifying ageing trends, justifying maintenance optimisation and predictively evaluating lifetimes.

Several case studies were performed to demonstrate the methods and approaches which could be applied for steps I and II. A summary of the results is presented in paragraph 4.3. The case studies on Bayesian analysis and unavailability factor estimation are currently being conducted.

#### 4.2. Reliability data needed for ageing assessment. Availability and accessibility.

Before presenting reliability models and statistical approaches, it must be made clear what data are needed and available for age-dependent reliability assessments.

For this purpose, Network participants answered a questionnaire about their reliability data collection and data availability.

Figure 3 is a greatly simplified representation of relations between three types of data considered potentially available for age-dependent reliability analysis:

- PSA reliability data,
- Other specific reliability data collections,
- Raw operating and maintenance data.

Engineers involved in PSA development and applications are familiar with PSA reliability data, which include initiating event frequencies and component reliability parameters. These data are directly used in PSA Event Tree and Fault Tree models.
Most important information collected and treated during PSA reliability data collection and processing is normally documented in the relevant PSA task reports and/or databases. These processed data are usually well structured and of high quality.

However, Network participants stated that the PSA reliability data collection process does not include any requirement to perform a statistical validation of assumptions about constant failure rate or trend analysis.

Processed data about failures and component performance could be certainly used for age-dependent reliability analysis, but is not enough for this purpose. Consequently, additional data has to be extracted and processed from raw data sources.

For different potential applications, three types of time-dependent reliability models were identified:

- Type 1: simple age-dependent reliability models or trend assessment techniques;
- Type 2: age-dependent reliability models including test and maintenance effect evaluations;
- Type 3: comprehensive age-dependent reliability models, for use in APSA, maintenance optimisation and lifetime analysis.

For each type of model, categories of additional data were specified:

- Type 1: Categories of reliability data needed other than PSA are:
  - component commissioning date (age 0),

**FIG. 3. Potential data sources for age-dependent reliability analysis**
- failure/censoring times (age at the time of failure/censoring),
- component replacement – date and cause.

- Type 2: Categories of additional data needed are the data listed for Type 1, plus:
  - characteristics of applied tests and maintenance strategy – type and periodicity,
  - degree of component renewal during maintenance (corrective maintenance, preventive maintenance).

- Type 3: Categories of additional data needed are the data listed for Type 1 and Type 2, plus:
  - component lifetime (design/manufacture specification, qualification tests results),
  - real cumulative number of hours in operation, number of demands,
  - information about average and extreme levels of operating and environmental stressors.

Unfortunately, raw data are not always available or easily extractable. An expert evaluation of availability and accessibility of data for different types of reliability models is shown in Figure 4.

The diagram reflects an average situation with availability and accessibility of raw data between 8 different organisations that responded to the questionnaire. This diagram demonstrates that even for simple age-dependent reliability assessments for which most of the data are available, the cost of additional data processing could be quite high. If one has to apply reliability models to maintenance analysis and optimisation, or to lifetime evaluation and prediction, additional data collection and processing efforts would have to be made. Network participants agreed that improving reliability data collection could greatly help with Ageing PSA and age-dependent reliability analysis applications.

![Availability and accessibility of data for different types of reliability models](image)

**FIG. 4. Availability and accessibility of data for different types of reliability models**

### 4.3. Demonstration of statistical approaches to identifying component ageing by means of operational data assessment. Case study [9].

**Objectives and scope**

Where there are many SSCs and good collection of operating experience data, statistical methods could be applied to identify the onset of the ageing effect on SSC reliability. In that
case, the simplest task of statistical analysis is to investigate whether the SSC failure rate is approximately constant.

Various statistical tests could be used to validate or to refute the assumption of constant failure rate. Some of them are discussed in NUREG/CR-6823 [10]. According to the statistical technique used they can be divided into three groups:

- graphs (visual evaluation),
- nonparametric hypothesis tests,
- parametric hypothesis tests.

The purpose of the study was to demonstrate available statistical techniques that could be used for ageing analysis of reliability data collected in the framework of PSA development.

### Data specification

To demonstrate the methods’ applicability and compare the results of the case study the data set presented in Appendix B2 of reference [9] was used. This data set represents the “virtual” failure and replacement dates of “virtual” electrical or I&C components. The data profile is quite close to the real operating experience data collected, for example, on French [9] or German [11] nuclear power plants. In particular, it is a large sample that represents one technological group of components. The data are censored by interval, that is, the times in operation are truncated right and left. The components in the sample (at various units) were not all put into service on the same date, and consequently are not all the same age on the starting and end dates of observation.

Such a data set could be constructed using PSA reliability data with the addition of two further assumptions:

- dates of equipment commissioning, at which time the component age = 0, are equal to unit commissioning dates;
- in the event of replacement, installed (replaced) equipment was new immediately after equipment replacement.

An example of the data set referred to as “T-A” rearranged by age of components is given in Figure 5. The white/green areas on the “age” scale correspond to the data collection periods. The oldest units, T-13 and T-14, were already over 4 years old when data collection began, and the youngest unit, T-10, was not commissioned until data collection had been underway for over 4 years.
FIG. 5. T-A data set, critical failures other than CCF failures

Trend analysis: visual evaluation

Two types of graphical evaluation were demonstrated (see Appendix B1 of reference [9]) and applied to the proposed data set: a cumulative failure plot and side-by-side confidence intervals. Examples of these graphs are presented here.

Figure 6 shows the cumulative plot for the 132 critical failures that are not common-cause failures. Figure 7 shows the plot of confidence intervals for the same data set. Both of these plots show a steady increase in the failure rate $\lambda$ as the components age, as shown by the curvature (changing slope) in Figure 6 and the rise (changing level) in Figure 7. This appears to be a textbook example of ageing behaviour.

![Cumulative Failure Plot](image-url)
**Trend analysis: nonparametric hypothesis tests**

An alternative to a plot is a hypothesis test. The hypothesis test can give a quantitative answer to the question of whether ageing appears to be present, by measuring the strength of the evidence against the null hypothesis

\[ H_0: \text{no ageing occurs.} \]

This contrasts with plots, which give a visual impression but nothing quantitative.

Two nonparametric tests were proposed and demonstrated during the case study:
- the inversion criteria test, which is a version of the Kendall \( \tau \) test,
- the “two-cell test”, a simple variation of the chi-squared test.

**Inversion test**

The inversion criteria test was mentioned by Bendat and Piersol [12] and is a version of the Kendall test [13]. The test could be applied for the statistical samples of repairable components installed at one or several units, where the components are identical in design and operation. A detailed description of the test is provided in Appendix B2 of reference [9].

The test was applied to the T-A data, with each \( \lambda_i \) plotted as a dot in Figure 8. The result shows strong evidence of an increasing trend, significant at the 0.01 level when the one-sided test is considered. The inversion test confirms the conclusion from the cumulative failure plot or side-by-side confidence intervals, and gives a quantitative justification from the statistical point of view.

**Two-cell test**

This very simple test was proposed in [9]. It is a particular application of the chi-squared test. In the T-A case, \( H_0 \) is rejected at the 7E-5 significance level.

**Trend analysis: parametric hypothesis tests**
Several functional forms have been proposed [9] for $\lambda(t)$:

- **Linear**: $\lambda(t) = \lambda_0 + \Box t$,
- **Log-linear**: $\ln\lambda(t) = a + \beta t$, or $\lambda(t) = \lambda_0 \exp(\beta t)$
- **Power-law (Weibull)**: $\lambda(t) = \lambda_0 t^{\beta}$, or $\lambda(t) = \lambda_0 \exp[\beta(\ln t)]$

In all these formulas, $\Box$ is an “ageing” parameter. The failure rate $\lambda(t)$ is an increasing function of $t$ if and only if $\Box > 0$. Note: these simple parametric models for ageing do not allow modelling of both burn-in and ageing failures.

The test consists of trying to find evidence to reject the hypothesis $H_0$: $\lambda(t) = \text{constant}$

in favour of the alternative hypothesis $H_1$: $\lambda(t)$ in increasing in $t$.

The test could be performed by checking if the “ageing” parameter is 0. Or in other words $H_0$ could be rejected if the confidence interval for the “ageing” parameter is strictly greater than 0.

Two steps are involved, and both must be performed. They involve questions about two different hypotheses.

1. Does the model fit the data adequately? Answering this question involves a goodness of fit test, or model validation.
2. If so, is the ageing parameter significantly greater than zero?

The results of the parametric modelling application are described next. The analysis was carried out for several sub-sets of T-A data.

For comparison purpose, the results of nonparametric tests applied to each sub-set are presented in Table 2.

<table>
<thead>
<tr>
<th>Data</th>
<th>Test</th>
<th>Statistics</th>
<th>Significance Level for Ageing</th>
</tr>
</thead>
<tbody>
<tr>
<td>T13-T16</td>
<td>Inversion</td>
<td>$M = 11, A = 15.5$</td>
<td>between 0.025 and 0.05</td>
</tr>
<tr>
<td>T13-T16</td>
<td>Two-cell</td>
<td>$X_1 = 40, n = 62, p = 0.5$</td>
<td>0.015</td>
</tr>
<tr>
<td>all but T13-T16</td>
<td>Inversion</td>
<td>$M = 12, A = 18$</td>
<td>between 0.025 and 0.05</td>
</tr>
<tr>
<td>all but T13-T16</td>
<td>Two-cell</td>
<td>$X_1 = 35, n = 64, p = 0.5$</td>
<td>0.27</td>
</tr>
</tbody>
</table>

The final two rows of the table show a disagreement between the two tests. The inversion test says that the older components clearly tend to fail more often than the younger ones. The two-cell test says that individual components do not show strong evidence of failing more often as they age.

An extrapolation of T13-T16 data by log-linear model (Figure 8) gives

$$0(t) = 2.81 \times \exp(0.098t).$$

A chi-squared goodness-of-fit test said that the model would only be rejected at significance level 0.6 or higher — that is, the data fit the model well. In the fitted model, $\beta$ equals 0.098 where the standard error is 0.034. Therefore, the estimate of $\beta$ is 2.87 standard errors from 0, which corresponds to rejecting $H_0$ at the 0.002 level of significance.
FIG. 8. Fitted log-linear trend, for T13-T16 data

For the sub-set other than T13-T16, the following results were obtained (see Figure 9). The fitted log-linear $t(t) = 7.18E-3 \times \exp(0.134t)$. The goodness-of-fit $p$-value was 0.17; that is, the data fit the model acceptably. The ageing parameter $\beta$ equals 0.134, where the standard error is 0.037. Therefore, the ageing parameter is 3.6 standard errors from 0, which corresponds to the $2E^{-4}$ level of significance for rejecting $H_0$.

FIG. 9. Fitted log-linear trend, for data sub-set other than T13-T16

Application of the power-law (or Weibull) model leads us to the same conclusions (see Figure 10): $t(t) = 3.88E-3 \times t^{0.86}$ with goodness-of-fit $p$-value of 0.23. The ageing parameter is $\beta = 0.8595$, and the standard error 0.25. Therefore, $H_0$ could be rejected at the 0.0003 level of significance.
If we compare this with the results of the nonparametric tests (Table 2), it should be noted that the parametric test rejects the no-ageing hypothesis more strongly than the nonparametric tests do, in all the cases considered above.

5. Conclusions

As discussed above, the PSA could be used as a tool for ageing analysis. It enables a particular SSC ageing assessment to be linked to the overall plant safety effect via risk evaluation.

In this context, the purpose of EC JRC Ageing PSA activities is to make available to PSA engineers practical approaches, methods and advice on how evaluate the importance of ageing issues by means of PSA modelling.

The results of case studies performed within the Task 4, demonstrate that the methods could be used in identifying and modelling ageing effects on active components where reliability data is available.

Two important issue were identified:
- the lack of existing PSA reliability data collection from an ageing assessment of point of view,
- statistical model uncertainties and extrapolation capabilities.

These issues are under discussion and development in the Network.

The following topics are also planned for further development:
- areas of possible PSA application in ageing management and risk-informed approaches,
- the selection of SSC to be addressed in Ageing PSA,
- reliability data collection and parameter estimation,
- common cause failures,
- passive component age-dependent reliability models,
- the incorporation of ageing effects into the PSA model.
REFERENCES


