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Application Of Advanced Reliability Models To Operational History Of Maria Research Reactor

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Abstract

The reliability data from 20 years of operation of Maria Research Reactor in Poland was analyzed as a subtask in safety classification project and the results are presented in this work. The authors employ state of the art reliability analysis models that are not widely used in nuclear industry, where Probabilistic Safety Assessment models dominate the field. The utilized models are: Mean Cumulative Function and two models originating from Nonhomogeneous Poisson Process (NHPP): General Renewal Process and Power Law model, developed under the name Crow-AMSAA. The presented analysis focuses on three types of equipment commonly used in nuclear reactors: main cooling water pumps, heat exchangers and cooling fans. The results suggest that throughout the operation of a research reactor the failure rates of various types of equipment may change. It is, therefore, recommended to use the same or similar failure rate drift monitoring tools to track the actual performance of systems important for safety.

Keywords: safety classification, probabilistic safety assessment, failure rate

1. Introduction

Reliability analysis is obligatory activity in the design of a nuclear facility. Its results are used to feed Probabilistic Safety Assessment (PSA) models that predict accident frequencies for a given design. PSA models are also utilized in Safety Classification of the structures, systems and components (SSC) to identify how are they important for safe operation, which translates to more stringent requirements for designers and manufacturers.

PSA models are using historical reliability data from existing facilities (not only nuclear) and this is what goes into the design of a new nuclear facility. After the facility is built, it accumulates operational history and within few years enough historical data is accumulated to verify “theoretical” PSA models.

Currently in Poland there is only one nuclear reactor in operation. It is the 30 MW(th) MARIA Research Reactor located in National Center for Nuclear Research (NCBJ). MARIA is in operation since 1974, with major upgrades done in 1985, 2002 and 2014 - a substantial operational history.

Around the year 2000, Polish regulatory body, which is the National Atomic Energy Agency agreed with NCBJ to run the classification process (required for new nuclear facilities) for MARIA despite the fact it was not a new facility. One of the major reasons was to gather experience in the methodology, which was important for both organizations. The safety classification team was formed from selected members of the reactor personnel and analysts experienced in environmental and probabilistic safety studies. The classification project consists of several activities:

- Design of safety classification procedure in accordance with national and international requirements.
- Analysis of reactor design and identification of Initiating Events (IE), that may lead to accidents.
- Identification of safety functions that reduce the consequences of IEs.
- Analysis of accident consequences.
- Building PSA models consisting of IE fault trees, safety function fault trees organized into events trees that compute accident sequence frequencies.
- Identification of input data (component failure frequencies) to PSA fault trees.

The output for the last task was initially a selection of public databases that component failure frequencies:

- IAEA database of research reactor reliability (IAEA 2020)
- US NRC nuclear power plants reliability database (INL 2015)

The reason for using public databases was that typically, when using internal historical records, often the samples used in failure rate calculations are small (sometimes one or two failures) which increases the uncertainty of PSA results.

At the time of the study the IAEA database was missing many components present in Maria Reactor. US NRC database for nuclear power plants was used in such cases. It was questioned by the Polish regulatory body due to large discrepancy in terms of reactor power and equipment sizing. In the end the conclusive argument was that US NRC database provides satisfactory sample sizes for multiple components which improve the uncertainty and general quality of PSA models.

The remaining question is if frequencies from public databases are similar to the failure frequencies observed in operation of Maria Reactor. This is an objective for further studies.

The key objective of this work was to apply and verify the performance of a more complex reliability analysis techniques than typically used in PSA data analysis – which is a novelty in the field of research reactors.

2. PSA data analysis techniques

Main reference for development of PSA analysis is (IAEA, 2010) from IAEA. However, it provides little guidance in terms of statistical analysis of historical data from nuclear reactors. The second document from a regulatory body worth mentioning is (US NRC, 1984) from US NRC – the regulator with the longest history and the largest supervised fleet of nuclear reactors. It was published in 1984 but is still a very comprehensive PSA guide. In terms of statistical analysis it recommends the use of exponential distribution for component failure frequencies. The document provides a proper justification for its use, which is that constant failure rate that characterizes it, is a realistic model of failure frequency for most components in their useful life period i.e. before wear out processes become prominent.

One of the leading trends in research related to PSA studies is the use of Bayesian methods in the statistical data analysis. Most notably Bayesian updating (Ayoub, Ariu, and Nusbaumer 2020; Zubair and Zhijian 2013) that is utilized for priors of component failure frequencies updated with historical data as soon as it is available. Bayesian updating is the most significant alternative to frequentist methods presented in following chapters.

Another trend is the use of Bayesian networks in the PSA procedure e.g. as a replacement for fault trees (Kaszko, Kowal, and Potempski 2020).

Research related to the use of reliability growth models (that are utilized in this work) is overrepresented in recent years by software reliability topic (Park and Jang 2014; Son, Kang, and Chang 2009). One intriguing application is found in safety related events frequency analysis in Russian nuclear submarines (Reistad, Hustveit, and Roudak 2008). A very practical approach to reliability data from nuclear power plant is similar to this work in terms of model selection but is focused on operational, rather than safety related applications of described Crow AMSAA model (Doyle, Tuomi, and Rowley 2007).

A similar model of generalized renewal process was also found to be already covered in the context of nuclear engineering, for high level safety analysis (Sakurahara et al. 2019) or maintenance optimization (Spangler, Agarwal, and Cole 2023) in nuclear power plants.

It is important to mention the effects of component ageing in nuclear reactors on the accident frequencies. Ageing control is a topic of interest for IAEA and national regulators and some recent research reflects that (Nitoi and Pavelescu 2010)(Volkanovski 2012)(Stefanov and Petkov 2010)(CNSC 2014). Ageing control is one of the key factors influencing model selection in this work.

3. Maria Research Reactor historical records

Whenever a failure in a piece of equipment is discovered in the reactor, a record is created. It is called the Malfunction Card. On the Card the following information is recorded:

- Date of diagnosis
- Name of the failed equipment
- Reference number of the failed equipment
- Description of the failed equipment and effects of the failure
- Prescribed corrective action signed by the shift manager
- Description of actions taken

- Date of closure (with signature from shift manager)

The authors analyzed records starting from the year 2000 with the last record being dated at 13 July 2023. The total number of analyzed records is 214.

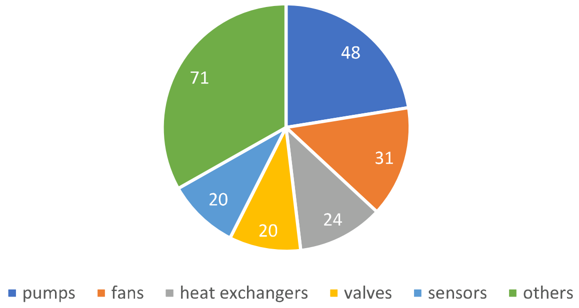


Fig. 1. Number of records per equipment type in the Maria Reactor dataset.

The quality of records is assessed to be high, based on the authors experience with industrial reliability data analysis. In majority of records, the failure is described with a lot of details and typically the root cause of the failure is identified. In few records the date of closure is missing. Several records contain brief descriptions and lack details. The failure descriptions often contain richness of technical details pointing to high skill of maintenance personnel.

Another set of data needed for statistical analysis is the number of hours per year when Maria Reactor was operated at full power. The reactor is operated in approx. 170-hour production cycles, which is the irradiation duration needed for production of medical isotope of molybdenum-99. Typically, the number of reactor hours accumulated at full power per year is around 4000. There were years with only few production cycles – usually due to extended maintenance periods – for example recent modification of electrical power distribution inside the reactor that took the whole year 2023.

4. Reliability analysis assumptions

In reliability engineering field, it's common that reliability dataset (even of high quality) is missing some important data. This could be details on type of failure, exact time of failure, uncertainty to which piece of equipment failed, no information on actual operating hours etc. In such cases assumptions have to be made to make the statistical analysis possible. In case of Maria dataset there are assumptions done on the dataset level and then few others about specific type of analyzed equipment.

On the dataset level, as mentioned before, the date of failure is provided in the records and a number of operating hours per year is also given. But at the date of failure, the exact number of accumulated operating hours per year is not known. It is therefore assumed that production cycles are evenly distributed during the year. For a given date of failure, the number of accumulated operating hours is estimated as below.

$$N_{hacc} = \frac{days\ since\ January\ 1st\ of\ a\ given\ year}{365} \times total\ hours\ accumulated\ given\ year \tag{1}$$

The analyzed equipment was not new at the beginning of the dataset (January 2000). Older records exist but are still in the process of digitalization. For the purpose of this work the equipment is treated as new (starting at time zero) by the applied models. However, due to the inner workings of the models, it should not be seen as a major flaw, but rather as a typical shortcoming in practical work with reliability data.

4.1. Main cooling water pumps

Maria Research Reactor is a water pool type reactor. Each fuel element has its separate cooling channel inside the core. The core is submerged in a pool with demineralized water that provides shielding from radiation. Cooling circuits of the pool and fuel channels are separated. There are four main pumps that are pumping cooling water to the fuel channels. During production cycle two pumps are operating and two are in standby mode. The operators are switching active and standby pumps from time to time. Therefore, the assumption is made that each pump accumulates the same number of operating hours per year (half of total number of hours accumulated per year).

The pump is defined as a system consisting of the pump itself, the shaft, its bearing and sealing plus electric motor driving the pump.

There are 26 records in total on the failures of the four main pumps.

In 2014 all pumps were replaced by new units.

4.2. Heat exchangers in cooling channels loop

Main cooling water pumps are pumping water through three parallel heat dumping lines. Each line has two U-pipe heat exchangers in series. It is assumed that both exchangers in a line are accumulating age at the same rate, even if one may be closed for secondary cooling water. Primary cooling water always flows through both of them. From the maintenance records one can see that primary failure mode is the leakage through the tube from primary to secondary side of the exchanger. In such case the faulty tube is welded, the exchanger goes through pressure testing and is installed back on the line. That means, the exchangers are degrading over time and at some point the decision is made to install new units. This process may be visible in failure rate analysis but is not captured in any specific way in the utilized models.

There are 19 records on heat exchangers in the cooling channels loop.

Starting from 2010 heat exchangers were gradually replaced by new units.

4.3. Cooling tower fans

There are three fans installed inside the cooling tower that are moving the air cooling the water in the secondary loop. It is assumed all three are working all the time during power operation. In fact, the fans are used by the ventilation system of few selected reactor rooms. The actual operating time is, therefore, longer than for reactor operating at power, but it's not all three running continuously. For the purpose of statistical analysis the accumulated operating time is limited to power operation of the reactor.

The fan unit consists of the fan with blades, shaft and its bearings and the electric motor driving the fan.

There are 11 records on cooling tower fans.

In 2012 all fans were replaced by new units.

5. Models used in the study

A commercial software package Reliasoft Weibull++ was used to analyze the dataset. Weibull++ is not a general purpose statistical package but a tool dedicated strictly to reliability data analysis. The software was originally created by scientists from University of Arizona that started Reliasoft company and published multiple papers on the use of statistical models in reliability engineering, and on repairable systems analysis in particular.

Presented tools, in general, are used to verify the behavior of the mean time between failures (MTBF) for a given technical system. MTBF here is simply defined as the operating time accumulated by all samples of a given device type, divided by the number of failures. Operating environment and usage scheme for all devices in the sample should be the same or similar.

First tool is not a model in strict sense, but rather a way of visualizing the repairable systems operational history. It's called the Mean Cumulative Function. The MCF in Weibull++, according to software documentation, is based on work from Wayne Nelson (Nelson 2003). It does not produce any model line which makes predictions not possible. However, it does calculate confidence bounds on number of failures at a given time. The authors used MCF because it allows for quick reliability behavior diagnosis. If the failures on the MCF plot create a trend that looks like a straight line, it means that MTBF is stable. That is the most important piece of information for reactor operators. If MTBF value is stable, then PSA results i.e. accident sequence probabilities are also valid. If MTBF would be increasing, probability of accident sequences that include analyzed equipment would also increase, translating to increased operational risk.

MCF is also useful to identify any irregularities in the data e.g. "clumps" of failures that occur close to each other, or failures that happen at the same time, which could point to errors in data collection (with another explanation being multiple failures found during inspections).

Next model used in this work is based on Nonhomogeneous Poisson process i.e. the process where reoccurrence of certain events may not be happening at a constant rate. It is used in the context of reliability of repairable systems, where failures occur at constant or not constant rate and are being repaired so the operation can continue. The name is General Renewal Process (GRP) - it is a model developed by Kijima (Kijima and Sumita 1986)(Kijima 1989) for repairable systems analysis. The work was taken by Reliasoft scientists and put into practical use (Mettas and Zhao 2005) in Weibull++. The model does not account for repair duration and focuses only on the time of occurrence of a failure. It uses likelihood function to fit the parameters that include the effectiveness of repairs, which could be one of three cases:

- A system is as good as new, after repair.
- A system is as bad as before failure, after repair.
- A system is partially repaired, with quality of repair being the model parameter taking values from 0 to 1.

Kijima introduced another complexity layer to this model, with ability to specify two repair scenarios:

- Repair the damage (by reducing the age of a system) only to a point after last repair – type I.
- Repair the damage by a portion of full age accumulated by the system – type II.

The model used in Weibull++ is a mature tool that allows for extrapolations with confidence limits. In the context of historical records from Maria Research Reactor it was used to produce quantitative measures of failure rate behavior (quantified by the "beta" parameter of the model) and demonstrate prediction capabilities for future operations.

The third model used in the study is the Crow AMSAA model applied to repairable systems analysis. It was first applied in the field of military R&D programs for reliability growth analysis. The model was developed in 1970s by dr Larry Crow that worked at a time for US Army Materiel Systems Analysis Activity (AMSAA). The model in (Crow 1975) applied to repairable systems, is using nonhomogeneous Poisson process with Weibull intensity (failure rate) function:

$$U(t) = \lambda\beta t^{\beta-1} \tag{2}$$

where:

$\lambda > 0$

$\beta > 0$

$time\ t > 0$

The second parameter "beta" governs the failure intensity behavior, in similar way like in Weibull distribution, that uses beta and eta parametrization:

- Failure intensity is increasing for beta > 1
- Failure intensity is stable for beta = 1
- Failure intensity is decreasing for beta < 1

The application of the model in Weibull++ is a mature tool that allows for extrapolation of MTBF, failure intensity and expected number of failures. It produces confidence bounds on results using Fisher Matrix approach. In addition, the model produces two metrics:

- Cramer von Misses goodness-of-fit test
- Common Beta hypothesis test (i.e. if multiple systems in the dataset show similar failure intensity behavior)

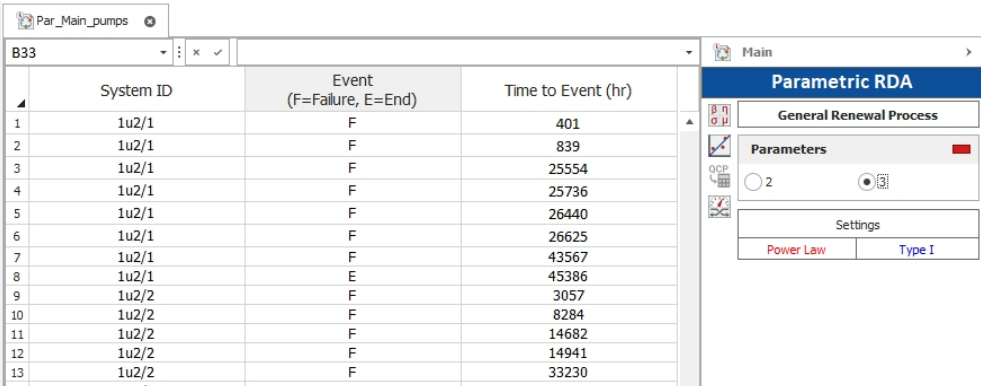
The GRP model explained before uses the same failure intensity equation (2) and, therefore, the produced model line is similar. Both models use likelihood function to calculate model parameters (although, GRP introduces Monte Carlo method for confidence bounds computation). However, historically, GRP focuses on metrics related to repairs in repairable systems, while Crow-AMSAA is dedicated to MTBF prediction considering various failure modes (in its extended form). As shown in the section below, some of the calculated metrics differ and the conclusions about the analyzed system behavior also can be different for these two closely related models. It makes sense to apply both to the same dataset and verify conclusions one may have about the results.

6. Analysis results

The following section presents the results historical data analysis using three models described above, grouped by equipment type selected for the study.

6.1. Main cooling pumps analysis

The screenshot below presents the main cooling pumps dataset imported to Weibull++ software and the interface for repairable data analysis, which is similar for all three applied models. The times are given in cumulative time-to-failure format e.g. each point is the "age" of a given system expressed in accumulated operating hours.



	System ID	Event (F=Failure, E=End)	Time to Event (hr)
1	1u2/1	F	401
2	1u2/1	F	839
3	1u2/1	F	25554
4	1u2/1	F	25736
5	1u2/1	F	26440
6	1u2/1	F	26625
7	1u2/1	F	43567
8	1u2/1	E	45386
9	1u2/2	F	3057
10	1u2/2	F	8284
11	1u2/2	F	14682
12	1u2/2	F	14941
13	1u2/2	F	33230

Fig. 2. Repairable systems data input in Weibull++ software.

The dataset was analyzed by the software algorithm and produced an MCF plot.

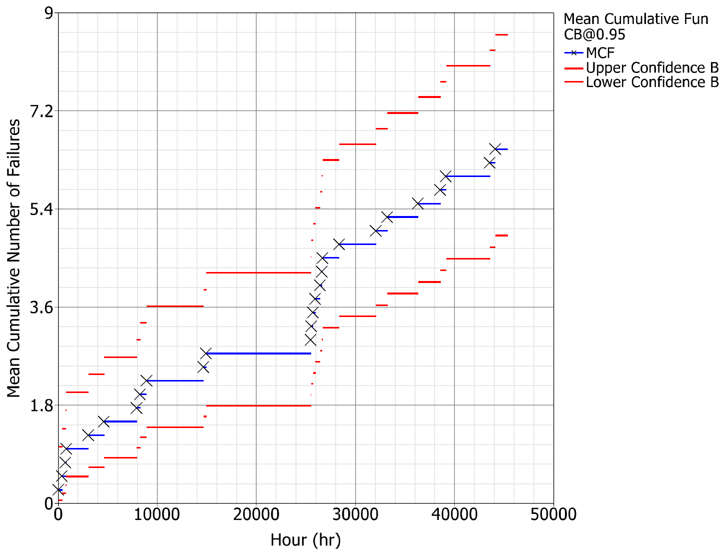


Fig. 3. MCF plot of the main cooling pumps dataset.

The plot shows the behavior of the failure rate in the dataset. In the central part of the plot a group of failures is visible that is not a random effect. Those data points are mostly due to leakages of sealing fluid in pump shaft seals. It was an issue with operations of newly installed pumps. The root cause of the increased rate of failures was the elevated temperature of the sealing liquid due to the inadequate cooling in the room where sealing liquid tank was kept. After the cooling was provided the rate of failures dropped, as can be seen in the plot.

Even if this plot does not provide model line, the analysts can deduce if the rate of failures is increasing or not by looking at the dataset behavior i.e. if the points are falling in a straight line (suggesting constant MTBF and failure rate) or if any curvatures are visible that would suggest the rate is changing.

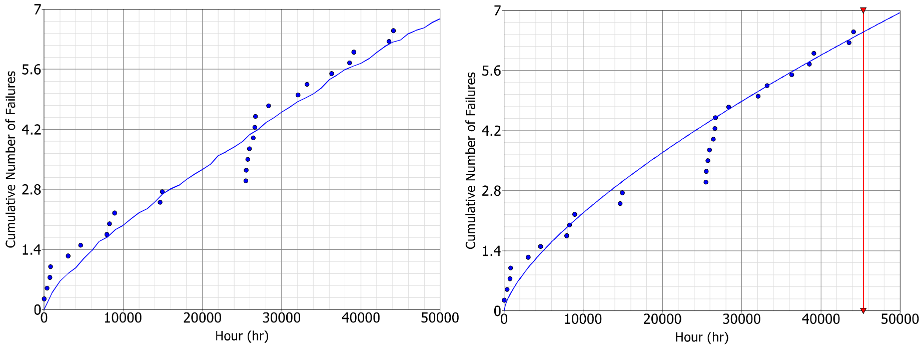


Fig. 4. GRP model (left) and Crow AMSAA plot (right) of the main cooling pumps dataset.

As can be seen in the plot above, the GRP model produces a good fit to the data, which should promote its use for prediction, although goodness-of-fit metrics are not calculated by the software. Produced model line suggests that the rate of failures is stable, considering a spike in failures after the pump fleet replacement in 2014.

Crow AMSAA model produces a line similar to the GRP model. The software also puts red line to clearly depict where the dataset ends and predictions start. This model traditionally uses logarithmic scales to assess the model fit. Interestingly, the CVM goodness-of-ft test is failed at 0.1 significance level. But the common beta hypothesis test is passed, which at least means that all four pumps show similar failure rate behavior.

6.2. Heat exchangers analysis

Heat exchangers dataset is presented using the same model settings as for the main cooling pumps.

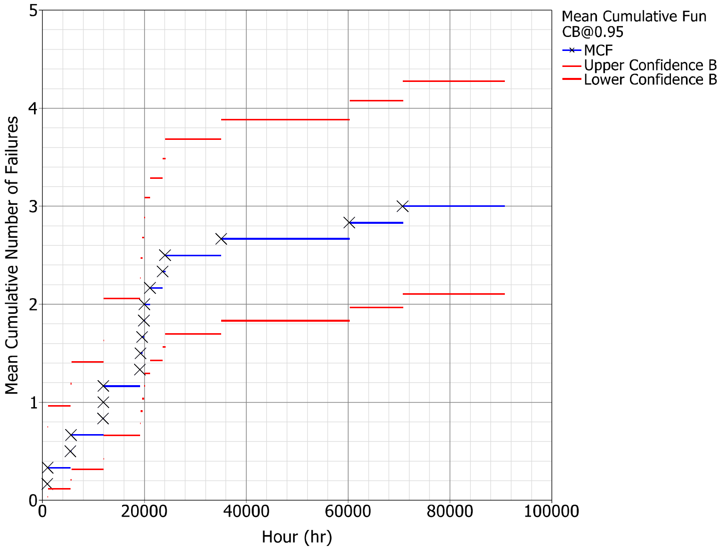


Fig. 5. MCF plot of the heat exchangers dataset.

In the plot a curvature is visible, even without the model line. It was suggested that few heat exchanger units have reached their end of life and were developing leakages at increased rate. Improvement in the leakage rate can be observed in the second half of the plot, which could also be linked to improvement of maintenance procedures. Around that time a pressure washer was introduced to clean the acidic solution that is applied to heat exchangers during cleaning.

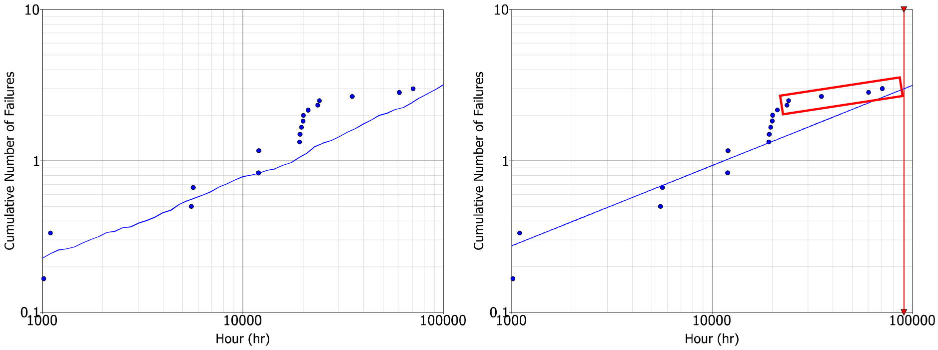


Fig. 6. GRP model (left) and Crow AMSAA plot (right) of the heat exchangers dataset (logarithmic).

GRP model does not produce a nice fitting model line using logarithmic axes. On the regular axis plot the model line strays even further from the data points and, therefore, is not shown. Irregularities in the failure rate behavior are clearly visible.

Again, the Crow AMSAA model plots the line similar to GRP. By looking at both plots, a changed slope can be observed in the dataset (highlighted red). The rate of failures is improved which could be the effect of largely replaced fleet of heat exchangers at that time. From the safety analysis point of view this could be a call to review PSA results, although the change of slope may be a random effect that will go away when new data comes.

6.3. Cooling fans analysis

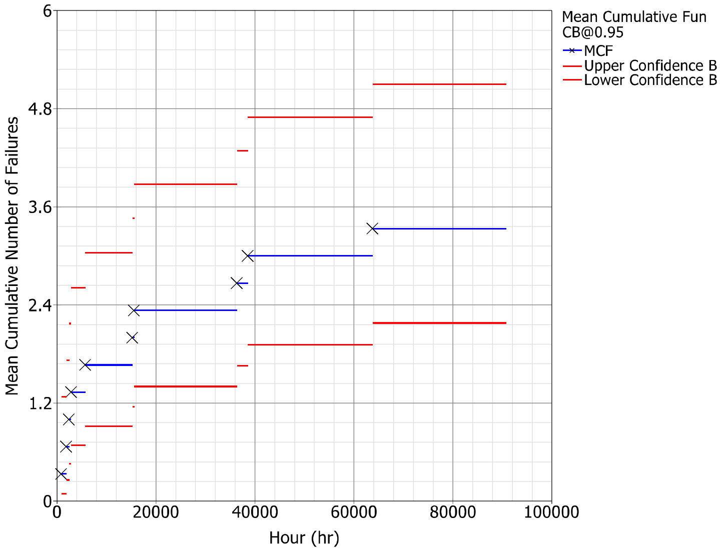
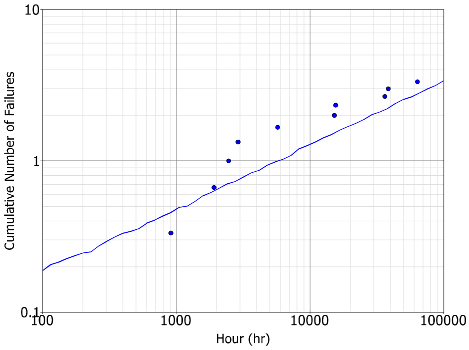


Fig. 7. MCF plot of the cooling fans dataset.

Cooling fans dataset shows potential change of slope in the beginning part, that would suggest the improving of the failure rate.



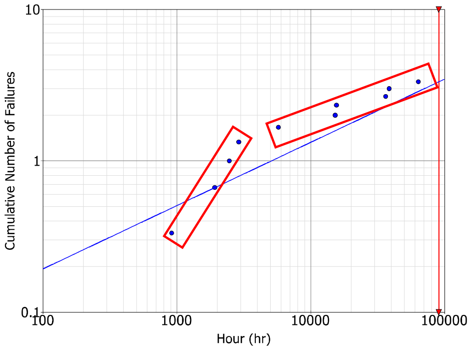


Fig. 8. GRP model (left and Crow AMSAA plot (right) of the cooling fans dataset (logarithmic).

GRP model plot does not produce a line following data points perfectly. Two slopes may be seen in the dataset. However, if it's due to a random effect, then the model line shows the expected failure rate behavior. The change of slope does not coincide with the fan fleet replacement in 2012.

Crow AMSAA plot shows almost the same failure rate behavior as the GRP line. The model is producing predictions according to the line that is a compromise between the two slopes visible in the data (highlighted red). If the new data shows behavior in accordance with the second slope, the model update will reflect the change and bend the line closer to the new slope.

7. Summary and conclusions

The presented models can detect changes in failure rate behavior of nuclear reactor systems and equipment when operational history in the range of tens of years is available. It can be detected in the form of different slopes formed by the points in the model plot. They are also capable of highlighting operational problems visible in the form of "clumps" of data points i.e. failures happening in short time intervals. The above is true if a significant amount of data is available, preferably from multiple systems that are the same and are used in the same environment.

GRP and Crow AMSAA models deliver similar results. GRP, however, can be extended by additional parameter to calculate repair effectiveness. Crow AMSAA also has an extended form, where failure modes can be designated and an improvement from eliminating selected failure modes can be calculated.

A significant difference in GRP vs Crow-AMSAA is in the confidence bound calculation, which was not covered in detail here, but may be a deciding factor for analytical model selection in safety related analysis.

With capable software both models can be used on the same dataset with minimal effort to draw conclusions on maintenance (GRP) or reliability improvements (Crow AMSAA extended).The main difficulty in their application lies in the data requirements. Provided examples are calculated from a sample of more than twenty years of operation but the trends that are visible in the plots are created using several points and, therefore, are sensitive to new observations and not conclusive from statistical point of view.

With that considerations, application of presented models is recommended in research reactors with long operational history to uncover failure rate changes that may be due to ageing equipment. As shown, it is also possible to detect improvement in failure rate caused by improved understanding of equipment limitations and weak points and eliminate them by better operational or maintenance procedures. In any scenario, new values of failure rate should be included in the review of PSA models of the facility to understand the impact on the safety of operations.

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