Investigation of time-dependent trends in plant-specific data for active components - Can A.Y. Khinchine be rejected?

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1 Introduction

As a part of the cooperation within the APSA network and of the application of the newly implemented procedure for trend analysis for risk-important active components a time-dependent trends investigation was performed on failure data collected for the Goesgen plant-specific PSA. The investigation included the following component groups:

- Emergency power diesel generators (two types, EY11..41D001 (4) and FY11/21D001 (2))
- Diesel driven cooling water pumps VA91/92D001 (2)
- Motor –operated valves in the closed intermediate cooling water system TF (28)
- Motor-operated valves in the core cooling and residual heat removal system TH (69)

Other component groups were analyzed, too. Due to the lack of failure events, a detailed quantitative analysis was regarded as not being meaningful.

2 Complexity of the problem and applied methodology

2.1 Traditional PSA methodology for the time-dependent failure evaluation

Traditional PSA-methodology[1] is based on the assumption of a Poisson process for the occurrence of failures in time. The underlying assumptions for a Poisson process are:

- Failure events occurring at different time intervals are statistically independent (property of a memoryless stochastic process).
- Exact simultaneous events do not occur.
- The probability of failure in different, but equally long time intervals is constant.

The assumption of a Poisson process (more exactly of an Homogeneous Poisson Process, HPP) is also strongly supported by of one of the most important theorems of the stochastic process theory, originally derived by Khintchine in queuing theory. This theorem states, that the superposition of weakly nonhomogeneous stochastic processes (more exactly of Levy processes[2]) can be approximated by a homogeneous Poisson process if none of the underlying stochastic processes dominate and the events considered are rare.

[1] Handbook of Parameter Estimation for Probabilistic Risk Assessment, NUREG/CR-682, 2007
[2] Daley, D.J., Vere Jones, D. Introduction to the Theory of Point Processes, Volume I, Elementary Theory and Methods, 2002

Because active components considered in PSA represent essentially “supercomponents” consisting of many different parts and the failure modes considered (e.g. “fail to start” or “fail to run”) are composed of many different failure mechanisms leading to the same functional impact, the theorem of Khintchine is fully applicable here. This means, that the assumption of a Poisson process of failure occurrence has a sound theoretical basis reaching much further than the simple assumption of the “bath tube” behavior of the failure frequency curve in time, which is exactly applicable only for a single failure mechanism. Additionally, in practical life we have to deal with competing failure mechanisms. In case of some of them dominating we have to expect a decreasing overall failure rate because the dominating failure rates are easy to recognize and the corresponding failure mechanisms “will die out” with increasing operational experience (except for complete ignorance of operational experience). This confirms the asymptotic convergence of the occurrence of failure events towards a homogeneous Poisson process. Pooling of data from different plants (the failure events in each of the plants have to be expected to follow stochastic processes with different characteristics) makes the problem even more complex.

These circumstances challenge an investigation to discover time-dependent trends in failure data of active components. Therefore, a meaningful investigation should comprise various methods to improve the chances to discover time dependent effects notably deviating from the expected asymptotic behavior. With respect to PSA applications, it is worth to mention, that in many cases usual common cause failure (CCF) models may include ageing failure events, because ageing degradation can be regarded as a special form of a common failure mode.

2.2 Applied methods

The methodology applied follows the general outline of the proposed (by the APSA network participants) guideline for analyzing data of active components. It includes a combination of different methods:

- Graphical visualization (Nelson –Aalen indicator) to test the assumption of a constant failure rate
- Non-parametric testing (Laplace test)
- Direct parameter estimation techniques (exponential distribution and Weibull distribution) under the assumption of a renewal process.

Additionally, a best-estimate fit for the selection of the distribution model is performed using the distribution wizard of WEIBULL++7[3]. WEIBULL++7 analysis has been performed using the MLE (Maximum Likelihood Estimator) option: The parametric analysis is performed for effective observation times of the whole population of equipment.

3 Raw data

The data collection for the Goesgen PSA covers the time period from August 1, 1980 to December 31, 2004. In same cases (diesel generators) the time period was extended till the last observed

[3] WEIBULL++®7, User’s Manual, Reliasoft Publishing, 2007

diesel generator failure. This was feasible, because these events are reportable incidents according to the Swiss reporting system.

3.1 Raw data for emergency power diesel generators

The raw failure data for the emergency power diesel generators at NPP Goesgen are given in table 1. Diesel generators are normally standby-operated pieces of equipment. Because all observed failures corresponding to the fail to run failure mode occurred rather early after the start of the diesel generator (usually during the first hour), it was simply assumed that all failures can be related to standby failure modes (failure during standby). The total population consists of 6 pieces of equipment (4 diesel generators EY11/21/31741D001, 2 diesel generators FY11/21D001). The diesel generators Eyxx and Fyxx are of different sizes, but manufactured by the same vendor and maintained by the same maintenance team.

Table 1. Raw data describing failure events of Goesgen emergency power diesel generators

Plant-ID	**Trouble –report ID**	**Date**
	Begin of observation	01.08.1980
EY31D001	**KKG-D/80-2310**	30.10.1980
EY31D001	KKG-D/82-998	12.06.1982
EY21D001	KKG-D/84-1144/1163	19.06.1984
EY11D001	KKG-D/84-1153	13.08.1984
FY61D001	KKG/D85-1499	20.08.1985
FY51D001	KKG/D85-1565	29.08.1985
FY61D001	KKG-D/86-1993	15.10.1986
EY31D001	KKG-D/87-361	24.02.1987
EY21D001	KKG-D/87-365	26.02.1987
EY41D001	KKG-D/92-0113	27.01.1992
EY41D001	**KKG-D/92-917**	01.05.1992
EY41D001	KKG-D/92-946	02.05.1992
FY51D001	KKG-D/92-1690	15.09.1992
FY51D001	KKG-D/92-1694	16.09.1992
FY61D001	KKG-D/96-435	27.02.1996
FY51D001	KKG-D/96-686	09.04.1996
EY11D001	KKG-D/2001-04	20.2.2001
EY21D001	KKG-D/01-1017	06.05.2001
EY11D001	KKG-D/02-1812	01.08.2002
EY41D001	KKG-D/04-0998	15.03.2004
EY21D001	KKG-D/04-4163	20.10.2004
FY61D001	KKG-D/06-02	27.02.2006
	End of Observation	31.12.2006

The data is censored, because on the left side of the time axis the observation period is incomplete (power operation started November 1, 1979), and on the right hand side of the time axis the observation was extended without observation of any additional failure.

For parametric analysis purposes (renewal problem) the time periods were extended assuming a non-informative distribution (Jeffrey's prior) of the time to failure. This approach essentially assumed that the start of commissioning of the component is known exactly for the left censoring, while for the right censoring side an additional fictive failure was predicted. This can be done similarly for an additional analysis based on a separation of the different types of diesel generators. Table 2 shows the resulting data with this extension of the observation period.

Table 2. Prepared raw data for the analysis. Effective Observation times between failures.

All diesel generators, d	**EY diesel generators, effective observation time between failures, d**	**FY diesel generators, effective observation time between failures, d**
1081	721	7381
3539	2360	18
4428	2952	824
330	220	4324
2232	3700	2
54	8	2518
2472	7184	84
792	380	7222
12	4	615
10776	12864	
570	300	
6	1808	
816	2368	
6	876	
7554	6417	
252		
10668		
450		
2712		
3552		
1314		
2970		

3.2 Raw data for diesel driven cooling water pumps

Another group of components with significant operational experience is the group of diesel driven cooling water pumps. NPP Goesgen has two diesel driven cooling water pumps, which are normally operated in standby, except for the time period, when the main cooling water intake is in maintenance. The diesel driven cooling water pumps (VA91/92D01) are important for the safety of the plant because they provide cooling water in case of an earthquake. The diesel driven pumps are driven by the same type of diesel engine as is used for the bunkered system (special emergency feedwater system – diesels FY51/61D001).

Table 3 shows the critical failure events observed for the diesel driven pumps and the associated effective, total observation time (for two pieces of equipment, in analogy to table 2) between failures.

Table 3. Raw data describing failure events of Goesgen diesel driven cooling water pumps

Plant-ID	Trouble –report ID	Date	Effective, total observation time, d
	Begin of observation	1.8.1980	
KKG-D/VA91D001	KKG-D/80-2869/2894	11.12.1980	529
KKG-D/VA92D001	KKG-D/81-462	05.03.1981	697
KKG-D/VA91D001	KKG-D/82-655	02.04.1981	753
KKG-D/VA92D001	KKG-D/81-3870	19.08.1981	1031
KKG-D/VA91D001	KKG-D/82-1158/1159	13.07.1982	1687
KKG-D/VA92D001	KKG-D/82-2059	16.12.1982	1999
KKG-D/VA92D001	KKG-D/84-879	08.05.1984	3017
KKG-D/VA92D001	KKG-D/84-1007	22.05.1984	3045
KKG-D/VA91D001	KKG-D/84-1660	09.09.1984	3265
KKG-D/VA92D001	KKG-D/85-241	14.02.1985	3581
KKG-D/VA92D001	KKG-D/86-1045	04.06.1986	4531
KKG-D/VA92D001	KKG-D/88-965	01.06.1988	5987
KKG-D/VA92D001	KKG-D/89-2332	07.12.1989	7095
KKG-D/VA92D001	KKG-D/MO93-11a	04.11.1993	9951
KKG-D/VA92D001	KKG-D/MO93-12a	10.12.1993	10023
KKG-D/VA91D001	KKG-D/95-2031	02.11.1995	11407
	End of observation	31.12.2006	19561

3.3 Raw data for motor operated valves in the core cooling and residual heat removal system TH

NPP Goesgen collected failure data for 69 motor operated valves of the core cooling and residual heat removal system for the time period between August 1,.1980 and December 31, 2006. The "fail to close” and “fail to open” failure modes were combined into the joint failure mode “failure on demand”. Table 4 shows the raw data describing the failure events. The table also gives the effective observation time for the population observed (69 valves).

Table 4. Raw data describing failure events of Goesgen motor operated valves in the TH-system

Plant-ID	Trouble –report ID	Date	Effective, total observation time, d
	Begin of observation	1.8.1980	
KKG-D/TH20S008	KKG-D/80-2259	23.10.1980	11455
KKG-D/TH10S007	KKG-D/82-996	11.06.1982	41124
KKG-D/TH10S001	KKG-D/82-1087	08.07.1982	1863
KKG-D/TH20S008	KKG-D/83-191	22.01.1983	13662
KKG-D/TH31S002	KKG-D/84-1037	02.06.1984	34293
KKG-D/TH53S002	KKG-D/85-528	19.03.1985	20010
KKG-D/TH53S002	KKG-D/85-958	15.05.1985	3933
KKG-D/TH52S001	KKG-D/87-1308	31.07.1987	55683
KKG-D/TH36S001	KKG-D/01-0167	24.01.2001	339894
	End of observation	31.12.2006	299115

3.4 Raw data for motor operated valves in the closed loop intermediate component cooling system TF

NPP Goesgen collected failure data for 28 motor operated valves of the core cooling and residual heat removal system for the time period between August 1,1980 and December, 31, 2006. The “fail to close” and “fail to open” failure modes were combined into the joint failure mode “failure on demand”. Table 5 shows the raw data describing the failure events. The table also gives the effective observation time for the population observed (28 valves).

Table 5. Raw data describing failure events of Goesgen motor operated valves in the TF-system

Plant-ID	Trouble –report ID	Date	Effective, total observation time, d
	Begin of observation	1.8.1980	
KKG-D/TF32S011	KKG-D/81-4264	20.10.1981	24921
KKG-D/TF12S011	KKG-D/81-4437	12.11.1981	5602
KKG-D/TF12S011	KKG-D/82-382	04.03.1982	2515
KKG-D/TF12S011	KKG-D/90-1975	28.11.1990	86324
KKG-D/TF10S001	KKG-D/01-0322	14.02.2001	18311
	End of observation	31.12.2006	120204

4 Results of non-parametric tests

4.1 Evaluation of the Nelson-Aalen Indicator

The Nelson-Aalen Indicator is a special form of the Kaplan-Meier Indicator with respect to testing the assumption of an exponential distribution with a constant failure rate. This indicator is an estimator for the cumulative hazard function dependent of time:

$$H(t) = \sum_{\{i=1,n,t_i \leq T\}} \frac{1}{n-i+1} \qquad (1)$$

Here the index i corresponds to the number of the failure event, T is the total observation time, t_i is the point in time, when the failure event n was observed and n is the total number of observed failures. The graph of this function should be a straight line and run through the origin of the coordinate system to prove the assumption of an exponential distribution with a constant failure rate as a valid model. In some cases it may not run through the origin but form a straight line indicating a shift of the coordinate origin, which can be expressed by a double parametric exponential distribution introducing a location parameter. Frequently the start-up period of a nuclear power plant (usually the first year of operation) is eliminated from data analysis because this is considered as a learning and testing period for plant operations which is not characteristic for the overall long term plant performance. The need to introduce a location parameter may reflect such initial learning.

Figures 1 to 3 show the Nelson-Aalen Indicator for the diesel generators of Goesgen. The first figure is related to the total population (6 diesel engines), the second one to the normal emergency diesel generators only(EY, 4 diesel engines) and the third figure is related to the diesel generators of the special emergency feedwater system (FY, 2 diesel engines).
From the visual impression it can be concluded that some time dependent effect is observable but the model of an exponential distribution with a constant failure rate provides a meaningful approximation of the failure statistics of the diesel generators at NPP Goesgen. For the FY-diesels some deviation of the hazard rate from a constant value is noteable.

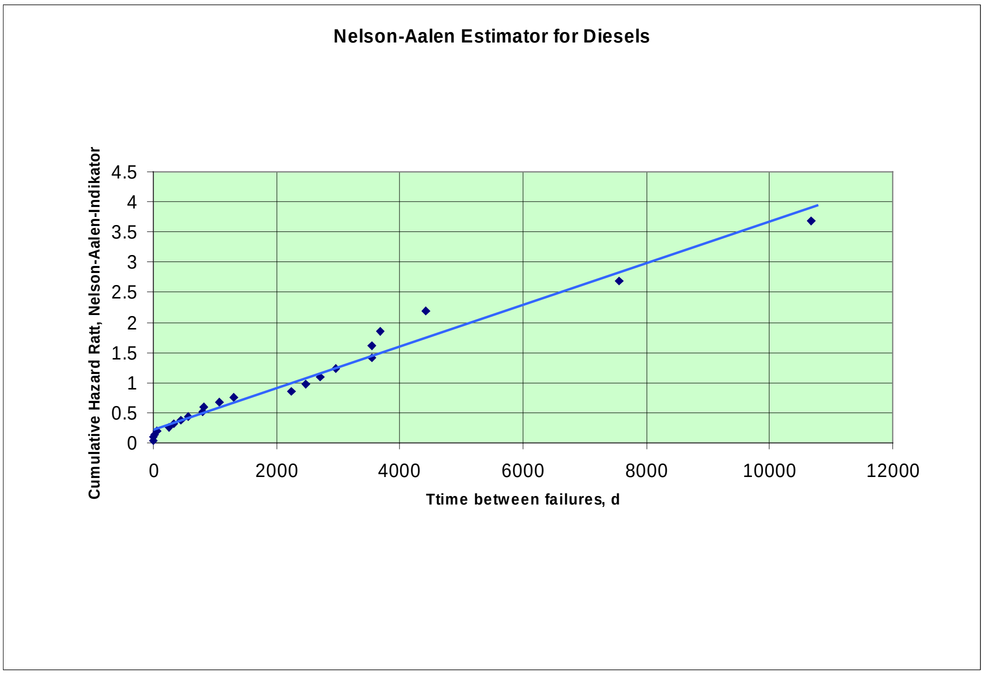

Figure 1. Nelson-Aalen estimator (cumulative hazard rate) for diesel generators at NPP Goesgen (EY+FY).

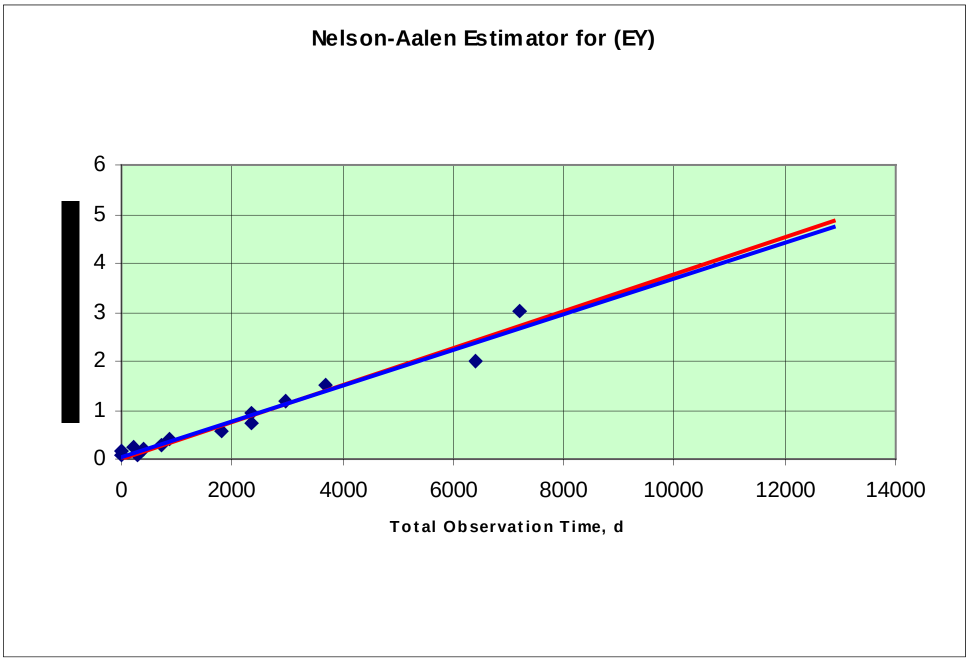

Figure 2. Nelson-Aalen estimator (cumulative hazard rate) for diesel generators at NPP Goesgen (EY).

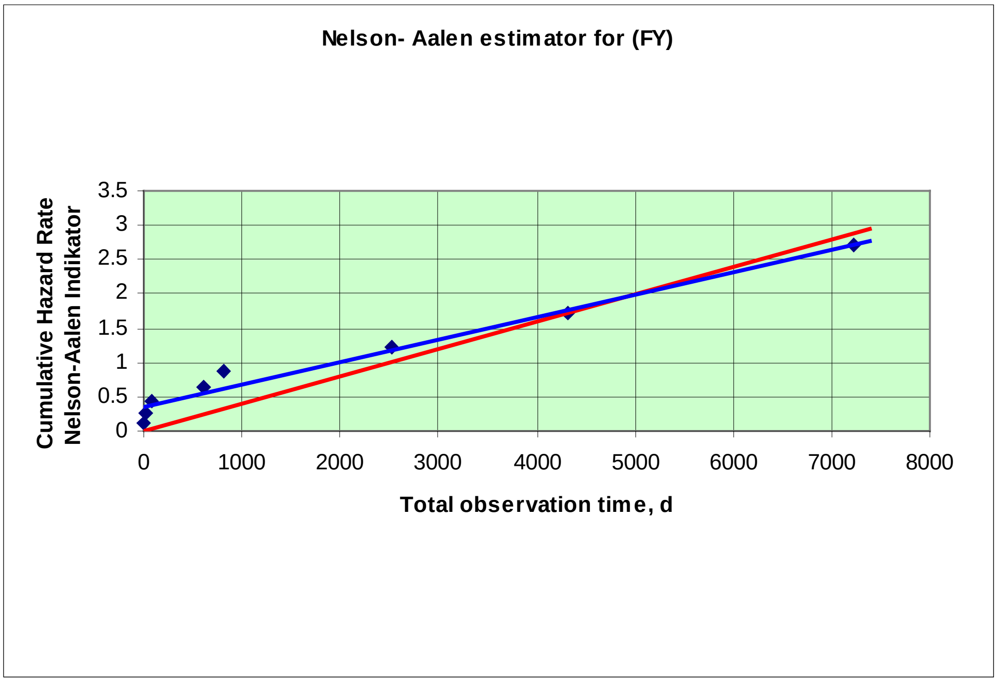

Figure 3. Nelson-Aalen estimator (cumulative hazard rate) for diesel generators at NPP Goesgen (FY).

Figures 4 to 6 show the Nelson-Aalen Indicator for the diesel driven pumps VA91/92D001, the motor operated valves in the core cooling and residual heat removal system TH and for the motor operated valves in the closed-loop intermediate component cooling system TF.

For the diesel driven pumps the exponential distribution model seems to be quite adequate although some learning from initial plant experience cannot be discarded because the time between the failure events has increased. This will especially be true, if we consider the large amount of time gone by since the last failure event.

For the motor operator valves in both considered systems we may conclude on some learning effects slightly reducing the failure frequency since the initial operational period.
In general, we may conclude from visual inspection that some time dependent trends are present in the data.

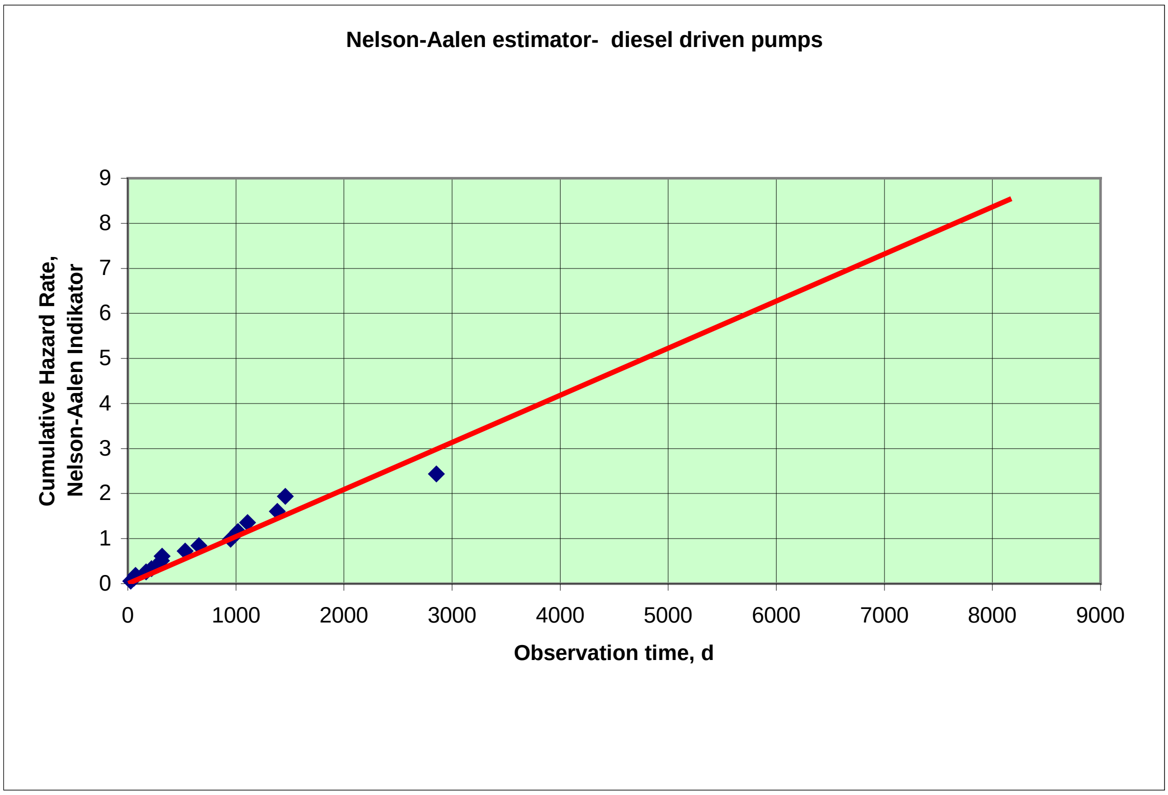

Figure 4. Nelson-Aalen estimator (cumulative hazard rate) for diesel driven pumps VA91/92D001.

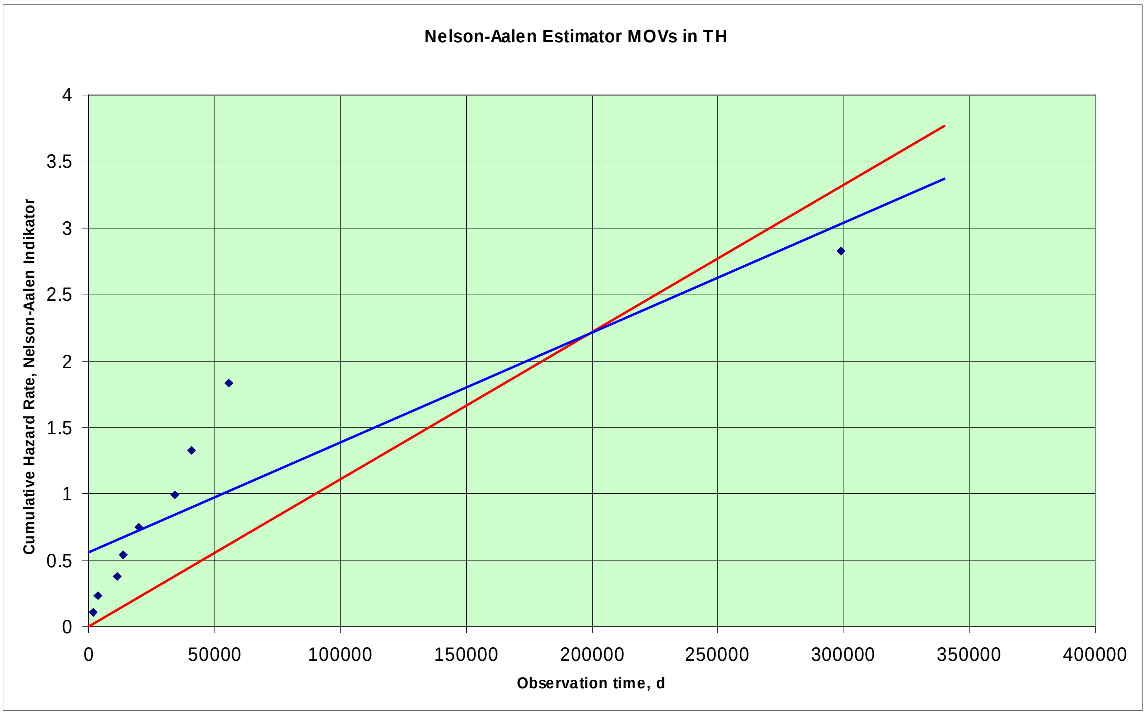

Figure 5. Nelson-Aalen estimator (cumulative hazard rate) for motor operated valves in TH.

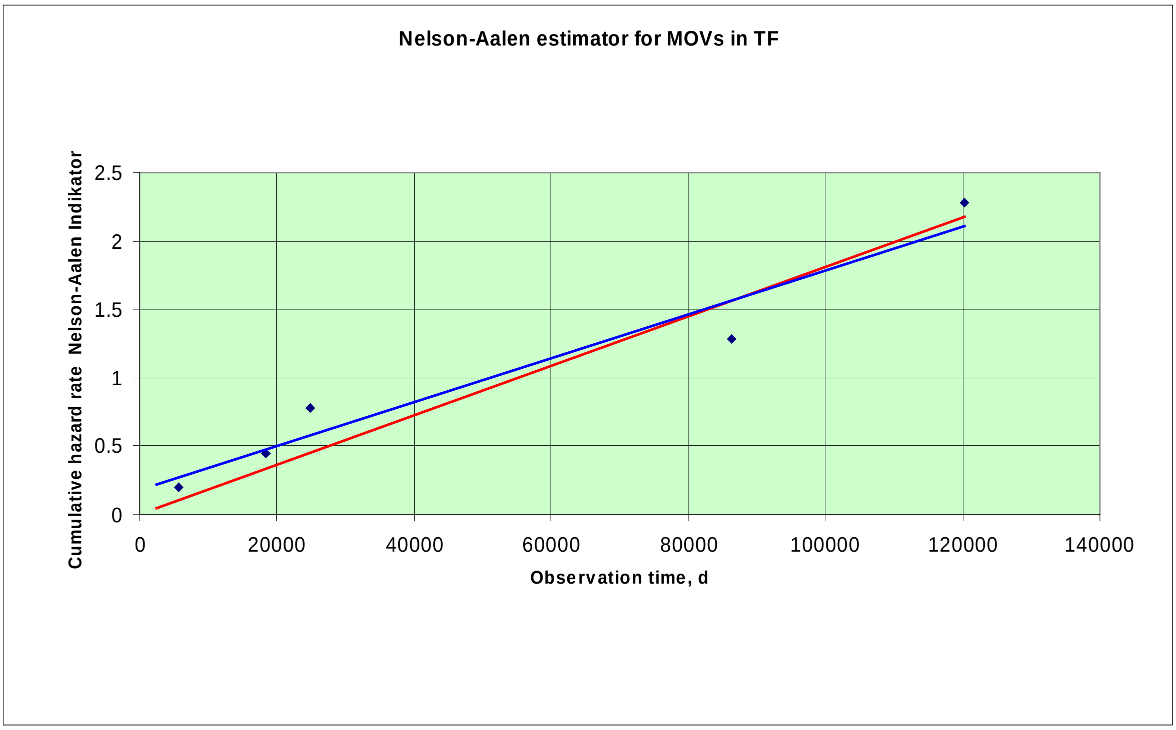

Figure 6. Nelson-Aalen estimator (cumulative hazard rate) for motor operated valves in TF.

4.2 Results of the Laplace Test

The Laplace Test is a powerful tool for testing monotonic trends in data. Here, we test the two following hypotheses :

H_0 - the failure rate is constant

H_1 - the failure rate is either an increasing or decreasing function of time.

The second hypothesis states that the failure events occur more at one end of the interval than at the other. Here the following test statistic was applied, which is based on the mean of the failure times $\bar{t} = \sum_i t_i \big/ n$, where n is the total number of failure events again and T is the observation period. The test statistic has the following format

$$U = \frac{\bar{t} - T/2}{T/\sqrt{12n}} \qquad (2)$$

The test rejects H_0 if $\bar{t}$ is sufficiently far from $T/2$. Positive values of U indicate an increasing trend, while negative values indicate a decreasing trend of failure occurrence. The test statistic is approximately normal for a number of failure events exceeding 3. At a 0.05 test level hypothesis H_0 rejects for $|U| \geq 1.645$.

Table 6 shows the results of the Laplace test for the different component groups.

Table 6. Results of the Laplace Test

Component group	**Test Statistic , U**	**Conclusion**
All diesel generators	-0.680	Constant failure rate cannot be rejected
Only EY diesel generators	-0.380	Constant failure rate cannot be rejected
Only FY diesel generators	-0.547	Constant failure rate cannot be rejected
Diesel driven pumps VA91/92D001	-4.04	Decreasing failure rate
MOVs in TH system	-2.963	Decreasing failure rate
MOVs in TF system	-1.655	Decreasing failure rate, close to the decision limit

5 Results of parametric tests for the different component groups (Lifetime analysis for mean time between failures)

5.1 Results for emergency diesel generators

The analysis has been performed base don the data in table 2. The underlying assumption is what we have to deal with a renewal process. Two model assumptions are made with respect to the efficiency of the renewal process:

- Complete renewal (Homogeneous Poisson Process (HPP)) following an exponential distribution for the failure rate
- Complete renewal (Homogeneous Poisson Process (HPP)) following an Weibull distribution for the time between failures
- The component remains as old as before (power law, corresponds to a special Non-homogeneous Poisson Process (NHPP)). The results of this model are given in chapter 6.

The model of an exponential distribution of failure times corresponds to the assumption of an Homogeneous Poisson Process (HPP), which is a stationary memory-less stochastic process. (complete renewal). As an alternative, the model of a two-parametric Weibull-distribution is used to describe another alternative for the renewal process. Additionally, a nonhomogeneous process is using the model of a power law process. This reflects the assumption that the component remains as old as before after any repair.

The analysis was performed with the standard reliability program Weibull++7 for the data given in table 2 using the maximum likelihood method (MLE).

Figures 7 and 8 show the cumulative probability distributions including the two-sided Fisher matrix 90% confidence intervals for the complete set of failure data applying the exponential (HPP) and the Weibull models according to the renewal assumption, respectively.

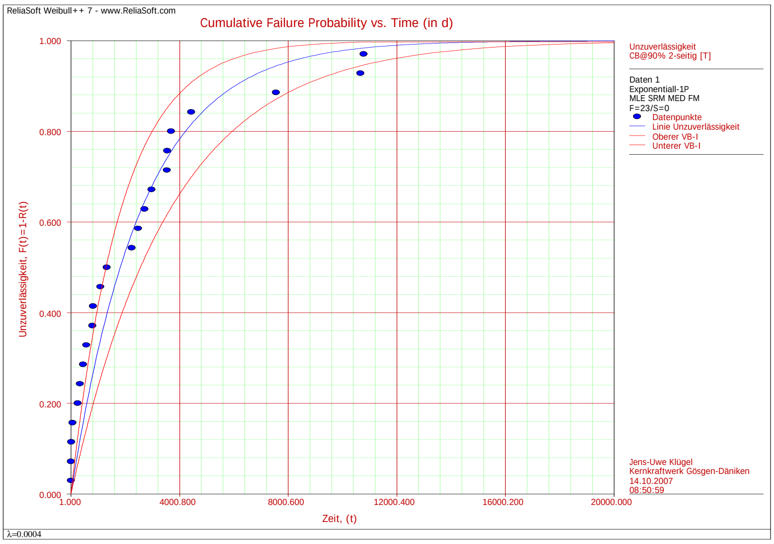

Figure 7. Cumulative Failure Probability for the exponential distribution model (HPP). All diesel failure events considered.

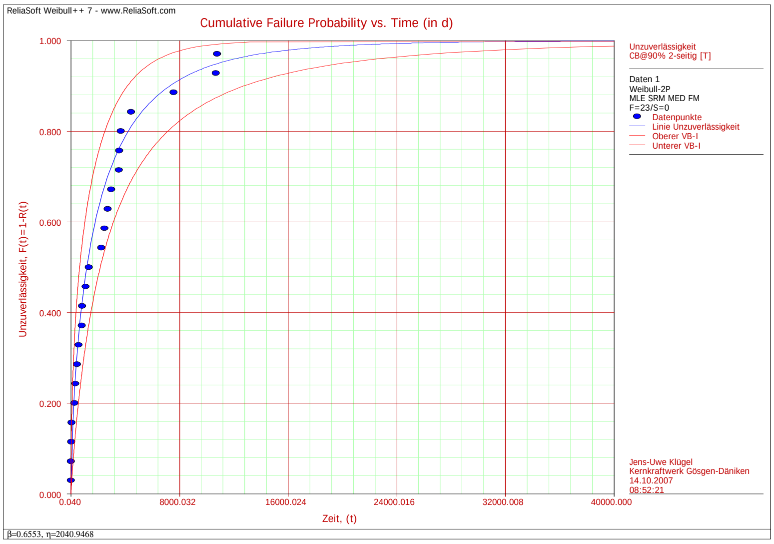

Figure 8. Cumulative Failure Probability for the Weibull distribution model. All diesel failure events considered.

Table 7 shows the parameters for the exponential model (λ and mean lifetime with the 0.9 two-sided confidence intervals. Table 8 shows the parameters for the Weibull distribution model (scale parameter η and shape parameter β and the lifetime with the 0.9 two-sided confidence intervals). Note that the lifetime estimates are related to the observed population (here 6 diesel generators).

Table 7. Parameters of the exponential distribution model (standby failure rate, HPP)

	Low level	Mean	High Level
λ	0.0003	0.0004	0.0005
Lifetime, [d]	1859.6	2620.5	3692.6

Table 8. Parameters of the Weibull distribution model (standby failure rate)

	Low level	Mean	High Level
β	0.4931	0.6553	0.871
η	1180.1	2041	3529.7
Lifetime, [d]	1628.6	2763.6	4689.5

The parameter estimation indicates some learning effect for the Goesgen Diesel generators, because the times between failures seem to increase according to the Weibull model. On the other hand, the analysis shows that the use of the constant failure rate model would lead to conservative results – the estimated mean value of the life time of an diesel generator is smaller than the corresponding value for the Weibull renewal model. For further analysis it is of some interest to compare the evaluated lifetimes with the best-estimate fit suggested by the distribution wizard of WEIBULL++®7 . It is also worth to analyze the data for the different types of diesel generators, separately .

The best fit of the data is provided by the generalized Gamma distribution according to the WEIBULL++7 analysis This does not come as a surprise, because the generalized Gamma distribution is frequently used to mimic other distribution types and is therefore very flexible. According to the analysis the exponential distribution model performs worse than the two-parametric Weibull model. This is another indication that a time dependent trend is present. Figure 9 shows the plot of the cumulative failure probability for the diesel generators according to the generalized Gamma distribution model.

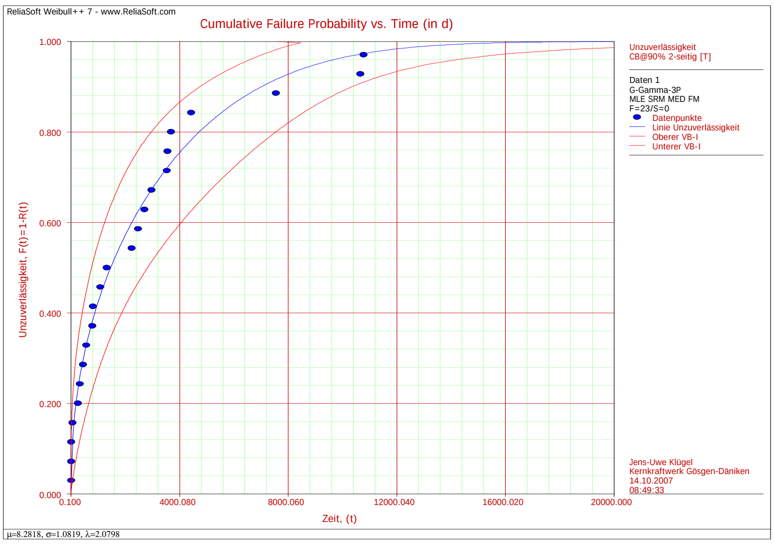

Figure 9. Cumulative Failure Probability for the generalized Gamma distribution model. All diesel failure events considered.

It is interesting to note that the estimated mean lifetime according to the generalized Gamma distribution model is located between the estimates provided by the exponential distribution model and the two parametric Weibull distribution models. The 90% confidence interval for the lifetime is given by *(1486.4, mean=2629.8, 4652.8)* days. A comparison with tables 6 and 7 shows that the exponential distribution model leads to conservative results, while the Weibull distribution model is slightly optimistic.

Figures 10 and 11 show the plot of the cumulative failure probability for the normal emergency diesel generators (EY) treated separately and respectively using the exponential and the Weibull models.

Table 9 shows the parameters for the exponential model (and mean lifetime with the 0.9 two-sided confidence intervals). Table 9 shows the parameters for the Weibull distribution model (scale parameter and shape parameter and the lifetime with the 0.9 two-sided confidence intervals).

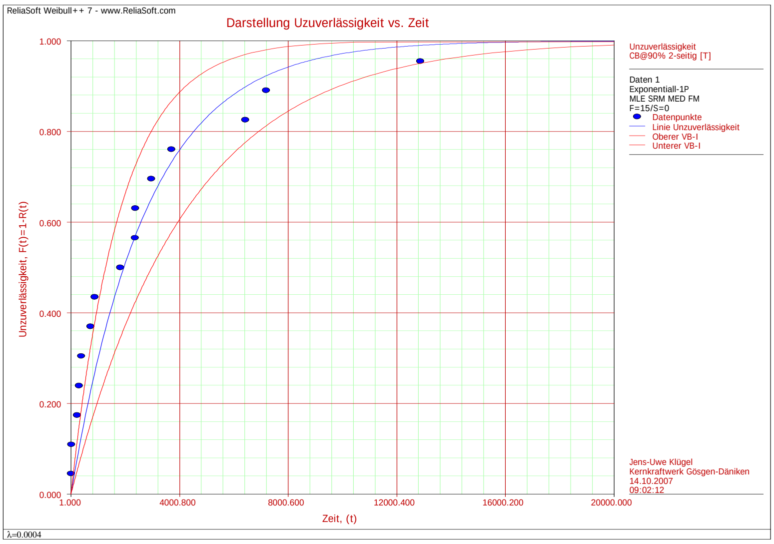

Figure 10 Cumulative Failure Probability for the exponential distribution model (HPP). Only diesel failure events of the EY-type considered.

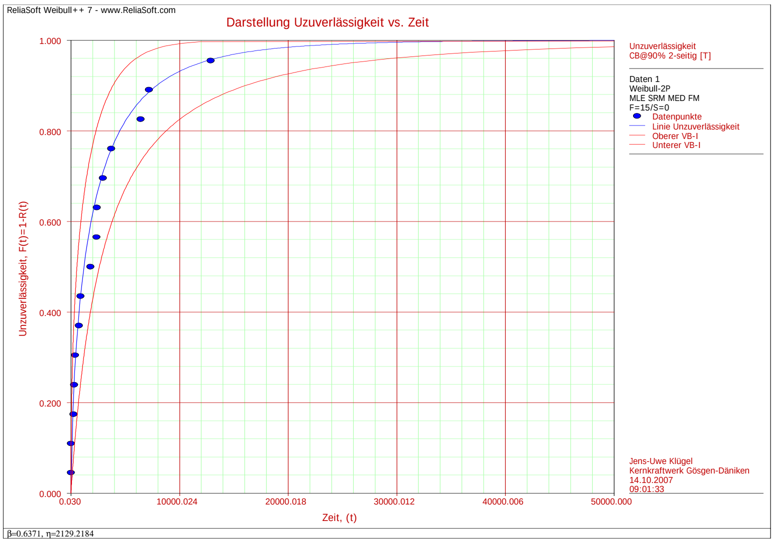

Figure 11. Cumulative Failure Probability for the Weibull distribution model (renewal model). Only diesel failure events of the EY-type considered.

Table 9. Parameters of the exponential distribution model (standby failure rate, HPP), EY-diesels

	Low level	Mean	High Level
λ	**0.0002**	**0.0004**	**0.0005**
Lifetime, [d]	**1838.2**	**2810.8**	**4298.1**

Table 10. Parameters of the Weibull distribution model (standby failure rate), EY diesels

	Low level	Mean	High Level
β	0.4487	0.6371	0.9048
η	1059.9	2129.2	4277.3
Lifetime, [d]	**1.37710E+04**	2.16400E+04	3.40040E+04

The results of the parameter estimate indicates that, for the normal emergency diesel generators, the model of an Homogeneous Poisson Process (constant failure rate) cannot be rejected as unacceptable, although the graphical representation (comparison of figures 10 and 11) indicates that the Weibull model is more suitable with respect to obtaining more accurate lifetime estimates for the observed components (no outliers outside the confidence interval). The analysis with the distribution wizard of WEIBULL++®7 confirms that the performance of the two models is close, giving a slight preference to the Weibull model. The best fit is once again provided by the generalized Gamma distribution. The estimated lifetime of the best fit is located above the estimates provided by the exponential model and the Weibull model. The confidence interval is given by *(1371.2, mean=2817.8, 5790.4).* The use of the exponential distribution model with constant failure rate is again conservative.
Figures 12 and 13 show the plot of the cumulative failure probability for the special emergency diesel generators (FY) respectively using the exponential and the Weibull model. The comparison of figures 12 and 13 indicates that the Weibull model provides a better representation of the data. Table 11 shows the parameters for the exponential model (and mean lifetime with the 0.9 two-sided confidence intervals). Table 12 shows the parameters for the Weibull distribution model (scale parameter η and shape parameter β and the lifetime with the 0.9 two-sided confidence intervals).

The results confirm that the performance of the special diesel generators in the bunkered system reflects some ageing effects. Nevertheless the estimated mean values for the lifetime of the FY diesel generators do not differ much from one data model to the other.

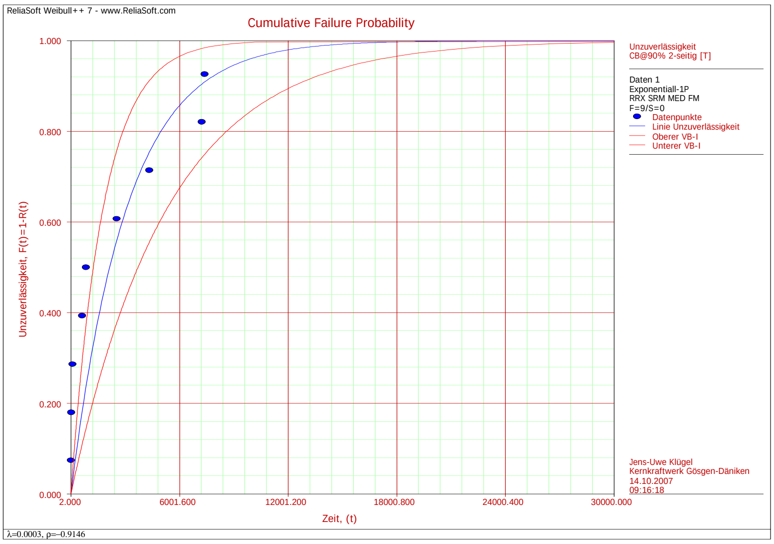

Figure 12 Cumulative Failure Probability for the exponential distribution model (HPP). Only diesel failure events of the FY-type considered

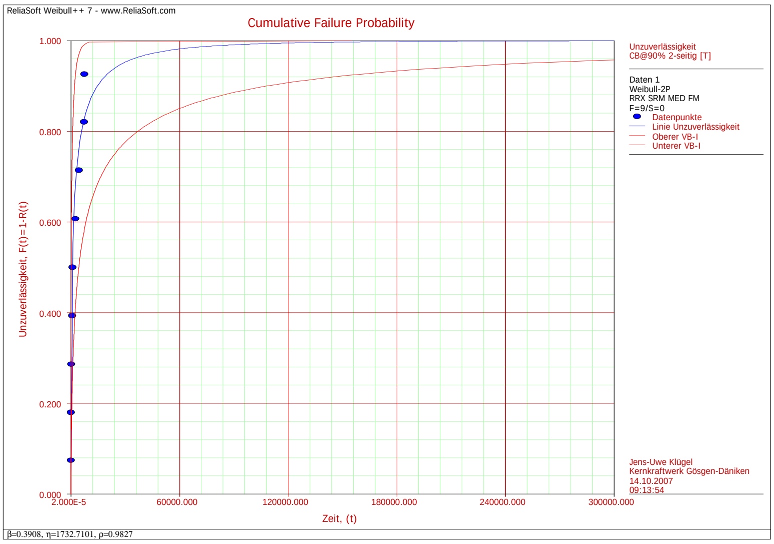

Figure 13. Cumulative Failure Probability for the Weibull distribution model. Only diesel failure events of the FY-type considered

Table 11. Parameters of the exponential distribution model (standby failure rate, HPP), FY-diesels

	Low level	Mean	High level
λ	0.0002	0.0003	0.0006
Lifetime, [d]	**1784.5**	3087.8	5342.7

Table 12. Parameters of the Weibull distribution model (standby failure rate), FY diesels

	Low level	Mean	High level
β	0.3198	0.5087	0.8091
η	509.5	1577.0	4880.7
Lifetime, [d]	**1039.8**	3056.6	8984.9

Once again a comparison with the best estimate fit provided by the distribution wizard of WEIBULL++®7 is somewhat interesting. This time, the best fit is provided by the Weibull model. The generalized Gamma-distribution also performed well. Figure 14 shows the plot of the cumulative failure probability of the special emergency diesel generators (bunkered system) for the generalized Gamma distribution model.

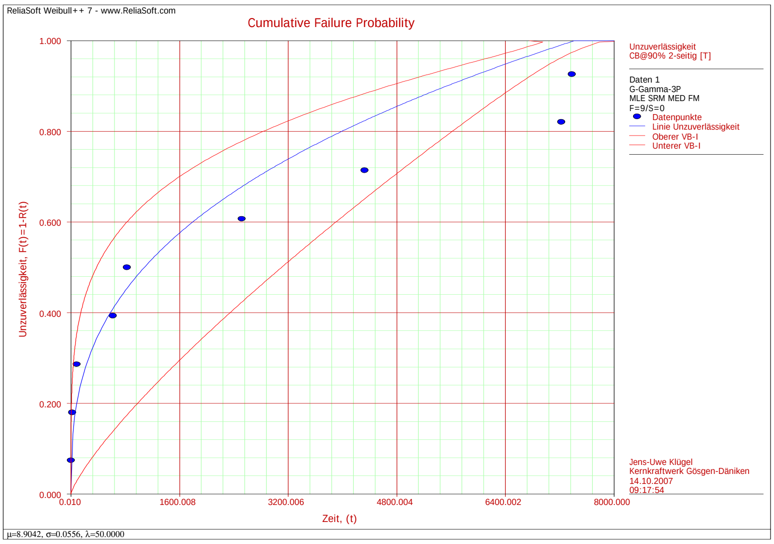

Figure 14. Cumulative Failure Probability for the generalized Gamma distribution model. Only FY diesel failure events considered.

The exponential distribution model possesses a rather poor performance while still providing a conservative estimate of the components' lifetime. On the other hand, the use of the exponential distribution model still leads to similar values of the mean lifetime as the best performing model.

5.2 Results for diesel driven pumps VA91/92D001

The analysis was performed following the same approach as described in section 4.1 for the diesel generators. Figures 15 and 16 show the plot of the cumulative failure probability for the diesel driven pumps respectively using the exponential and the Weibull models. The comparison of figures 15 and 16 indicates that both models represent a meaningful representation of the data. This is confirmed by similar values of the regression coefficient ρ, although the absolute value is slightly higher for the Weibull model (0.97 versus 0.923). Some minor learning effect may be recognized based on the long term positive experience which was observed since the last failure event, despite the evaluated shape parameter β >1.

Table 13 shows the parameters for the exponential model and the mean lifetime with the 0.9 two-sided confidence intervals. Table 14 shows the parameters for the Weibull distribution model (scale parameter η and shape parameter β and the lifetime with the 0.9 two-sided confidence intervals).

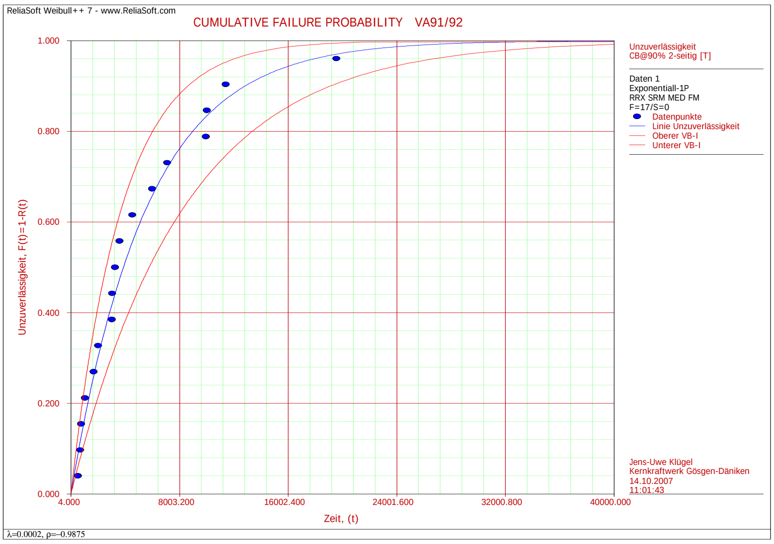

Figure 15. Cumulative Failure Probability for the exponential distribution model (HPP). Diesel driven pumps VA91/92D001.

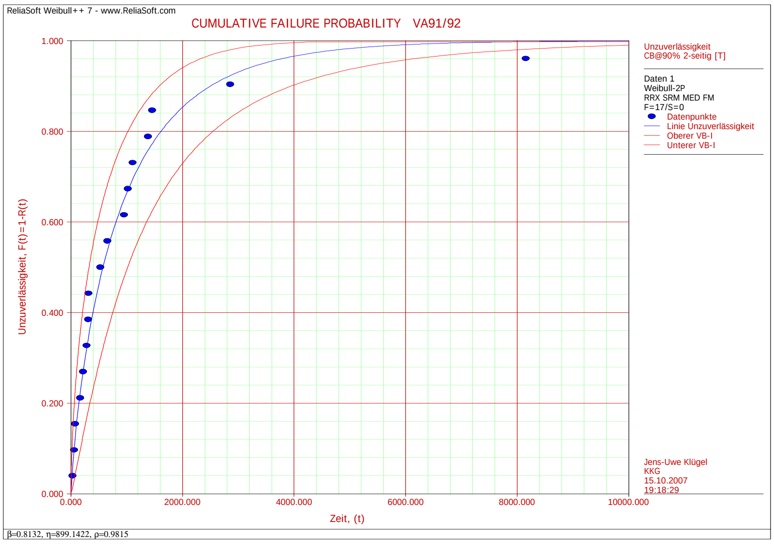

Figure 16. Cumulative Failure Probability for the Weibull distribution model. Diesel driven pumps VA91/92D001.

Table 13. Parameters of the exponential distribution model (standby failure rate, HPP), diesel driven pumps VA91/92D001

	Low level	Mean	High level
λ	0.0004	0.0006	0.001
Lifetime, [d]	**1036.8**	1545.0	2302.4

Table 14. Parameters of the Weibull distribution model (standby failure rate, NHPP), diesel driven pumps VA91/92D001

	Low level	Mean	High level
β	0.6137	0.8132	1.0775
η	542.28	839.14	1490-84
Lifetime, [d]	**615.6**	1007.1	1647.6

The best estimate value for the shape parameter does deviate from 1 (exponential model). It is obvious, that the exponential model does not provide a realistic estimate for the lifetime of the component. A further detailed analysis using the Weibull++7 distribution wizard indicates that the best data fit is provided by the model of a generalized (three parametric) Gamma-distribution, while the two-parametric Weibull distribution is regarded as a better model than the exponential model. It is interesting to compare the lifetime estimates obtained by using the best fit model (the G-Gamma distribution) with the data from tables 13 and 14. Table 15 presents the corresponding parameters for the G-Gamma distribution model.

Table 15. Lifetime estimates using the Generalized Gamma Distribution

	Low level	Mean	High level
Lifetime, [d]	552.18	1011.34	1852.33

It is worth to note, that the estimated mean value is located above the estimates provided by the exponential distribution and the two parametric Weibull distribution model. So the exponential model can again be regarded as sufficiently conservative. Figure 17 shows the corresponding plot of the cumulative failure probability (unreliability) for the generalized gamma distribution model.

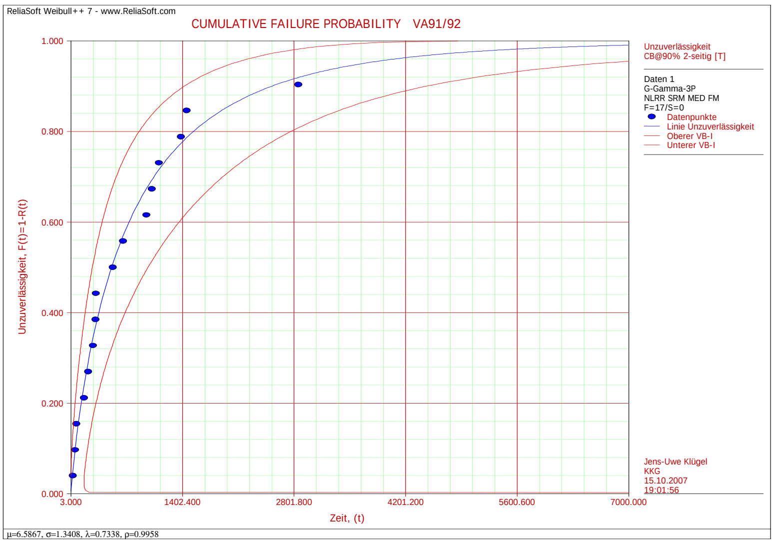

Figure 17. Cumulative Failure Probability for the G-Gamma distribution model. Diesel driven pumps VA91/92D001.

5.3 Results for motor operated valves in the core cooling and residual heat removal system TH

The analysis was performed following the same approach as described in section 4.1 for the diesel generators. Figures 18 and 19 show the plot of the cumulative failure probability for the motor operated valves (total population of 69 valves) respectively using the exponential and the Weibull model.

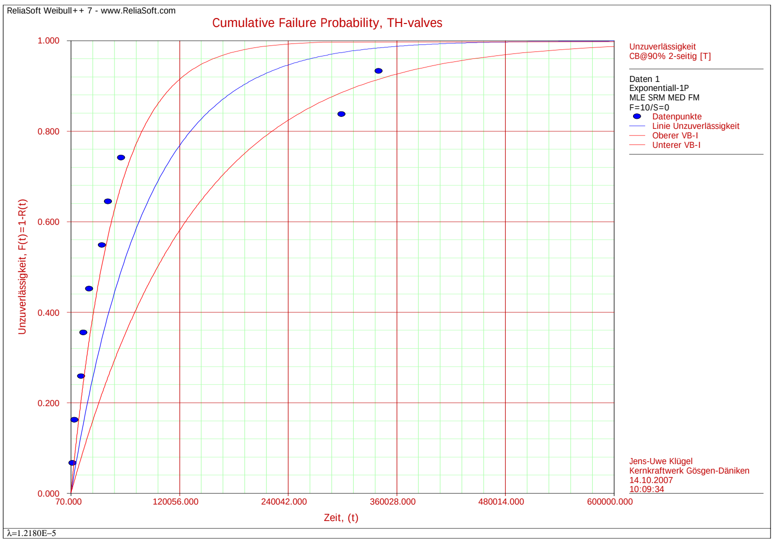

Figure 18. Cumulative Failure Probability for the exponential distribution model (HPP). Motor operated valves in the TH system.

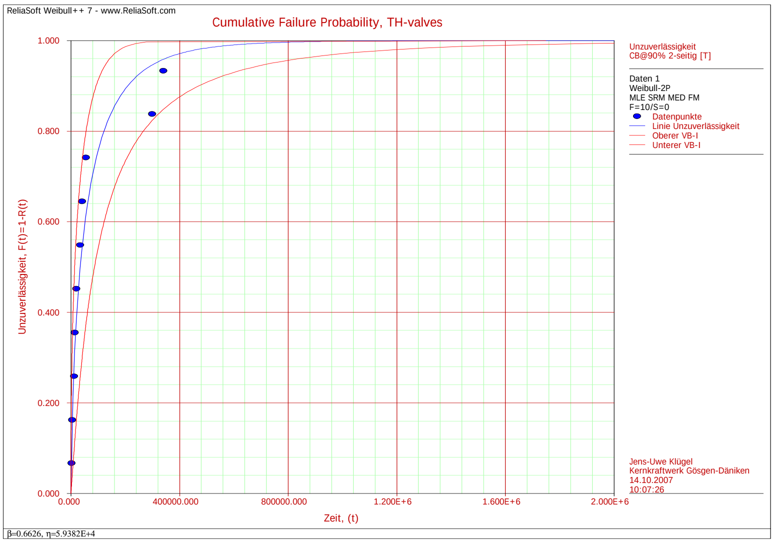

Figure 19. Cumulative Failure Probability for the Weibull distribution model . Motor operated valves in the TH system.

Tables 16 and 17 show the parameters respectively estimated for the exponential distribution model (HPP) and the Weibull distribution model. An analysis with the distribution wizard of WEIBULL++7 showed that the double-parametric Weibull is the preferable model in comparison to the exponential model. The best data fit is obtained again with the generalized gamma distribution model. Figure 20 shows the analysis results for this model, while table 18 provides the lifetime estimates.

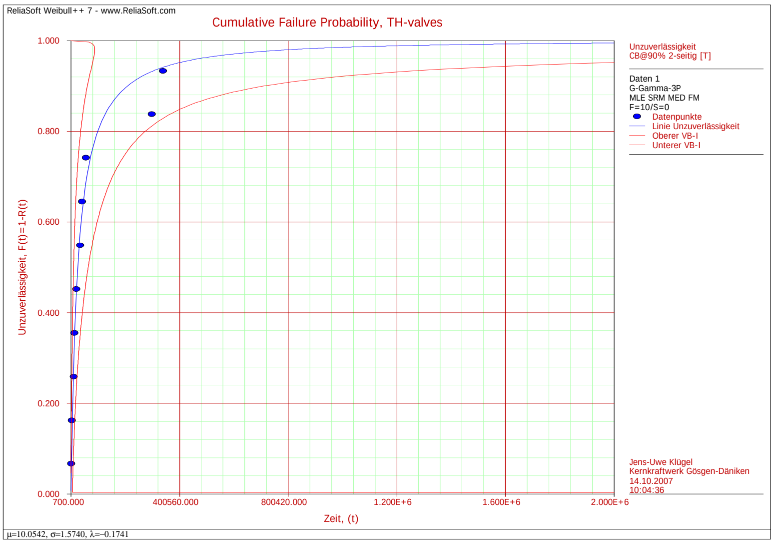

Figure 20. Cumulative Failure Probability for the generalized Gamma distribution model. Motor operated valves in the TH system.

Table 16. Parameters of the exponential distribution model (standby failure rate, HPP), MOVs in the TH system

	Low level	Mean	High level
λ	7.2401E-6	1.218E-6	2.049E-5
Lifetime, [d]	**4.88E+04**	8.21+04	1.38E+05

Table 17. Parameters of the Weibull distribution model (standby failure rate, renewal), MOVs in the TH system

	Low level	Mean	High level
β	0.4477	0.6626	0.9806
η	**2.582E+04**	**5.9382E+04**	**1.3657E+05**
Lifetime, [d]	**3.56E04**	**7.95E04**	**1.77E05**

Table 18. Lifetime estimates using the Generalized Gamma Distribution

	Low level	Mean	High level
Lifetime, [d]	3.85E04	1.08E05	3.0E05

It is interesting to note, that the best-estimate model predicts a significantly higher mean lifetime than the other two models indicating a significant learning process as predicted by the Laplace test. Nevertheless the uncertainties are significantly higher than for the other models, too. The confidence bounds are shifted to higher lifetime values.

5.4 Results for motor operated valves in the core cooling and residual heat removal system TF

The analysis was performed following the same approach as described in section 4.1 for the diesel generators. Figures 21 and 22 show the plot of the cumulative failure probability for the motor operated valves (total population of 28 valves) respectively using the exponential and the Weibull models. Tables 19 and 20 show the parameters estimated for the exponential distribution model (HPP) and the Weibull distribution model (renewal model) respectively.

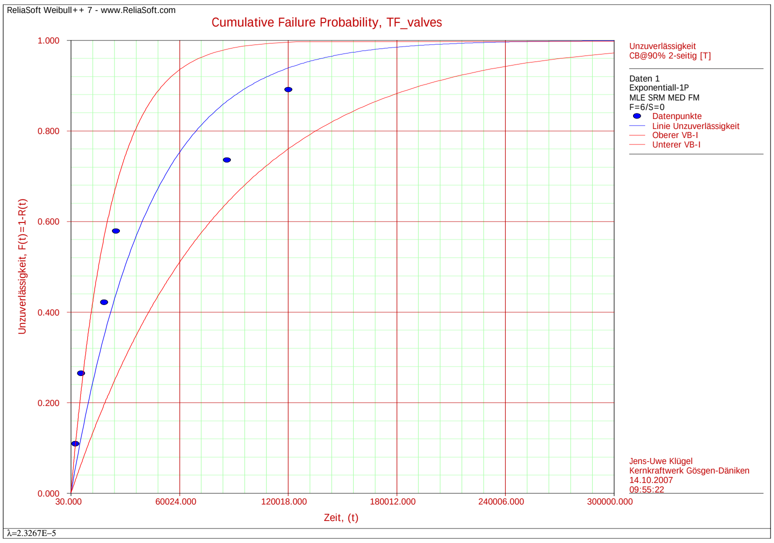

Figure 21. Cumulative Failure Probability for the exponential distribution model (HPP). Motor operated valves in the TF system.

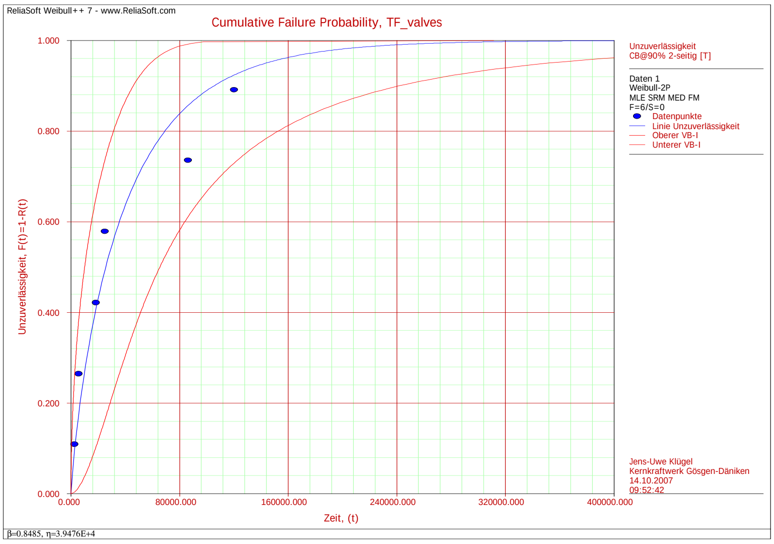

Figure 22. Cumulative Failure Probability for the Weibull distribution model. Motor operated valves in the TH system.

The results analysis shows that the exponential distribution model with constant failure rate is acceptable, the shape parameter of the double-parametric Weibull distribution is very close to 1.

Table 19. Parameters of the exponential distribution model (standby failure rate, HPP), MOVs in the TF system

	Low level	Mean	High level
λ	118883E-5	**2.3267E-5**	4.5538E-5
Lifetime, [d]	**2.20E+04**	4.30E+04	8.41E+04

Table 20. Parameters of the Weibull distribution model (standby failure rate, NHPP), MOVs in the TF system

	Low level	Mean	High Level
β	0.4965	0.8485	1.4499
η	1.7102E+4	3.9476E+54	9.1121E+05
Lifetime, [d]	**1.89E+04**	4.30E+04	1.89E+04

Again an analysis with the distribution wizard of WEIBULL++7 was performed to establish the model that best fits. This time, the three parametric Weibull distribution model appeared to be the best performing model, while the model of an exponential distribution with a constant failure rate performed better than the Weibull model. Table 21 shows the estimates for the lifetime of the valves according to the three-parametric Weibull model.

Table 21. Lifetime estimates using the three parametric Weibull distribution model

	Low level	Mean	High Level
Lifetime, [d]	1.79E04	4.39E04	1.12E05

It appears that the results from the exponential distribution model are quite close to the model that best fits. Figure 23 shows the cumulative failure probability for the motor operated valves in the closed loop intermediate component cooling water system using the best fit model.

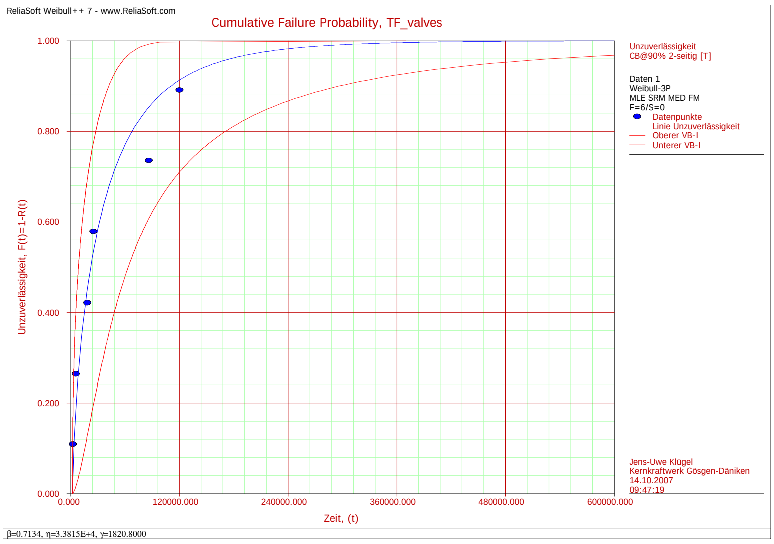

Figure 23. Cumulative Failure Probability for the three-parametric Weibull distribution model. Motor operated valves in the TF system.

5.5 Conclusions from the detailed lifetime analysis

The analysis of different models used for lifetime analysis (constant failure rate, or time dependent failure rate between the renewals) did show that time dependent effects are of minor importance with respect to the PSA, because the average lifetime estimates are rather close and the failure probabilities can be expected of similar size. Therefore, it makes some sense to perform an analysis under the assumption of a Non-Homogeneous Poisson Process (NHPP) assuming conservatively, that after each repair, the component remains as old as before. For this purpose the double-parametric power law model is applied.

6 Power Law Renewal Model

An extensive power law recurrence analysis is performed following the conclusions from the lifetime analysis. The analysis is performed using two different methods – a parametric recurrence data analysis based on the Cow –AMSAA model, and a nonparametric analysis. The later is closely related to the Nelson-Aalen estimator evaluation performed in section 4.1. For the analysis the WEIBULL++7 ® software was used (parametric and nonparametric RDA analysis).

6.1 Power Law Renewal Model – Results for Diesel generators

The parametric analysis leads to the following results for the parameters of the corresponding double- parametric Weibull analysis:

Table 22 Weibull Parameters for the Power Law Renewal Process

Component group	Shape parameter β	Cumulative Failure rate (90% confidence interval) over observation time
All diesel generators	0.9104	(0.0003,0.0004, 0.0006)
EY diesel generators	0.5890	(0.0002,0.0003,0.0005)
FY diesel generators	1.4884	(0.0002, 0.0003, 0.0006)

An analysis of the data provided in table 22 shows, that the failure occurrences observed for all diesel generators pooled together, follow the expected behaviour of a decreasing failure rate asymptotically converging to a constant failure rate, as expected for competing failure mechanisms and in compliance with the theorem of Khintchine. A more detailed analysis shows some strong learning effect for the normal diesel generators EY while for the special emergency diesel generators FY some ageing is detected.
Figures 24 to 26 show the cumulative failure rates for the diesel generators in dependence of the observation time.

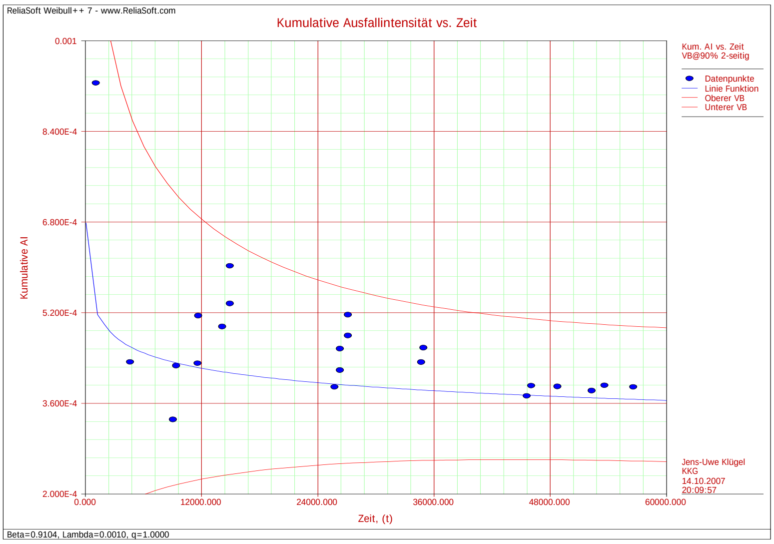

Figure 24. Cumulative Failure Intensity according to a power law process model – all diesel generators.

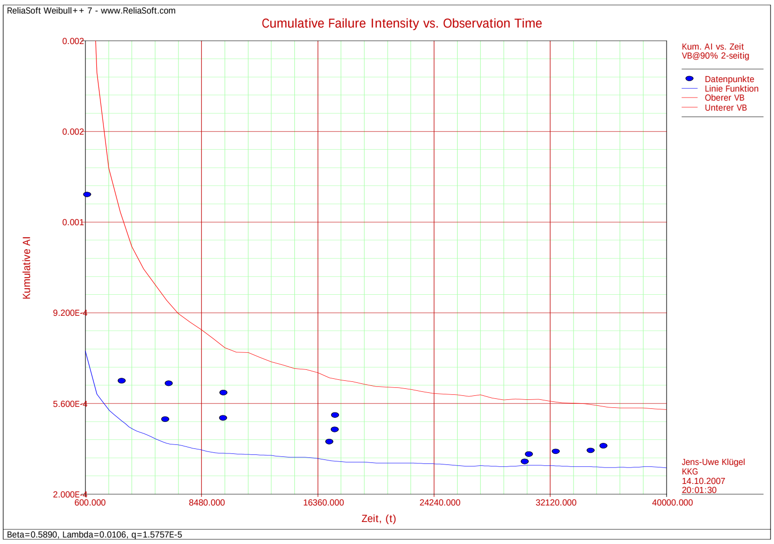

Figure 25. Cumulative Failure Intensity according to a power law process model – EY diesel generators.

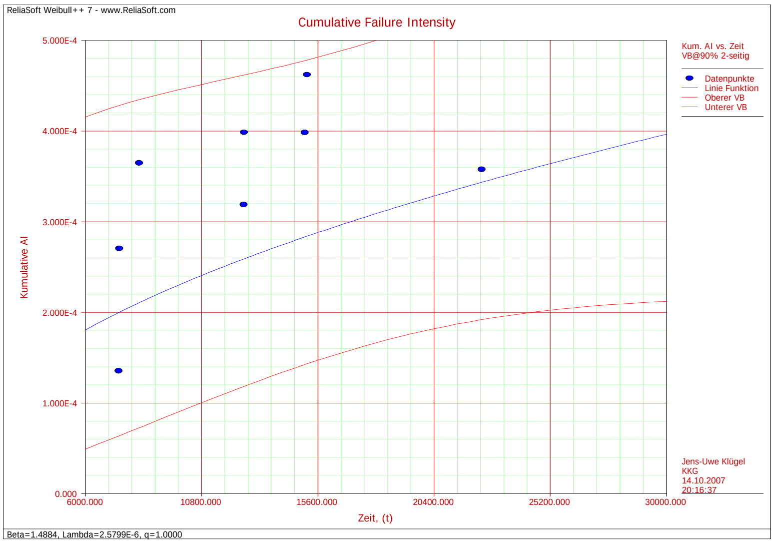

Figure 26. Cumulative Failure Intensity according to a power law process model – FY diesel generators.

Figures 27 to 29 show the corresponding nonparametric assessments of the mean cumulative distribution function for failures in dependence of observation time.

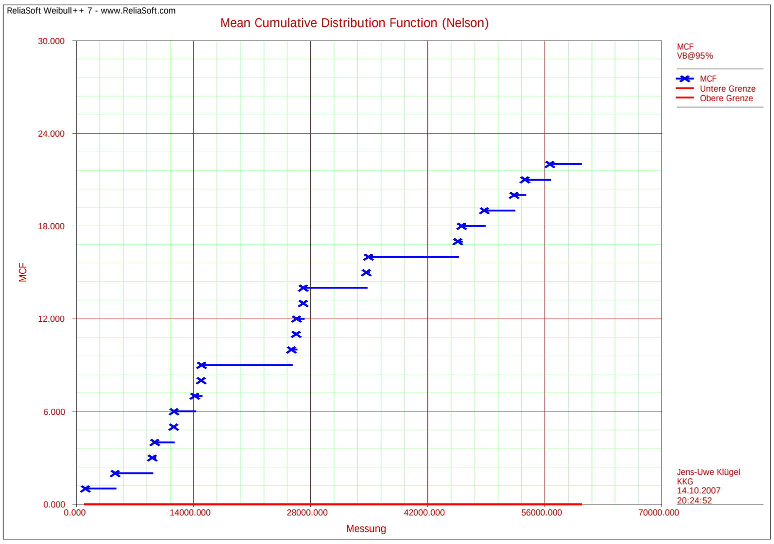

Figure 27. Main Cumulative distribution function (Nelson) for diesel failures in dependence of observation time.

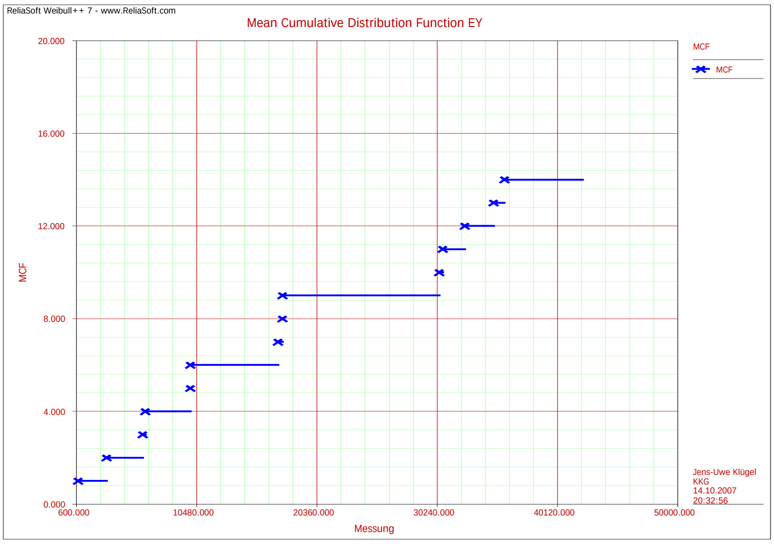

Figure 28. Main Cumulative distribution function (Nelson) for EY diesel failures in dependence of observation time.

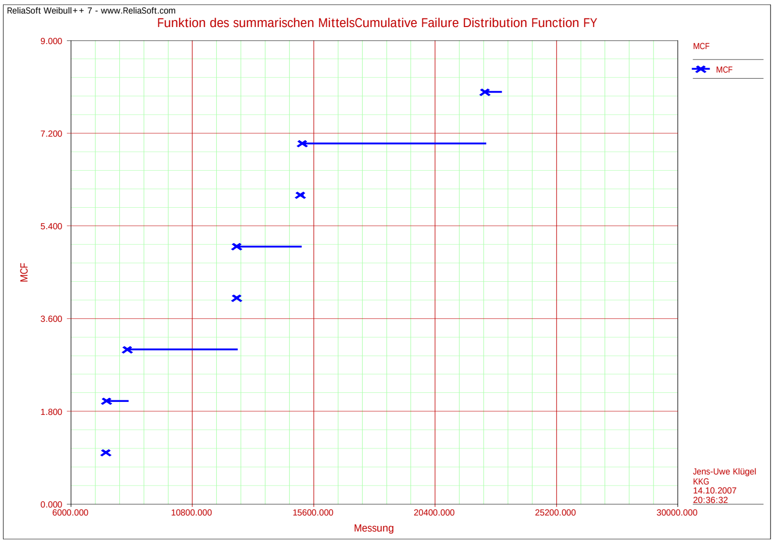

Figure 29. Main cumulative distribution function (Nelson) for FY diesel failures in dependence of observation time.

Based on the analysis, we can make the conclusion that pooling of data (as it happens in databases) may mask some time trends as it is observed in this case. Pooling data from the normal diesel generators EY and the special emergency diesel generators FY did mask the ageing effect observable for the special emergency diesel generators. The overall impression for all diesel generators would indicate some learning effects (shape parameter below 1), while an increase of the failure rate for the FY diesel generators is observed. On the other hand, the uncertainty bounds obtained for the cumulative failure intensity indicate that the effect of time trends is rather low and well captured by the uncertainty bounds usually considered in PSA. With respect of the time trend for the special emergency diesel generators the visual inspection of the Nelson indicator (Mean cumulative failure distribution function) indicates the possibility of “failure clustering” in time rather than a systematic, monotonic ageing trend.

6.2 Power Law Renewal Model - Results for Diesel Driven Pumps

The double-parametric power law recurrence model was also applied for the analysis of the diesel driven pumps VA91/92D001. Figure 30 shows the dependence of the cumulative failure rate in dependence of the resulting model.

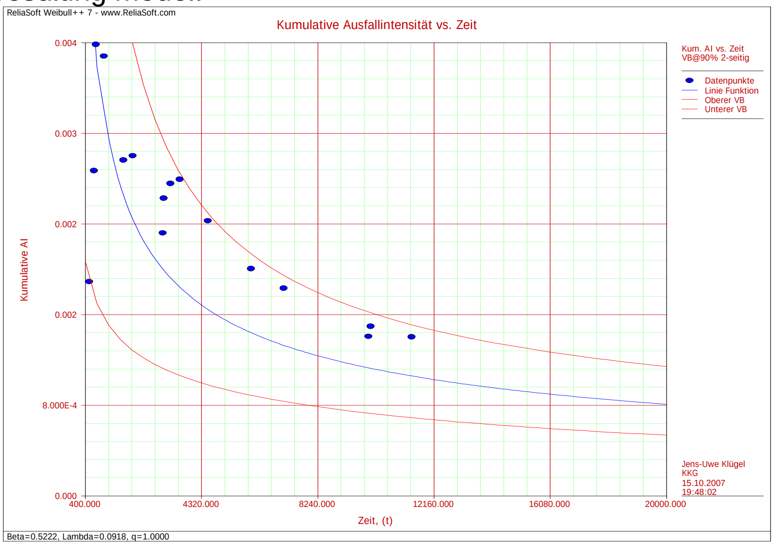

Figure 30. Cumulative Failure Intensity according to the power law process model –diesel driven pumps.

The graphical presentation clearly indicates a learning process – a decreasing with time failure rate. Table 23 summarizes the parameters of the resulting power law process.

Table 23. Parameters of the power law model.

Component group	Shape parameter β	Cumulative Failure rate (90% confidence interval) over observation time
Diesel driven pumps	0.5222	(0.0005,0.0008, 0.0012)

The parametric analysis is supported by the results of the nonparametric analysis (Nelson). Figure 31 shows the mean cumulative failure distribution function (Nelson) according to the nonparametric recurrence data analysis.

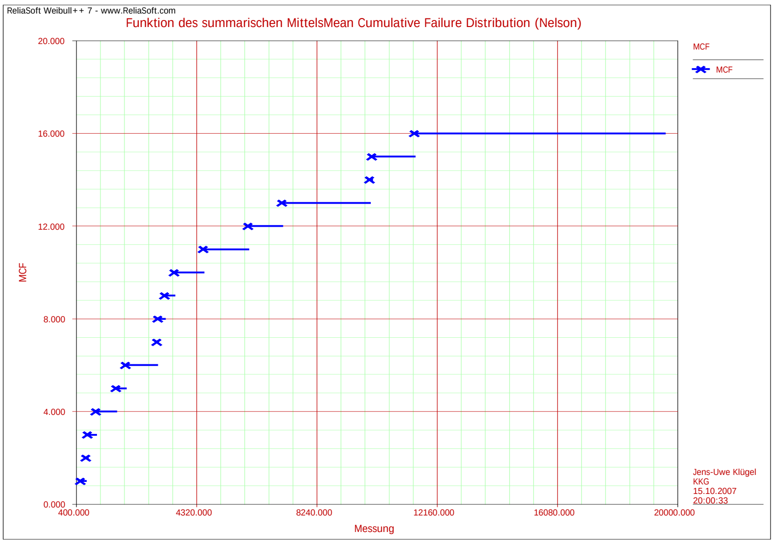

Figure 31. Main cumulative distribution function (Nelson) for the failures of diesel driven pumps in dependence of observation time.

6.3 Power Law Renewal Model – Results for Motor Operated Valves (MOV)

The parametric analysis leads to the following results for the parameters of the corresponding two parametric Weibull analysis:

Table 24. Weibull Parameters for the Power Law Renewal Process

Component group	Shape parameter β	Cumulative Failure rate (90% confidence interval) over observation time
MOV in TH-system	0.4491	1.096E-5 (6.34E-6, 1.70E-5)
MOV in TF-system	0.631	1.94E-5 (9.29E-6, 3.37E-5)

Figures 32 and 33 show the dependence of the cumulative failure rate on observation time. The analysis of the results demonstrates, that the failure rate of MOVs is decreasing (DFR). Therefore, a significant learning effect can be confirmed with respect to the maintenance work performed. On the other hand, it is necessary to note, that the double-parametric power law model does not represent the time dependence of the failure rate very well. The uncertainty associated with an estimate of the cumulative failure rates is in good agreement with the uncertainties usually considered in PSA studies (error factors between 2 and 5).

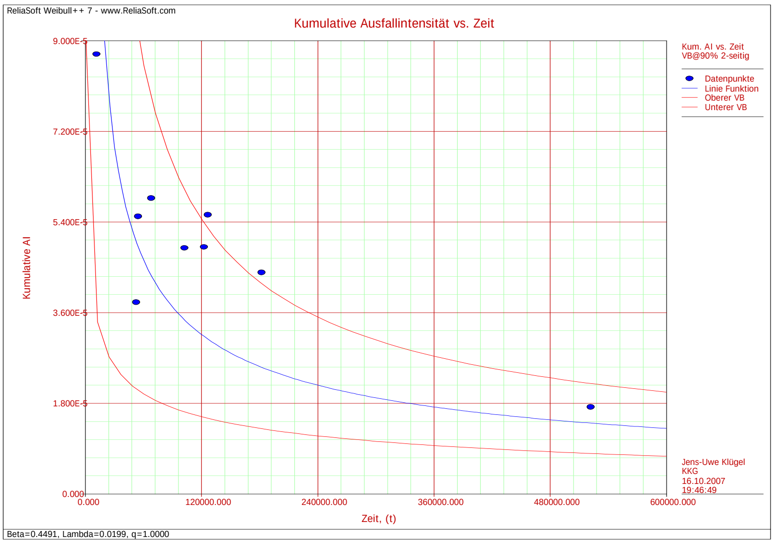

Figure 32. Cumulative Failure Intensity according to the power law process model –MOVs in TH-system

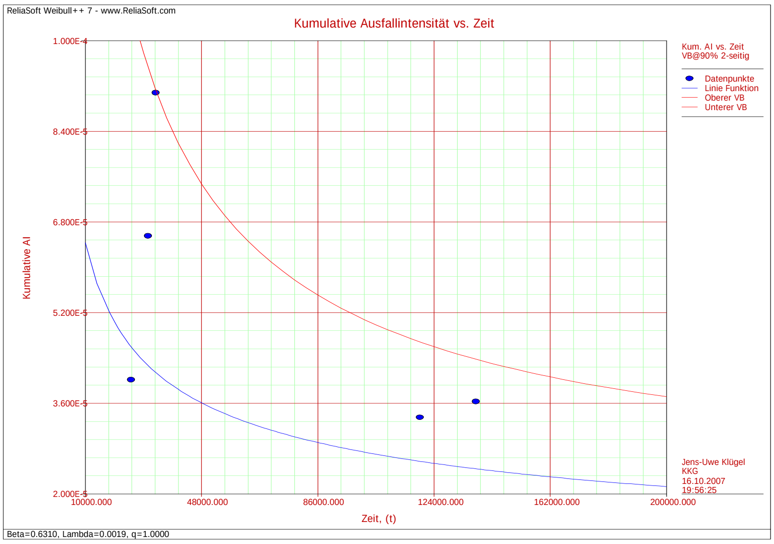

Figure 33. Cumulative Failure Intensity according to the power law process model –MOVs in TF-system

Figures 34 and 35 show the results of the nonparametric RDA-analysis (MCF-indicator, Nelson) for the MOVs. These figures confirm on one hand the learning effect, and on the other hand, they indicate that the learning effect is not manifested by a monotonic trend but rather by a strong improvement of the maintenance performance since the mid-nighties of the last century, while the first part of the presented graphs complies reasonably well with the model of a constant failure rate.

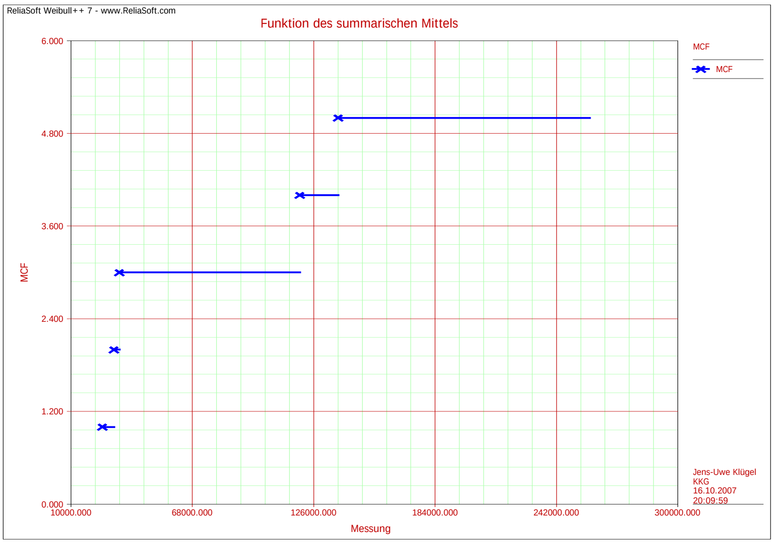

Figure 34. Main cumulative distribution function (Nelson) for the failures of MOVs in the TH-system in dependence of observation time.

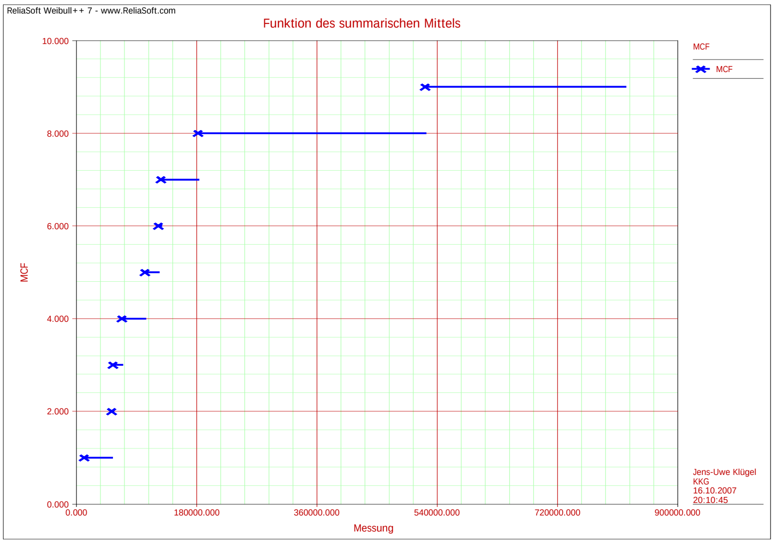

Figure 35. Main cumulative distribution function (Nelson) for the failures of MOVs in the TF-system in dependence of observation time.

7 Conclusions

A systematic investigation of time dependent effects in the failure data of active safety relevant components has been performed. In general, the assumption of PSA regarding the use of exponential distribution with a constant failure rate, reflecting a homogeneous Poisson renewal process (HPP) can be supported, although in most cases this model is not the best performing model according to the detailed data analysis. Visually observed ageing effects established for the diesel generators of the special emergency feedwater system (bunkered system), were supported by a detailed analysis. Nevertheless, the possibility of periodically clustered failure events cannot be excluded. For other component groups time dependent effects are of minor importance. This is an extensive confirmation of the theorem of Khinchine[4] stating that the superposition of several weak non-homogeneous stochastic processes asymptotically converges to a stationary homo-

[4] Khintchine, A.Y., 1933. Asymptotische Gesetze der Wahrscheinlichkeitsrechnung, Springer, Berlin.

geneous Poisson process. The incorporation of a more detailed time dependent data model for active components into the Goesgen PSA is generally not justified. The observed uncertainties of the data analysis are well captured by the subjective uncertainty distributions of the PSA currently in use. Typically, they consider an empirical error factor (of an equivalent lognormal distribution) in the range of 2 to 5. The results of the analysis confirm that this corresponds to the range of uncertainties to be considered for component failure rates. The periodic data update (once in 5 years) assures that the data used in PSA is asymptotically following the trend observed in the more detailed analysis. The more accurate evaluations of the mean value of lifetimes (or failure rates) can be used to adjust the mean values of component failure rates (standby failure rates) in the PSA as the basis for future Bayesian updates. They can also be used for predictive analysis. It was also observed, that pooling of data (from different plants or from different but similar types of equipment) can mask time trends. This effect is another manifestation of the theorem of Khintchine.

References: All references are quoted in footnotes.