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Trend analysis in input data for PSA

Master's Thesis in Nuclear Engineering

DIMITRI OSTROVSKII

Department of Physics & Engineering Physics
Nuclear Physics
Chalmers University of Technology
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Abstract

The focus of this paper is to form a conclusion on the validity of the postulate on absence of trends in reliability data for Nordic nuclear power plants. Trends in this case imply an increasing reliability parameter with time, corresponding to degradation in component malfunction frequency.

A non parametric test method, the Wilcoxon rank sum test, was applied to data sets representing observations of component malfunctions presented in the T-book. Linear trends of magnitude corresponding to that can barely be detected by the test were postulated and added to tabulated reliability parameters. The trend containing parameters were extrapolated in time till today and used in PSA models, comparing results to those obtained while running the same sequences with tabulated parameters.

The conclusions of this thesis are that time dependant trends can be observed in reliability data today. These trends are, in one case, insignificant with respect to PSA results. In the other case the trend is most likely decreasing with respect to frequency, yielding a lower malfunction probability, instead of a heightened as was postulated.

Acknowledgements

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List of abbreviations

SAR – Safety analysis report

PSA – Probabilistic safety analysis

NPP – Nuclear power plant

OKG – The company that owns the power plant in Oskarshamn, a company in the E.ON. Concern.

TUD – An operating safety system jointly owned by “Forsmarks Kraftgrupp AB”, “OKG aktiebolag”, “Ringhals AB” and “Teollisuuden Voima Oy”.

TVO - “Teollisuuden Voima Oy”.

SSM – “Strålsäkerhetsmyndigheten”, the Swedish radiation safety authority.

MLE – Maximum likelihood estimate.

CDF – Cumulative distribution function.

Reliability parameters – Parameters describing an average probability of failure per unit of time or use.

- q_0 Probability of failure on demand $[use^{-1}]$.
- λ_d Failure rate for continuously running components $[h^{-1}]$.
- λ_s Failure rate for stand-by components $[h^{-1}]$.

T-book – Collection of reliability parameters for the Nordic NPPs. Contains also description of the TUD-database and methodology used to produce the reliability parameters.

Contents

1

Introduction

1.1 Background

A common method of safety analysis in the nuclear power industry is probabilistic safety analysis (PSA). This type of analysis utilizes statistical information on failure rates of components. From SAR O3, chapter 6.18:

> Probabilistic safety analysis (PSA) is used to systematically identify, quantify and rank event sequences that can lead to core damage and radioactive releases to the environment.

For more information on how PSA analysis are used see [1].

A component can often fail in several different ways; a specific sort of failure is called a failure mode. For example a component can have two failure modes, spurious stop and failure to start. A failure can in many cases, in combination with other events, causes several outcomes. Information on such combinations of events is modeled in event trees where each event has a probability of happening. This type of analysis identifies vital components to the safety, event chains leading to unwanted consequences etc. In order to carry out a PSA analysis one requires information on the probability of each of the studied components to fail. The probabilities of failure are called reliability parameters, and are presented in the T-book. The T-book covers a variety of components in each of the Nordic nuclear power plants (NPPs). The data that is presented is a derivation of earlier experiences; therefore the T-book is regularly updated to include the latest observations. As stated in the T-book:

> The purpose of updating the T-book is mainly to generate and improve failure-data for reliability calculations incorporated in safety analysis of Nordic nuclear power plants.

1.1.1 Problem description

Reliability data used to analyze the safety of the Swedish nuclear power plants is gathered and presented based upon several assumptions and postulates. Among these is a postulate that states "The reliability parameters are trendless", in other words the true distribution of the reliability parameters is unchanged with time.

The consequence of this postulate is a perception that some true parameter, or distribution, exists that describes the failure frequency of components and that this parameter is unchanged with time. This true parameter is sampled by making observations of failure rates of components. As the number of observations increases the sample distribution converges to the true reliability parameter value. Please note that reliability parameters describe an average failure rate in time.

While physical components age and at some point become unusable, they are assumed to be replaced by new components or returned to starting condition, resulting in a constant average failure frequency, or probability. Today no study provides evidence to prove or disprove the validity of the postulate on absence of trends. Before continuing to question routines on gathering information and calculation of reliability parameters a study into the possible time dependency of the true reliability parameters must be made.

1.1.2 The T-book and its contents

The writing and updating of the T-book is done by the TUD-council (TUD-kansliet). The TUD-council has a system of reporting failures that is connected to all of the Nordic NPPs. Every power plant is responsible for reporting its failures to the TUD-database. These reports consist of a component code corresponding to the failed component, a description and a time of occurrence of the failure. At OKG a system is implemented where the maintenance reports are automatically forwarded to a contact person who is responsible for collecting, formatting and sending the information on to the TUD-database[2].

The TUD-database updates information in a program called "Bi-cycle". This program is used at the NPPs to analyze the current situation and enable smoother operating conditions of the power plant. A common use of the software "Bi-cycle" is to track recently failed components and predict when they need to undergo maintenance or be exchanged. Only a part of the information stored in the TUD-database is used to produce the T-book. The T-book is restricted in extent with respect to component types and failure modes. For more detailed information on the included systems and failure modes the reader is referred to the T-book[3].

The T-book presents components in groups of like components. For example one component group is "Centrifuge pump, MC-pump" [3] (table 1.4.1), there exist a total of 66 components in this particular group, summed over all the power plants. Each component group is assumed to be homogeneous with respect to failure rates, i.e. it is assumed that the generic[1] reliability parameters do not vary from one individual to

[1] Generic reliability parameters are estimated from the total amount of failures in all studied power plants. Later these are updated with plant specific observations to obtain plant specific reliability

another in the same component group. Even though every component group is assumed to be homogeneous these component groups have different reliability parameters for every power plant. This is intended and is the effect of the differing observations of failure in the different power plants[2]. Each component is unique in reality, but the assumption of homogeneity in component groups has been shown to be an adequate approximation[4]. The failures are assumed to be independent of each other, i.e. the components failure intensity is assumed to be unchanged through time. This leads to a Poisson-distribution time between failures (Δt).

$$p(X = x|\lambda) = \mathrm{e}^{-\lambda t}\frac{(\lambda t)^x}{x!} \tag{1.1}$$

Where $p(X = x|\lambda)$ is the probability of X events occurring given a rate parameter λ during the time t.

Further the T-book distinguishes between different component classes; those relevant for this thesis are stand-by and continuously running components. In the case of continuously running components the rate of failure is symbolized by $\lambda_d[h^{-1}]$. For stand-by components it is relevant to consider the time since the last activation as well as a constant probability of failure. This is modeled with a so called "$q_0 + \lambda t$"-model. Here $q_0[use^{-1}]$ symbolizes the constant probability of the component to fail and $\lambda_s[h^{-1}]$ describes the increasing probability with respect to the time since the component was last tested. Each of the reliability parameters is presented individually.

Please note that failure modes attributed to stand-by components are in some cases presented as those for continuously running. An example of this case is failure mode "spurious stop" for a stand-by component, for this failure mode a measure of the number of uses is irrelevant as the component is in operation by definition. From here on out components defined as continuously running are components with failure modes characterized by one parameter, either λ_s or λ_d, because these types of components failures are dependent only on total running or stand-by time. Figure 1.1 shows an example of a table from the t-book.

The reliability parameters are derived using a two step Bayesian method. The Bayesian method combines empirical data with a prior understanding of the studied phenomenon. Here the prior understanding of the phenomena is updated by the observations to produce a final estimate of the unknown parameter. The method implemented to derive data presented in the T-book is described below.

- A prior estimation $p(\Theta)$[3] is made. The parameters Θ have a correlation to the reliability parameter that is estimated.

$$\lambda = f(\Theta) \tag{1.2}$$

parameters.

[2]A more detailed description of the reliability parameter estimation method follows later in this chapter.

[3]Θ reflects some knowledge of the distribution of the reliability parameter λ. The reliability parameter is assumed to have a gamma distribution, which means that Θ is in practice the parameters α and β defining the gamma distribution.

Centrifugalpump, horisontell **Tabell 1.1.1**

Flöde: <75 kg/s
Tryckuppsättning: 0.2 - 2 MPa
Driftläge: Driftsatt

Antal komponenter: 38
Antal fel: 64
Drifttid: 0.391728E7

Felmod: **Obefogat stopp**

Felintensitet:		(λ_d 10^{-6}/h)			Effektiv medelreptid
Anläggning	5%	50%	95%	medelv.	(h)
Forsmark 1	18.8	37.9	68.9	40.1	17
Forsmark 2	12.2	26.8	51.6	28.7	20
Forsmark 3	0.4	6.4	23.6	8.4	-
Oskarshamn 1	1.9	9.1	29.6	11.5	12
Oskarshamn 2	5.3	15.5	33.9	17.1	8
Oskarshamn 3	0.3	5.2	19.3	6.9	-
Ringhals 1	3.3	25.6	73.0	30.7	8
Ringhals 2	3.1	12.1	29.8	13.7	5
Ringhals 3	0.8	12.7	39.0	15.3	26
Ringhals 4	0.8	10.6	32.4	12.8	7
Olkiluoto 1	1.4	14.5	46.0	17.9	16
Olkiluoto 2	0.8	8.7	28.6	10.9	20
Generisk	1.0	12.2	46.0	16.4	15

Figure 1.1: Table 1.1.1 from T-book version 7.

where $\lambda = \lambda_s$,λ_d or q_0.

- Bayes' theorem is applied to the prior, it is updated using the observations $\bar{x}$, for a component group independent of power plant, to produce a posteriori distribution of Θ. The quantity $p(\bar{x}|\Theta)$ is called a likelihood function.

$$p(\Theta|\bar{x}) \propto p(\bar{x}|\Theta)p(\Theta) \tag{1.3}$$

- The result from the previous step can be translated to $p(\lambda_{gen}|\bar{x})$, the generic distribution of the parameter λ, by the assumed relation in equation 1.2.

- A new distribution $p(\lambda)$ is produced as a function of $p(\Theta|\bar{x})$. $p(\Theta|\bar{x})$ is used as a prior, much like $p(\Theta)$ in the first step. This time plant specific observations, x, are considered and Bayes' theorem is applied.

$$p(\lambda|x) \propto p(x|\lambda)p(\lambda) \tag{1.4}$$

The final results of these calculations are the generic distribution of a parameter $p(\lambda_{gen}|\bar{x})$ and a plant specific distribution for each of the plants $p(\lambda|x)$. For more information on the Bayesian method see [5] [p.361-369] and for an in-depths description of how the two-step Bayesian method is applied for these calculations please see [6].

1.2 Purpose

The purpose of this thesis is to form a conclusion of the validity, with respect to applications of reliability data, of the postulate on the absence of trends.

1.3 Delimitations

This thesis questions only the postulate on absence of trends thus accepting the other assumptions described in the T-book. Far from all of the component groups described in the T-book will be studied because of the time constraints. Selection of the studied components will be discussed later on.

Only data contained in T-book versions 4 and newer [3],[7],[8],[9] will be considered during this thesis[4].

The validity of the postulate on absence of trends will be questioned with respect to the applications of reliability data, which are first and foremost PSA. The final conclusion will depend on whether a time dependent trend is detected weighed with the impact of increasing trends in reliability parameters on the result of PSA.

The possibility of improved reliability with respect to time is disregarded. Such improvement may occur if old components are replaced by new with higher quality.

1.4 Methodology

This thesis is divided into three stages. Each stage uses, in some way, results from the previous; this division is made to help the understanding and ease the reader into the contents. A part of every stage will include getting acquainted with appropriate theory and/or software.

The first stage aims at establishing a basis on what type of trends can be expected in reliability parameters, if any, as well as developing tools to analyze already gathered

[4]This is done purely because these T-book versions present the necessary data for the analysis.

data in the future. Results of this stage will be an effective algorithm or method of analyzing suitable data.

The second stage aims at answering the questions:

- What types of trends are detectable in reliability parameters, based on the data available?
- Is there reason to suspect that trends are present in the data today?

In order to answer these questions the method developed in the first stage will be implemented on the data available today.

The last stage of this thesis will assess the effect of time-dependent trends on PSA analysis. During this stage PSA analyses, which contain one or several components whose reliability parameters are altered to contain trends, will be carried out. Results from these will be compared to results of analyses carried out containing un-modified reliability parameters.

1.4.1 Generation of data sets

The method of generating random throughout the thesis data is the following:

1. An array of random variables, evenly distributed between 0 and 1, is generated.
2. A second array is created. Here every value is generated by a logical test of every element in the first array. If the corresponding element in the first array is greater than a constant (this will be called the logic value)[5], the element in the second array is set to 1. If the test failed, the element in the first array is less than the constant; the value of the element in the second array is set to 0, see table 1.1.

The randomly generated data is interpreted as an event occurring for each number 1 that appears in the second array. The time of the events is the corresponding position of the number in the array. Applying this on the example in table 1.1 one concludes that 4 events occur at times $t = 2,4,9$ and 11.

[5]The constant is in theory arbitrary and in practice affects only the number of events that will be included in the Poisson distribution therefore corresponding to a rate parameter of the real process.

Random generated variable	Outcome of logic test > 0.7
0.1172	0
0.7888	1
0.2075	0
0.9669	1
0.1380	0
0.3561	0
0.1683	0
0.3186	0
0.9184	1
0.6050	0
0.9516	1

Table 1.1: A sample of 11 random variables, evenly distributed between 1 and 0, generated in EXCEL (left column). The right column is produced by a logic test of the variables in the left column. This describes the method of productions of random Poisson distributions.

2

Survey of test methods

2.1 Selection of test method

The goal of this part is to establish a statistical method of testing sets, or distributions, to reveal significant differences in frequency. This knowledge is to be used in a later stage, applied on information gathered to this date, to conclude if reason to doubt the postulate on the lack of trends exists.

To compare suggested methods they were run on fictional (simulated) data. The T-book assumes that the probability of failures is Poisson-distributed, therefore Poisson-distributed data sets were considered. The suggested test methods differ inherently and thus require different input data. For example three of the four suggested test methods compare two distributions with each other, while the last one assumes a Poisson-distribution as a reference, therefore only requiring one distribution as input.

The method of producing fictional data was the same for all test methods. For those test methods that required a reference distribution a data set with a constant rate parameter λ and one where λ varies with time were produced[1]. These data sets represent a form of distribution of failures in time. Data containing a time dependent trend was modeled by altering the primary data with time in such a way that the mean value remained unchanged from the trend less case, described by equation 2.1.

$$
\begin{gathered}
x(t) = x_0 + f(t) \\
\text{where} \\
\sum_{t=0}^{T} f(t) = 0
\end{gathered}
\tag{2.1}
$$

[1]please note that here only the rate parameters of the general Poisson distributions are discussed, not the reliability parameters λ

For the test method that requires only one input distribution the set containing a variable $x(t)$ was used.

Two types of trends in reliability parameters have been proposed in the starting stage of this thesis. Pär Lindahl, initiator of the thesis, proposed a linear trend in time. Dan Kristensson, OKG responsible for maintenance report forwarding to TUD, suggested the possibility of exponential trends during [2]. Both of these trends have been taken into account during this stage of the thesis. A parameter α was used to quantify the magnitude of the postulated trends. For details on how the trends were modeled see 2.2.2.

Two desired characteristics of the test to be used were identified:

1. Efficiency

2. Sensitivity

Efficiency implies that the test produced a consistent result if the input data was unchanged or varied in string length. Unchanged input data means that the sting contained a constant trend, or lack of one. In reality the exact nature of the input data was different as the random numbers used to produce it were regenerated every time the test is run. The ability to handle different string lengths of input data is important because the number of observed failures presented in the T-book varies greatly between components.

Sensitivity is the test methods' ability to detect a trend. A method that detected a smaller trend, defined by a smaller factor α, was considered more sensitive. Four test methods will be analyzed with respect to efficiency and sensitivity. The method that proves most efficient will be chosen for implementation on real data further on in the project. The four studied methods are:

- Maximum likelihood estimate
- The rank sum test
- The Kolmogorov-Smirnov test
- Test method attributed to Laplace using the Z-statistic, described in [10].

2.1.1 Maximum likelihood estimate

The maximum likelihood estimate (MLE) is a method of parameter estimation that requires a model to which experimental data is to be fitted. A MLE of a parameter is the value that maximizes the probability of obtaining the results that were observed during an experiment. The MLE parameter is chosen as the value of θ that maximizes $L(\theta)$ in equation 2.2.

$$L(\theta) = \prod_{i=1}^{N} p(x_1|\theta)p(x_2|\theta)...p(x_N|\theta) \tag{2.2}$$

Where $p(x_1|\theta)$ is the probability of x_1 events occurring given a rate parameter θ, see equation 1.1. A Poisson-distributions MLE of the parameter λ is known to be the total number of events divided by the total time[2][11].

$$\hat{\lambda} = \frac{\sum_1^N x_i}{\sum_1^N \Delta t_i} \tag{2.3}$$

The MLE method was used to compare how well an estimated parameter (λ) for a trend less data set could describe the events of a data set containing a time-dependent trend. During this simulation a $\hat{\lambda}$ was estimated for a trend less data set, generated as described in section 2.1. The parameter was subsequently used in the general formula for a Poisson-distribution along with the time (t) in between the last N_1 events that occurred in the trend less data set, equation 2.4. This yielded a probability of the N_1 events occurring during that time. This probability was compared to the probability of the same parameter $\hat{\lambda}$ to predicting the N_2 number of events that occurred in the data set containing a trend during the same time (t), equation 2.5.

$$p_1 = \mathrm{e}^{-\lambda t} \frac{(\hat{\lambda} t)^{N_1}}{N_1!} \tag{2.4}$$

$$p_2 = \mathrm{e}^{-\lambda t} \frac{(\hat{\lambda} t)^{N_2}}{N_2!} \tag{2.5}$$

A high value of the quota of the two probabilities ($\frac{p_1}{p_2}$) would indicate that the estimated parameter does not describe the time dependent data sufficiently well in comparison to the time independent data.

2.1.2 Wilcoxon rank sum test

The Wilcoxon rank sum test, or the Mann-Whitney U test (from here on out called the rank sum test), is a nonparametric statistical test. In practice this means that the test does not assume a certain distribution of the input data, unlike the MLE method. The null hypothesis before carrying out a rank sum test is that two data sets have the same distribution, and the test determines if that can be accepted or rejected with a confidence of $1 - \alpha$[3]. It can be shown that the efficiency of the Rank-sum test is no lower than 0.864 compared to the t-test[11][p.341]. Another advantage with this test is that it is well established, hence there exist computer codes that carry out this test automatically. The code that will be used is the function *ranksum* in MATLAB.

The rank sum test calculates the test statistic U that is assumed to be normally distributed under the null hypothesis for large samples. To calculate the U statistic two randomly and independently selected samples $x_1, x_2, \dots x_n$ and $y_1, y_2, \dots y_n$ are ranked according to their magnitude. If two or more samples share the same value their rank

[2]Please note that in our case summing all the time intervals t_i yields the total time T if the last event occurred at $t = T$.

[3]Please note that α here does not have same meaning as in further chapters.

becomes equal to the average rank (example: ranks 6, 7 and 8 share a value of 3. All 3s are therefore ranked 7). Proceeding, the ranks are summed for all the components in each sample. The sum of ranks is referred to as W_x and W_y.

$$\begin{aligned} U_x &= n_1 n_2 + \frac{n_1(n_1+1)}{2} - W_x \\ U_y &= n_1 n_2 + \frac{n_2(n_2+1)}{2} - W_y \end{aligned} \tag{2.6}$$

The test statistic U is set to the minimum value of U_x and U_y calculated as shown in equation 2.6. U is used to calculate the Z-statistic as shown in 2.7

$$Z = \frac{U - (n_1 n_2/2)}{\sqrt{n_1 n_2(n_1 + n_2 + 1)/12}} \tag{2.7}$$

Where n_1 and n_2 are the number of components in samples one and two. The Z-statistic is compared to the z value of a normal distribution with the desired confidence resulting in a rejection of the null hypothesis if

$$Z \geq z_{\alpha/2} \text{ or } Z \leq -z_{\alpha/2} \tag{2.8}$$

2.1.3 Kolmogorov-Smirnov test

The Kolmogorov-Smirnov test (KS test) is a nonparametric test that is used to determine if one sample comes from a given distribution or if two samples are drawn from the same distribution (also known as the two-sample KS test), the latter form of the test will be used in this thesis. The KS statistic is the maximum distance between two samples' cumulative distribution functions[4] (CDF), mathematically represented as:

$$D_{n,n'} = max|F_{1,n}(x) - F_{2,n'}(y)| \tag{2.9}$$

Where $D_{n,n'}$ is the statistic and $F(x)$ is the CDF of the respective sample. It has been shown that the distribution of $D_{n,n'}$ can be approximated relatively easily [12]. This test, like the rank sum test, is well established meaning that computer codes exist for running the KS test. The code used to run the KS test is a function in MATLAB called $kstest2$.

2.1.4 Laplace Z-statistic

This test method is used to detect monotonic trends in Poisson processes. The test is appropriate for trends of the form:

$$\lambda = \beta t^{\beta-1} \tag{2.10}$$

[4] In the case of a one sample test the one CDF is exchanged with the proposed distribution.

Observe that setting $\beta = 2$ yields a linear time dependence of the rate parameter λ. The test method uses a test statistic Z,

$$Z = 2\sum_{i=1}^{n} log(\frac{\bar{T}}{T_i}) \tag{2.11}$$

Where $\bar{T}$ is the total time of observation, T_i are the times corresponding to event occurrences and n is the total number of events.

The null hypothesis, H_0, is equivalent to setting $\beta = 1$ in equation 2.10, which in turn yields a constant rate parameter. Testing H_0 versus H_1 is equivalent to testing $\beta = 1$ versus $\beta > 1$. For purposes of this thesis the case $\beta = 2$ is of interest, this however does not need to be specified for the test. This test method is proposed for applications matching this thesis in literature, [13] shows the tests power for different values of β, among other $\beta = 2$ while [10] compares this test method with others for application on homogeneous Poisson processes.

2.2 Results of test methods

The four proposed test methods were compared to each other in terms of efficiency and sensitivity. To compare a test methods efficiency, as defined in section 2.1, two results are required. Firstly each test method was run several times with input data of the same character, this will help conclude weather the methods produce consistent results. Secondly the length of the input data was varied to check that the methods can handle short input strings. The length of the input string was regulated by changing the value of the logic test used to produce the Poisson-distribution. As the primary random generated numbers are equally distributed between 0 and 1, the logic value can be directly converted into amount of positive outcomes of the logic test, for example an initial 1000 random variables will yield close to 300 outcomes if the logic value is > 0.7[5].

Sensitivity was tested by postulating a time-dependent trend for one of the input data strings. The postulated trend produced a mean frequency equal to that used in the trendless data. Two types of trends were postulated, linear and exponential.

2.2.1 Efficiency

The presented results were obtained from codes that create 1000 random values initially, run the corresponding test 100 times taking the average value of the result. This procedure is consequently redone 100 times in total, in the case of the rank sum, Z- and KS tests nothing was changed from iteration to iteration while in the case of the MLE method a different number of compared events N (N_1 and N_2) was changed (2.4).

[5]Please note that these values are true for very long sequences of initial values, the number of outcomes in the performed tests may vary.

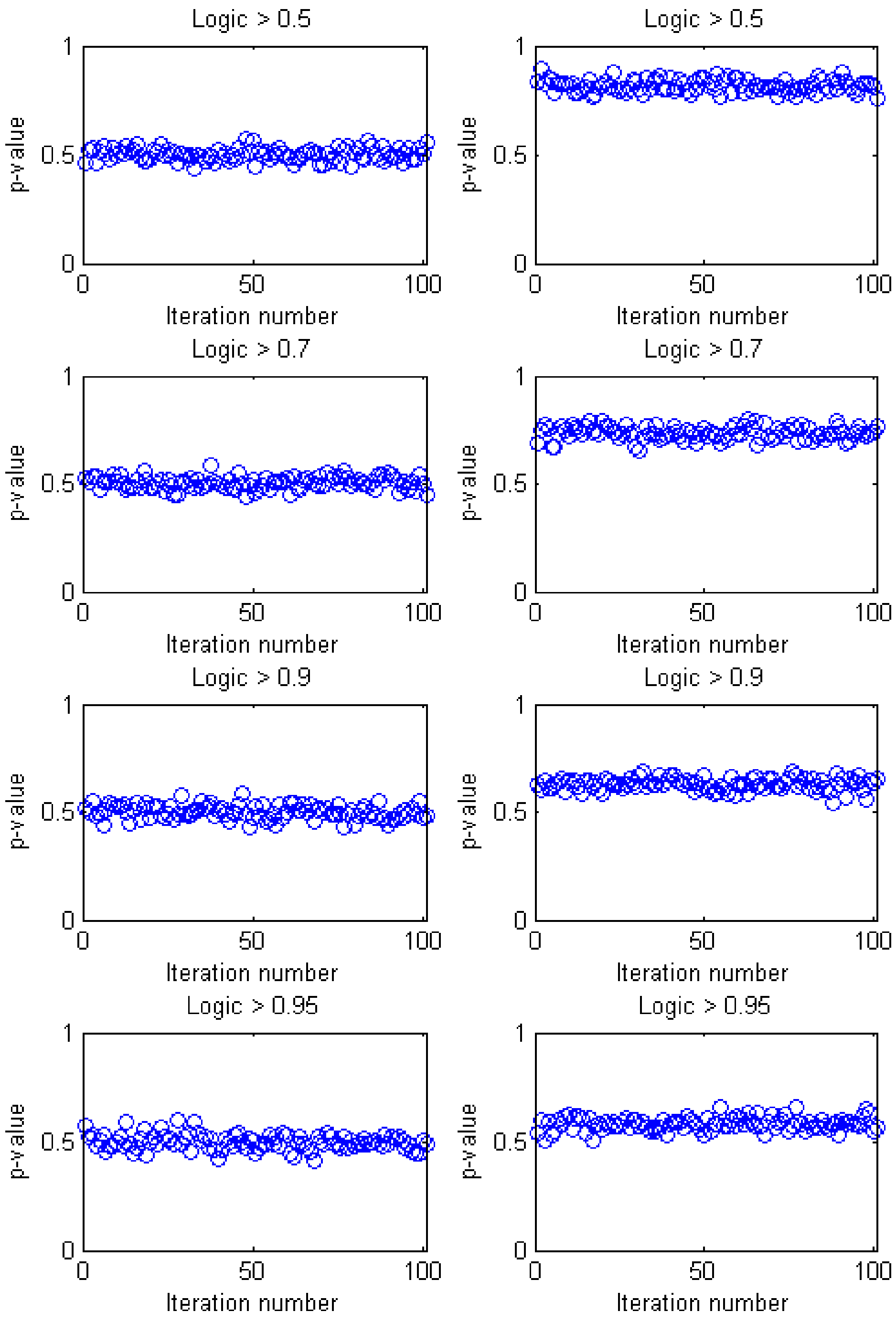

Figure 2.1: Tests run without trends. On the left the rank sum test and on the right the KS test.

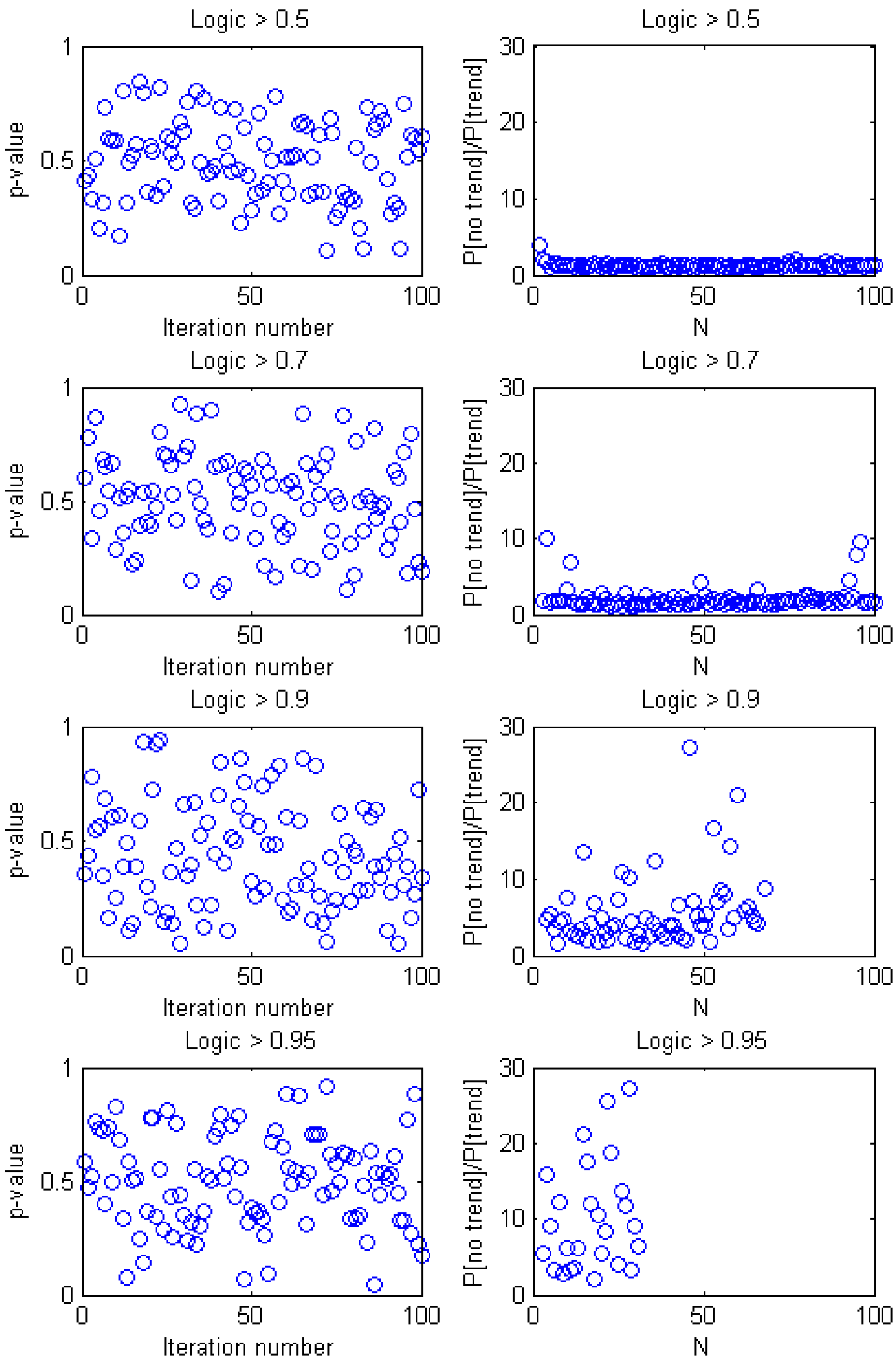

Figure 2.2: Tests run without trends. On the left the Z-test and on the right the MLE method.

Figure 2.1 presents results of the test methods carried out on trendless data sets for different logic values, and N values in the case of MLE method. A mean and variance of the data is presented in tables 2.1 and 2.2.

Test method	Logic > 0.5	Logic > 0.7	Logic > 0.9	Logic > 0.95
MLE	1.6977	100.621	247.635	30.145
Rank sum	0.5004	0.5041	0.5005	0.4971
KS	0.8163	0.7355	0.6293	0.5804
Z-test	0.4954	0.5056	0.4350	0.5012

Table 2.1: Table of mean values for different Logic. The last two values of the MLE method take into account results up to N = 60 and N = 30 respectively.

Test method	Logic > 0.5	Logic > 0.7	Logic > 0.9	Logic > 0.95
MLE	0.0063	13.856	$8.15*10^5$	$6.62*10^6$
Rank sum	0.0008	0.0007	0.0010	0.0012
KS	0.0008	0.0009	0.0008	0.0009
Z-test	0.0316	0.0399	0.0512	0.0415

Table 2.2: Table of variances for different Logic. The last two values of the MLE method take into account results up to $N = 60$ and 30 respectively.

As shown in figure 2.1 and tables 2.1 and 2.2 the MLE method cannot be considered efficient. It produces consistent results for logic values below 0.7, corresponding in this case about 300 events, but seems to handle smaller amounts of input data very poorly. The Z-test also seems to handle this form of random data poorly, but will be considered in the next step because it is suggested as the method of choice for this application in literature [10].

2.2.2 Sensitivity

Linear trends

The postulated linear trend is modeled by adding a coefficient, depending on the position of the studied random variable, to the variable itself. In mathematical terms each random variable in the trended data set is described:

$$x(t) = x_0 + \alpha \left(\frac{t}{T} - \frac{1}{2} \right) \tag{2.12}$$

Where T is the total time, or practically the length of the vector x. The results of the tests are presented in the form of a p-value[6] versus a relative slope α.

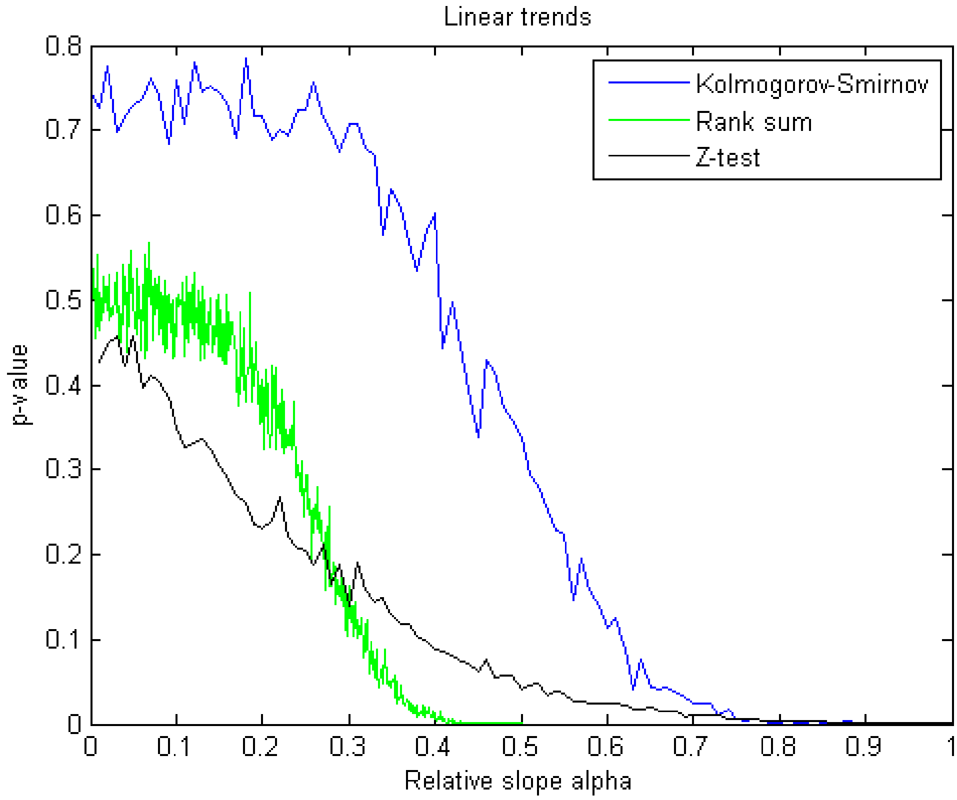

Figure 2.3: Tests run with linear trend

The data in figure 2.3 shows critical values α_{crit}[7] of 0.356 for the rank sum test, 0.50 for the Z-test and 0.65 for the KS test.

Exponential trends

The postulated exponential trends are modeled in a similar fashion to the linear trends. The equation used for calculating the time dependence is:

$$x(t) = x_0 + \left(\mathrm{e}^{\alpha \frac{t}{T}} - \frac{\sum_{t=1}^{T} \mathrm{e}^{\alpha \frac{t}{T}}}{n} \right) \tag{2.13}$$

The results are presented in the same way as in section 2.2.2.

[6]Reminder, the definition of p-value is the probability that the given data is observed given that the null hypothesis is true.

[7]α_{crit} is defined as the value that corresponds to p = 0.05.

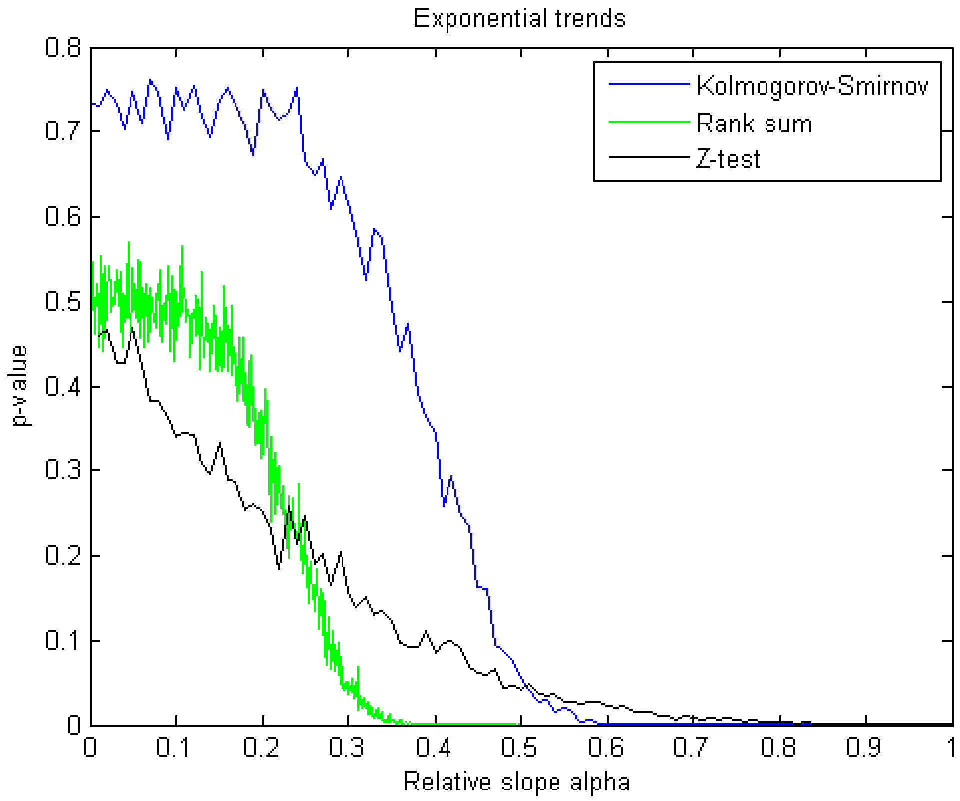

Figure 2.4: Tests run with exponential trend

The data in figure 2.4 yields critical values α_{crit} of 0.298 for the rank sum test and 0.5 for the Z- and KS test.

2.3 Discussion, on appropriate test methods

Four methods of testing distributions were compared to each other with respect to efficiency and sensitivity for detecting time dependent trends in frequency. Two of these tests are nonparametric, meaning they are not sensitive to the distributions of two compared data sets. These tests answer the question: "Are the two data sets from the same distribution?". The other two tests rely on knowledge of the distribution of analyzed data.

A big point of question during this stage is the number of random variables and reruns performed during the sensitivity and efficiency tests. These numbers were chosen arbitrarily and bear no connection to the real data. The advantage of this methodology is that it is very general. At this stage of the process the most important feature was to discard test methods that are inefficient. One might argue that input data should be chosen to resemble the observations used in following sections. This is a valid argument but would lead to slightly higher computational requirements and thus be more time consuming.

During this stage a greater attention was paid to the choice of test methods rather than the input data. Probably the most interesting result was that the test method discussed in literature, the Z-test, was poor in comparison to the rank sum test. An explanation for this might be that the Z-test is in fact superior in efficiency when dealing with a single exact distribution but is sensitive to small variations in the input data and thus not compatible with the methodology of this thesis. This would give rise to an interesting question of exactly how sensitive this test method is, as a pure Poisson-process is only the ideal case while real failure distributions surely deviate from it.

The rank sum test seems to be most appropriate for purposes of this thesis.

3

Trend analysis

Software complimenting the T-book, called T-code, is used to calculate reliability parameters presented in the T-book. T-code does not utilize any form of time dependence of the observed failures, only the total count and total observation time. Therefore it is not possible to discern between reliability parameters produced using two different distributions of failures through time as long as the total counts are the same. Calculations made by T-code follow, in order, equations 1.2, 1.3 and 1.4. In theory the first step of T-codes calculations is meant to be derived from an uninformative sampling of θ. Parameters in T-codes source code that control this have been changed leading to the conclusion that they cannot be fully uninformative. Sadly there is a lack of documentation on and general knowledge of changes to the source code making it difficult to fully describe the extent and effect of them. Because of these changes reliability parameters from different versions of the T-book cannot be compared to each other as they are, this is described in detail in [14].

During this stage of the thesis a time distribution of the observed failures is needed. Such a distribution is not available. To obtain such data one is to use software called "Bi-cycle" to go through all maintenance reports from the 12 NPPs and find the reports that ultimately resulted in failures recorded in the T-book. This process is extremely time consuming and is therefore not considered as an option.

3.1 Calculation prerequisites

Because of the constraints on available data several approximations had to be made and the method of analysis adjusted to fit a specific form of input data. Data used to calculate the final results was:

- Number of observed failures (F), this is presented cumulatively in T-book versions 4-7.

- Number of observations (N), this is presented in different ways depending on the component type. For continuously running components a total running time; and for stand-by components a total time in stand-by and the number of uses is presented.
- Relative time between the publishing's of T-books (T), this time is presented as the total number of reactor years on which data in each T-book is based.

3.1.1 Detectability

To test for detectability a distribution containing a time dependent frequency will be compared to one with a constant[1]. The two distributions analyzed represent the predicted number of failures using, in one case, a constant rate parameter q_{true}, and in the other, a time dependent rate parameter q_{trend}. The distributions were produced with a function that placed a given number of events randomly into time intervals of given lengths. Input to this function was the predicted number of failures during a time interval and the time intervals length. These time intervals were chosen to fit the publishing's of the T-book versions. Following is an explanation of how the predicted number of failures was calculated corresponding to each distribution. This process is illustrated in figure 3.1.

True q_{true} was used together with the number of uses (N) and the total observation time (T) to produce an expected number of failures ΔF_{ref}. This process was carried out X number of times and the average number of failures per time interval was calculated. The result was a vector containing the average predicted number of failures during each time interval ($\Delta \bar{F}_{ref}$).

Trend q_{trend} was used together with the number of uses (N) and the total observation time (T) to produce a new set of expected number of failures. This was done Y times and each result was saved, resulting in a matrix with dimensions [number of time intervals]x[Y].

Time distributions were produced, through the function, for each set of "trend" and the average "true" numbers of observed events. Finally each of the distributions containing a time dependant trend was compared to the "true" distribution, producing a p-value. An average of the p-values was used as the final result.

3.1.2 Real distributions

During this stage an approximate distribution of the observed events was compared to a distribution of the same number of events randomly distributed in time. This process is illustrated in figure 3.2.

[1]For the three test methods that require two distributions as input. For the last test method only one, the trend containing distribution, will be used.

$$\begin{cases} \left(q_{true} \xrightarrow{N,T} \Delta F_{ref}\right) * X \xrightarrow{average} \overline{\Delta F_{ref}} \xrightarrow{Function} Distribution_{ref} \\ \left(q_{trend} \xrightarrow{N,T} \Delta F_{trend}\right) * Y \rightarrow Y * \Delta F_{trend} \xrightarrow{Function} Y * Distribution_{trend} \end{cases}$$

Figure 3.1: Flow chart describing the methodology behind calculations of time distributions corresponding to section 3.2.1

True distribution Each "new" observed failure on a given version of the T-book (ΔF_i) was placed randomly in the time interval between the previous and current versions publishing's of the T-book.

Random distribution The total amount of observed failures (ΔF_{tot}) were each placed randomly in the interval between the publishing of the first and last studied versions of the T-book.

The two distributions described in the steps above were compared. The procedure was redone several times and the average p-value was used as a final result.

$$\begin{cases} \Delta F_{true,i} \xrightarrow{\Delta T_i} Distribution_{ture} \\ F_{tot} \xrightarrow{T_{tot}} Distribution_{random} \end{cases}$$

Figure 3.2: Flow chart describing the methodology behind calculations of time distributions corresponding to section 3.2.2

3.1.3 Choice of component groups

Four component groups have been chosen for the study of time dependant trends. One failure mode for each component was studied, which corresponds to 4 tables in total in the T-book. Table 3.1 shows the chosen components, failure modes and the corresponding T-book table number. The motivations behind the choices of components varied. Following is a brief explanation of why each component group was chosen.

- The centrifuge pump was chosen for no apparent reason other than that the amount of statistical data, in the form of observed failures and running time, was perceived as sufficient.
- The valve was chosen because of a recommendation made by Dan Kristensson during [2], where it was mentioned that valves in general have good statistical data since there are usually many components in the component groups leading to a larger number of observations.

T-book table number	Component	Failure mode
1.1.1	Centrifuge pump	Spurious stop
3.7	Pneumatic closing valve	Failure to reposition
4.1.1	Heat exchanger, flat	Insufficient cooling capacity
7.1.2	Diesel generator	Failure to start

Table 3.1: Description of the chosen component groups.

- The heat exchanger was chosen for the same reasons as the centrifuge pump. A second valve type was analyzed to begin with. Sadly the failure mode that was chosen was not present in the PSA model studied during the last stage of this project. The heat exchangers were chosen instead.
- The diesel generator component group was studied for several reasons. Firstly diesel generators are a critical component in all power plants because of the need for emergency cooling. Secondly diesel generators in general are currently a topic of interest at OKG due to resent and persisting problems. This was also mentioned during [2].

3.2 Analysis and results

During the simulations run in sections 3.2.1 convergence was hard to reach. Because of this results will be presented as a mean value ± variance. These quantities are calculated from 5 points, the variance is defined as:

$$Var = s^2 = \frac{1}{n-1}\sum_{j=1}^{n}(x_j - \bar{x})^2 \tag{3.1}$$

Where n is the sample size, in this case 5 and $\bar{x}$ is the mean value of the sample.

3.2.1 Detectability

In the study of actual component groups two stand-by and two continuously running components were chosen. A list of how many reactor years of experience each version of the T-book is based on can be found in [3]. This was chosen as an absolute time measure and the time intervals between the publishing's were therefore the same for all components. The difference in number of observed failures was calculated by simply subtracting the number of observed failures in the previous version from the number in the present T-book. The time discretization, which will be discussed later on in this chapter, and choice of rate parameter differed depending on the component type.

T-book version	T	ΔT	N	ΔN	ΔF
4	178	178	$1.497{*}10^6$	-	-
5	234	56	$0.212{*}10^7$	$6.2299{*}10^5$	10
6	315	81	$0.299{*}10^7$	$8.733{*}10^5$	15
7	378	63	$0.392{*}10^7$	$9.2399{*}10^5$	15

Table 3.2: Input data for centrifuge pump, failure mode spurious stop. T-book table 1.1.1. The values in the last column are calculated using a constant rate parameter $\lambda_d = 16.4{*}10^{-6}$.

The values ΔF, in tables 3.2 and 3.3, were calculated as an average of several simulations for each component group[2]. The final results are an average p-value of the rank sum test for different trend slopes. For each trend slope a variety of calculated p-values were obtained, most likely due to the fact that all random numbers were regenerated. The number of iterations, or times the test was run for each slope (symbolized by Y in figure 3.1), was chosen empirically to minimize the variance of the end result. In practical terms each program was run as many times as MATLAB could handle without crashing, this was not enough to reach convergence and therefore the variance was considered.

Continuously running components

For continuously running components a total running or stand-by time is presented in the T-book in [h] and the rate parameter λ_s or λ_d $[h^{-1}]$. The time discetization was therefore made in steps of 1 [h] from 1 to the presented running time. This representation resulted in a model which treated each hour as a probability of the component to fail. The rate parameter was chosen equal to the mean value of the generic λ_s or λ_d presented in [3]. The input data to the model for each of the component groups is presented in tables 3.2 and 3.3.

The rank sum test was run on each pair of trend-less and trend-containing distributions to produce a p-value. The averages of these p-values for each slope α are presented in figure 3.3.

Stand-by components

As mentioned in section 1.1.2 two reliability parameters are presented for stand-by components. A decision to run analysis on one parameter was made, hence two reliability parameters $q_0[use^{-1}]$ and $\lambda_s[h^{-1}]$ had to be weighed into one value. In the T-book a total number of uses is presented for the stand-by components, which implied that a convenient method of weighing the two parameters was to convert λ_s into units of $[use^{-1}]$. Data used to make this conversion was, for each version of the T-book:

[2] A quick investigation showed that averaging over 10 simulations was enough to yield consistent results with respect to total number of failures.

T-book version	T	ΔT	N	ΔN	ΔF
0	0	0	0	-	-
5	234	234	$0.2462{*}10^7$	$0.2462{*}10^7$	19
6	315	81	$0.6996{*}10^7$	$4.5339{*}10^6$	28
7	378	63	$1.513{*}10^7$	$8.132{*}10^6$	66

Table 3.3: Input data for heat exchanger, failure mode inadequate cooling capacity. T-book table 4.1.1. The values in the last column are calculated using a constant rate parameter $\lambda_s = 6.6 * 10^{-6}$. This failure mode is not present in T-book version 4 and older; hence the first data point was extrapolated from the origin.

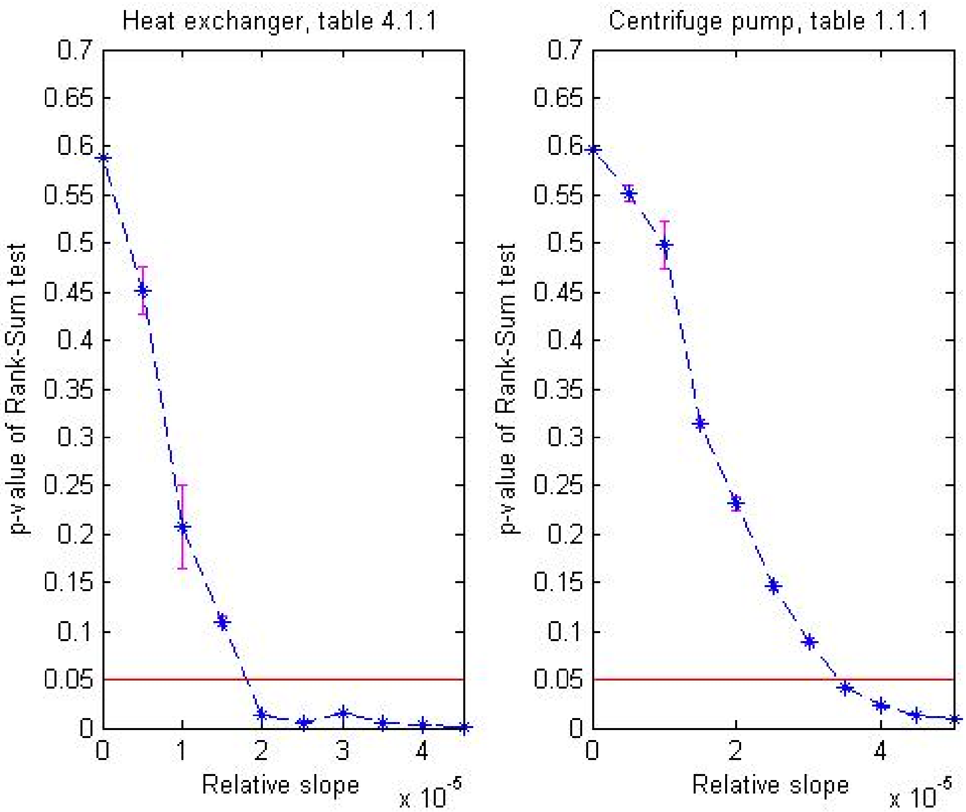

Figure 3.3: Simulations run on components presented in tables 1.1.1 (right) and 3.13.1 (left). Results are averaged from 10000 and 2000 simulations respectively. Bars indicate $\pm 2\sigma$.

- Number of observation years for each reactor T_x[3].

[3] A note on notations, i symbolizes each individual component, x symbolizes each reactor and n

- Period between maintenance for each component and reactor T_{ix}.
- Number of components that have the different maintenance periods for each reactor N_{ix}.
- Total time of observation T.

A sample of actual values used in the averaging process is shown in table 3.4. The vectors T_x were the same for both of the studied components, these are presented in table 3.5.

Reactor	# components with maintenance period $1 month$	# components with maintenance period $3 months$	# components with maintenance period $1 year$	Total number of components	Average time between maintenance [years] $(\frac{T_{ix} \cdot N_{ix}}{\sum_i N_{ix}})$
B_1	2	4	1	7	0.3095
B_2	2	2	3	7	0.5238
O_1	0	2	8	10	0.85
O_2	11	0	11	22	0.5417
O_3	10	10	76	96	0.8264
F_1	4	7	8	19	0.5307
F_2	4	7	8	19	0.5307
F_3	8	31	90	129	0.7629
R_1	8	0	2	10	0.2667
R_2	5	5	4	14	0.4048
R_3	3	9	32	44	0.7841
R_4	6	9	29	44	0.7216
TVO_1	0	4	14	18	0.8333
TVO_2	0	4	14	18	0.8333

Table 3.4: Number of components for each different maintenance period and reactor. Values for closing valve, corresponding to table 3.7 in T-book v.7.

T-book version	B_1	B_2	O_1	O_2	O_3	F_1	F_2	F_3	R_1	R_2	R_3	R_4	TVO_1	TVO_2	Sum (T(i))
7	0	2.5	5	5	5	5	5	5	5	5	5	5	5	5	62.5
6	3	6	6	6	6	6	6	6	6	6	6	6	6	6	81
5	4	4	4	4	4	4	4	4	4	4	4	4	4	4	56

Table 3.5: Number of observation years per reactor for each analyzed version of the T-book (T_x).

symbolizes the version of the T-book.

An average time between maintenance for each version of the T-book was calculated as shown in equation 3.2.

$$T_{avg} = \frac{\sum_{x=1}^{14} T_x \cdot (\frac{T_{ix} \cdot N_{ix}}{\sum_i N_{ix}})}{T(n) * (365.25 * 24)} \tag{3.2}$$

The average maintenance time T_{avg} was used to calculate an average contribution of the "stand-by degradation" term $\lambda_s t$. As the final model for the probability of failure uses a linear time dependency, the contribution was calculated by $\frac{T_{avg}\lambda_s}{2}$. The final form of the averaged reliability parameter is shown in equation 3.3.

$$q_{avg} = q_0 + \frac{T_{avg}\lambda_s}{2} \tag{3.3}$$

After obtaining an average reliability parameter q_{avg} the approach was the same as described in section 3.1 with the exception that the time discretization was based on number of uses instead of running time. Just as in the case of continuously running components, no data on when the observed failures occurred or the time distribution of the uses is available. Therefore the number of predicted failures was placed randomly in the time interval between the publishing's of T-books. Results of the rank sum test for pairs of trended and trend-less data sets are presented in figure 3.4.

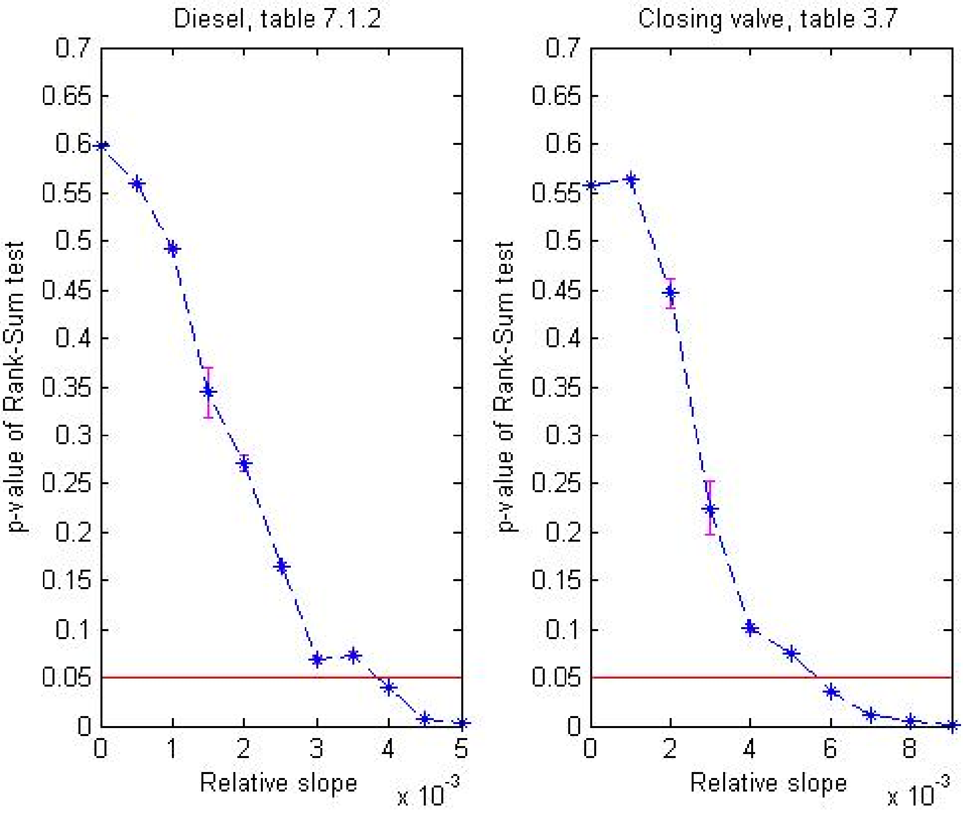

Figure 3.4: Simulations run on components presented in tables 3.7 (right) and 7.1.2 (left). Results are averaged from 30000 and 20000 simulations respectively. Bars indicate $\pm 2\sigma$.

Exponential trends

When the algorithms were run for exponential trends a disturbing result was obtained. It shows that the average p-values of the rank sum test converge slower than in the case of linear trends. Convergence could not be reached for any of the four components, a notable difference in average p-values could be observed for iteration numbers reaching a height that MATLAB could not handle properly. Because of this no further investigation of exponential trends was carried out.

3.2.2 Real distributions

Using the same methodology as previously the approximation of the true time distributions were analyzed. Input data to the rank sum test were: a distribution with the difference in number of observed failures between T-book version randomly distributed in the time intervals between the publishing's of T-books, and a distribution with the same total number of failures placed randomly in the total time interval. This procedure was performed several times to obtain an average p-value for each component versus the random distribution. Results of these calculations are presented in table 3.6.

Component	Average p-value	Trend suspicion
Centrifuge pump	0.6163	Trend highly unlikely
Closing valve	0.4965	Trend highly unlikely
Heat exchanger	~ 0	Trend likely
Diesel generators	0.0128	Trend likely

Table 3.6: Components, their corresponding p-values and a conclusion on trend likeliness.

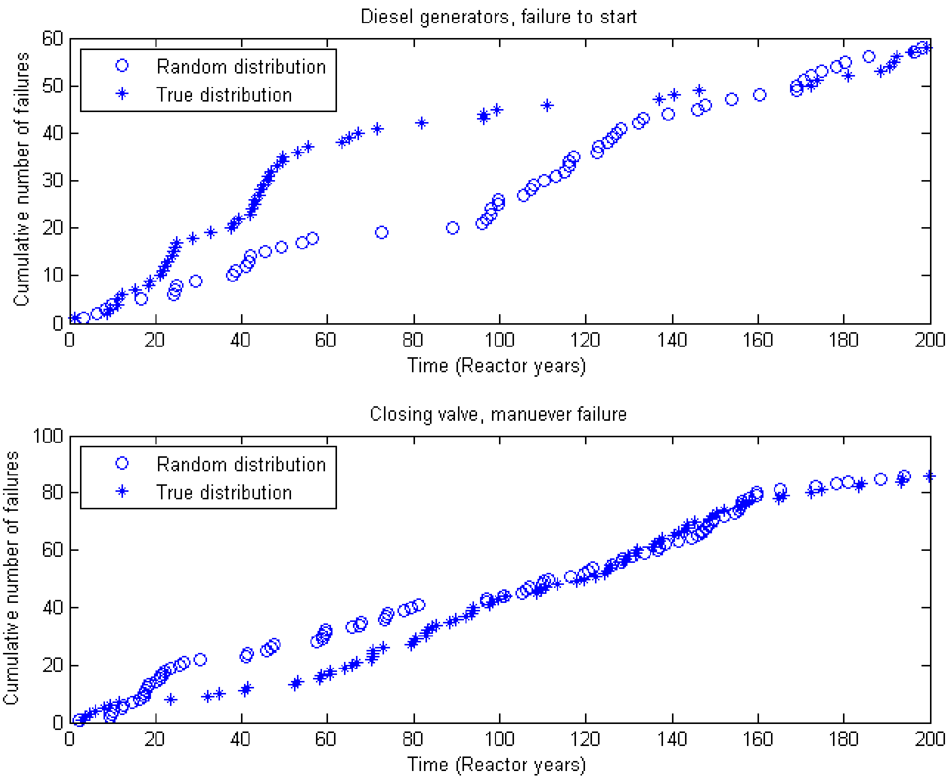

Figure 3.5: The approximations of the true and random distributions for the diesel generators and closing valve. The failures are presented cumulatively against time in reactor years.

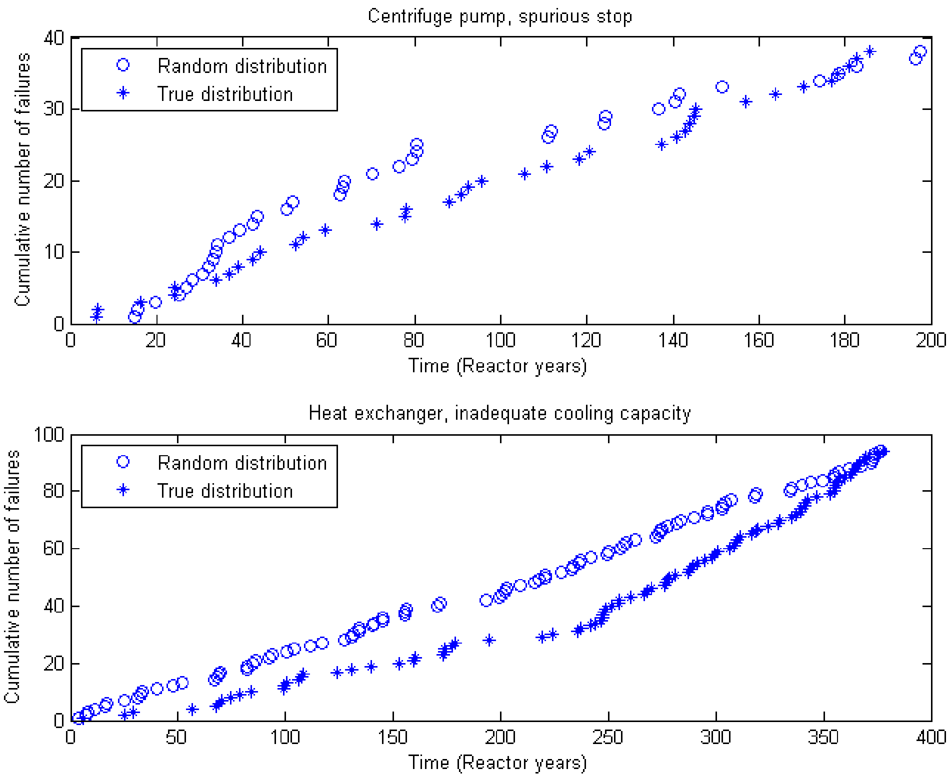

Figure 3.6: The approximations of the true and random distributions for the centrifuge pump and heat exchanger. The failures are presented cumulatively against time in reactor years.

3.3 Discussion, on detectable trend and the analysis of trends

In this section rest probably the largest approximations made during this thesis. Most of these originate in the fact that an exact time distribution of the observed failures is not available. As described in 3.1 an approximate distribution was used. There is no way to estimate how precise this distribution is, therefore this is considered the largest source of uncertainty in the results. The way in which the time distribution was produced may seem crude, but it was considered the best and only reasonable option at the time.

Following the approximated time distribution new problems arose. The greatest one was the problem of convergence in the results presented in figures 3.4 and 3.3. The convergence problems that were encountered most likely result from the variation in time of the observations in the approximated distributions. Thus it is reasonable to believe that these convergence problems will not persist if an exact time distribution is used. It is worth mentioning that the results in question are not critical to the final conclusion as they are used to estimate the magnitude that a trend should have to be detectable. The variation in the results presented in section 3.2.1, decreases greatly for increasing trend slopes. This fact allows for an accurate, under the circumstances, estimation of detectable trends despite convergence problems for lower slope values.

A last point of discussion at this stage is the averaging of the time between maintenance for the stand-by components. All of the data used to carry out this averaging was taken directly from the different versions of the T-book, and therefore uses all of the available information. It could be that the maintenance periods were changed several times in between some publishing's of the T-books resulting in a loss of information. Hypothetically the maximum relative change in the parameter λ_s resulting from a change in the maintenance period is 52 times the original value. This is a very large change that assumes that all components in the group had the maximum maintenance period of 1 year to begin with, and receive the minimal maintenance period of 1 week instead. Such a change is highly unlikely as it involves simultaneous changes in maintenance periods for all nuclear power plants in Scandinavia. Again the exact uncertainty due to the possible loss of information on maintenance periods is hard to approximate as no additional information is available. In order to approximate the uncertainty access to all of the power plants safety documentation is required; one would have to go through the old maintenance documentation and manually check that it is consistent with that presented in the T-books.

4

PSA with postulated increasing trends in reliability parameters

This, last, stage of the thesis will present comparisons of PSA analysis results using tabulated and generated reliability parameters. Software called "Risk Spectrum" will be used to carry out the PSA analysis. Up until this point the project regards generic reliability parameters, calculated based on all observations from a component group, not specific to a power plant. Due to the nature of PSA analysis plant specific parameters will have to be used during this stage.

To run a PSA analysis a model is required. A complete model consists of a fault tree containing events that represent component failures or their consequences. Events are combined by gates[1] leading to a new event or consequence. This sort of branching carries on until some final consequence, for example "fuel damage". Table 4.1 explains some basic functions used by Risk Spectrum.

Because PSA models describe the behavior of a plant in such detail they are naturally specific to that plant, and use plant specific reliability parameters. Risk Spectrum allows running of sequences specified by the user, in other words parts of the full model that end in a specific event or consequence.

The methodology of this stage will be that some suitable sequences of events, containing an altered reliability parameter, will be executed. The results of these sequences will be compared to results obtained with the tabulated reliability parameter. The choice of sequence or sequences will differ for each of the studied components and is described later on in this chapter.

[1]See table below.

Symbol	Name	Brief explanation
$\triangle$	Transfer	A transfer from a part of the fault tree to a specific sequence. Used to help the user by limiting the number of events displayed at the same time.
$\bigcirc$	Basic event	Symbolizes that the given event is not dependant on previous events.
$\overset{\cap}{\frown}$	OR-gate	A coupling between one or more events symbolizing that the consequence occurs if a given number (usually 1) of the connected events occur.
$\underline{\cap}$	AND-gate	A coupling between one or more events symbolizing that the consequence occurs if all of the connected events occur.

Table 4.1: Description of the basic notations used by Risk Spectrum.

4.1 Preparation of input data

During the second stage of this thesis generic reliability parameters were discussed. Those exact parameters will not be used in the PSA model due to the fact that the model treats plant specific parameters. Instead the calculations and trend analysis performed in the previous stage will be altered to obtain plant specific reliability parameters with the same trend.

To fulfill the purpose of the project an assumption that reliability parameters contain a linear trend of magnitude corresponding to that is just not detectable will be made. Further the time dependency of the parameters presented in the latest T-book version will be extrapolated to the current date.

In order to translate the trend contained in the generic parameters a quota (Γ) of their nominal value[2] and their extrapolated up-to-date value will be calculated, equation 4.1.

$$\Gamma = \frac{\text{parameter}_{\text{today}}}{\text{parameter}_{\text{nominal}}} \tag{4.1}$$

The plant specific parameter corresponding to the studied generic parameter will con-

[2]The value presented in T-book v. 7.

sequently be multiplied by the factor Γ. The PSA software allows the user to choose boundary conditions before performing an analysis. Pre-defined sequences were assumed to have optimal boundary conditions specified from the start, these were not changed. Fault tree analyses that were defined manually required more attention. Details about chosen boundary conditions can be found under their corresponding failure mode in section 4.1.1.

4.1.1 Choice of analysis sequences

In general the analyzed sequences were chosen with respect to each failure modes' importance. Of the failure modes studied in this thesis only the "Diesel generators, failure to start" is closely related to a system in the power plants. The other three failure modes relate to components that are most often sub-parts of various systems, increasing the risk of their statistical significance being drowned in larger analyses. For two of these failure modes it seemed most reasonable to create custom made analysis studying the probability of failure of a specific system that contains the component attributed to the studied failure mode.

Diesel generators, failure to start

This failure mode is contained in several places in the fault tree, most often in sequences starting with a power outage. One of many pre-defined consequence analysis in the model will be run, this analysis is initiated by the event "Loss of off-site power" (TE) and results in a core damage frequency due to inadequate cooling (HS2).

Pneumatic closing valve, maneuver failure

This type of valve is located in many places in the studied power plant model and therefore its failure is present in several places in the event tree. A pre-defined analysis case including a larger portion of the fault tree was chosen. This analysis case is called S and models pressure release in the condenser. The failure mode "maneuver failure" is present as part of several system failures included in this analysis.

Centrifuge pump, spurious stop

The centrifuge pumps that are described in table 1.1.1 in the T-book are used to cool the fuel pool. A sequence leading to the event "Failure of system 324"[3] was studied. Boundary conditions had to be specified for this sequence. The chosen boundary conditions correspond to a case when the plant is in its yearly outage period and the pumps are connected.

[3]System 324 is the cooling and cleaning chain of the fuel pool.

Heat exchangers, inadequate cooling capacity

The heat exchangers are used for various purposes and appear in many places in the fault tree. For example the diesel generators are cooled by these heat exchangers when they are in operation, therefore the failure mode in question appears in the analysis case used for the diesel generators discussed previously. For the sake of diversity another sequence of events was studied. A sequence of events leading to the failure of the sprinkler system inside the reactor building, system 322, was run.

The heat exchangers are in operation at all times, yet the fault tree branches out into two separate cases corresponding to the power plant in operation and in outage. The branch modelling the power plant in operation was chosen and because of the construction of the model no boundary conditions needed specifying.

Joint cases

As mentioned earlier several of the studied failure modes can be present in one analysis case. To study the effects of postulated trends in reliability parameters on a larger scale several such sequences were run. The sequence previously used to analyze the diesel generators failure mode, consequence analysis TE HS2, was re-run with modified input data for diesel generators and heat exchangers.

A custom, so called, analysis case group was prepared to study all of the analyzed failure modes. An analysis case group is simply a way to run several pre-defined analyses in sequence. This custom case consisted of consequence analyses for all pre-defined initiating events such as LOCAs, transients and common cause initiators[4]. The analysis case covered power plant states: in operation, effect increase and effect decrease. In further stages this analysis case group will be referred to as “full model”.

4.2 PSA results

Linear trends were assumed for each of the studied component groups. The plants specific reliability parameters were extrapolated in time from the date of printing of the latest version of the T-book (approximately 6 years ago) to their value today. Table 4.2 shows the assumed trends and parameter values.

[4] A common cause initiator is an event that causes a reactor SCRAM and degrades a part of some safety system.

Failure mode	Trend slope (α)	Scaling [Γ]	Tabulated parameter/s	Extrapolated parameter/s
Centrifuge pump	$4e^{-5}$	2.21	$6.9e^{-6}$	$1.53e^{-5}$
Heat exchanger	$2e^{-5}$	2.5	$5.6e^{-6}$	$1.4e^{-5}$
Closing valve	$6e^{-3}$	4.4; 1.07	$q_0 = 7.8e^{-4}$ $\lambda_s = 14.8e^{-7}$	$q_0 = 3.43e^{-3}$ $\lambda_s = 15.8e^{-7}$
Diesel generator	$4e^{-3}$	6.73; 1.63	$q_0 = 4.1e^{-4}$ $\lambda_s = 19.4e^{-6}$	$q_0 = 2.76e^{-3}$ $\lambda_s = 31.6e^{-6}$

Table 4.2: Extrapolation details for each component group and reliability parameter.

When extrapolating the test-interval dependent parameter λ_s the same testing intervals as presented in the latest version of the T-book were assumed. To study the effect of the parameter extrapolation two values were observed for each sequence. The first was the total frequency (F) or probability (Q) and the second was the Fussel-Vesssly (FV) parameter of the failure mode in question. The FV parameter is defined as:

$$FV = \frac{Q_i(t)}{Q(t)} \tag{4.2}$$

Where $Q_i(t)$ is the probability of a specific event occurring at time t and $Q(t)$ is the probability of the top event of the studied sequence occurring at time t. By definition the FV value for a basic event will change if the frequency of probability of the top event is altered. Therefore the FV values were normalized by the F or Q values for the simulations.

Table 4.3 shows all analyzed sequences and their corresponding results. (Results omitted in this report. Complete results are available in [15])

Sequence	Failure mode	Result (tabulated)	FV (tabulated)	Result (extrapolated)	FV (extrapolated)
Failure of system 324	Centrifuge pump, spurious stop	-	-	-	-
Failure of system 322	Heat exchanger, inadequate cooling capacity	-	-	-	-
Analysis case S	Closing valve, Failure to maneuver	-	-	-	-
Consequence analysis TE;HS2	Diesel gen. failure to start	-	-	-	-
Consequence analysis TE;HS2	Diesel gen. and Heat exchanger	-	-	-	-
Full model	All	-	-	-	-

Table 4.3: Results of the PSA analysis. Tabulated indicates sequences run with the tabulated reliability parameters (assumed trendless) while extrapolated indicates sequences run with reliability parameters including a postulated trend and extrapolated to the present time. The FV parameters were summed for all basic events originating in the same failure mode.

4.3 Discussion, on trend significance

Converting the studied generic parameters to plant specific ones was inevitable. The application of reliability parameters is primarily PSA analysis. These analyses are always plant specific due to the complexity of each individual power plant. At the starting stages of this thesis generic parameters were considered due to better documentation and statistical information on number or errors and running time. The possibility of studying plant specific parameters was not even considered and would most likely result in poor statistical basis for the calculations performed.

The results show that an increase in reliability parameters affects the FV values of the studied basic events in each case. This means that the increase in the reliability parameters was not totally quenched by other event probabilities. Although it is clear that an increase in reliability parameters due to a linear trend in time has different outcomes depending on which component is affected. Increase in the diesel generators' and closing valves' reliability parameters showed significant change in the end result. While a change in the centrifuge pumps' and heat exchangers' reliability parameters was barely noticeable. This leads to the conclusion that time dependant trends in reliability parameters can have a big impact on the PSA analysis depending on what failure modes are affected by the trend.

An after study was made to compare the impact of negative trends for the diesel generators. The value of one, weighed, parameter q was considered. The equation below shows the calculation of q.

$$q = q_0 + \frac{\lambda T}{2} \tag{4.3}$$

Where q_0 and λ are the two reliability parameters and T is set to 28 days [5]. Both q_0 and λ were calculated using a trend corresponding to an α value of $-4 \cdot 10^{-4}$ instead of $4 \cdot 10^{-4}$ as was done previously in this thesis. The results were

$$\begin{aligned} q &= 1.595 \cdot 10^{-4} \text{ Decreasing trend} \\ q &= 8.9 \cdot 10^{-3} \text{ Increasing trend} \end{aligned} \tag{4.4}$$

The difference in these results is very large and due to the crude methods used in this thesis they should not be used directly. What these results show is the fact that the trend magnitudes that are discussed in this thesis are large thus giving strength to the claim that decreasing trends can turn out to outweigh the increasing ones when taking into account all components.

[5] This is done according to how the "$q_0 + \lambda T$" – model is implemented at OKG.

5

Conclusion

Based on results presented in section 3.2.2 one can conclude that time dependent trends in reliability parameters can be discovered with the rough method presented in this thesis. The results in section 4.2 show that increasing time dependent trends can in some cases have a big impact on the application of reliability parameters, PSA analysis. Although, as figure 3.6 indicates, trends resulting in both an increased and decreased frequency of failures are discovered. The test method applied does not discern between and increasing and decreasing trend, thus a negative trend in one component may turn out to be outweighed by a positive trend in another component.

An increasing trend in the diesel generators' reliability parameters was shown to have the largest affect on the PSA results, while figure 3.6 shows that in reality a decreasing trend is most likely. An increasing trend in the heat exchangers' reliability parameters has been detected but the related failure mode is shown to have small significance in PSA analysis. Thus a conclusion that the postulate on absence of trends stands through this investigation is reached. Although further studies are required to confirm that this finding is true for all components presented in the T-book.

5.1 Future studies

As the scope of this thesis does not cover all potential cases pertaining to the purpose, further studies are recommended. The following is a suggestion on how these/this study can be performed.

To fully assess the validity of the postulate on absence of trends a study in which failure modes bear most importance to the PSA is required. Reliability parameters connected to the failure modes that are shown to have a certain degree of significance are to be studied for trends. In the study of trends the test methodology described in this thesis could be used, considering improvement regarding simplification of the used assumptions. For example, the author recommends refining the test methodology by acquiring more accurate time distributions of the observed failures.

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