Estimating component repair times of a nuclear power plant

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1 Introduction

Loviisa nuclear power plant (NPP) is operated by Fortum in Loviisa, Finland. The plant site has two VVER-440 type pressurized light water reactors, each having a net capacity of 507 MWe. The two units started their commercial production use in 1977 and 1980, and in 2023 the Finnish Government granted Fortum permission to continue operation of the plant until the end of 2050.

Technical specifications (TS) of a nuclear power plant define allowable conditions for safe operation of the plant. These limiting conditions for operation (LCOs) include allowed outage times (AOTs) for different equipment in the plant. Since both the unavailability of a component and changing operational state of the NPP induce an increase in risk, the length of the AOT can be considered as an optimization problem.

A risk-informed evaluation of AOTs defined in TS of Loviisa NPP has been carried out by Sirén (2013). The evaluation uses a probabilistic risk assessment (PRA) model of Loviisa NPP. Moreover, the evaluation uses an AOT optimization model created by Sirén (2007a), which requires a model of realized component repair times presented by Sirén (2007b). Due to practical reasons, it is not practical to constantly update TS of a NPP. However, because the PRA model of Loviisa NPP has been continuously developed and improved and the operating licence of the plant has been extended, a need for updated risk-informed evaluation of the TS has been recognized at Fortum (Ronkainen and Sirén, 2023).

The main objective of this study is to update previous component repair time estimation model by Sirén (2007b), and to verify if the modelling assumptions used in the previous model are still valid. This is achieved by using more recent plant maintenance data for model fitting. Another objective is to analyze whether the realized component repair times at Loviisa NPP have changed as the plant maintenance procedures and practices have been updated.

The remainder of this study is organized as follows. In Section 2 we define the allowed outage time, present the history of risk-informed AOT analysis in Loviisa NPP and briefly review the literature on repair time estimation. In Section 3 we present the methods and data used in this study. In Section 4, we present results from the repair time estimation and preliminarily study its effect on the AOT optimization model. In Sections 5 and 6, we discuss and conclude the findings of this study.

2 Background

2.1 Allowed outage time

The allowed outage time (AOT) is a time limit defined in the TS for restoring failed equipment back to operation. If the failure cannot be repaired within AOT, the plant operational state should be changed such that the LCOs are satisfied — typically this means that the plant should be driven to a cold shutdown state. According to the TS of Loviisa NPP, the AOT should only be applied to repairs of randomly occurring critical failures. However, AOT can also be used for planned maintenance tasks, if approved by the supervisory authority, and for repair of noncritical failures that considerably lower the reliability of the component in the long run (Ronkainen, 2023).

For practical reasons, the AOT times used in TS are divided to discrete classes. Most typical AOT values used are immediate shutdown (2 hours available to prepare for plant shutdown), 8 h, 24 h, 3 days (72 h) and 3 weeks (504 h). The AOT of a failure is determined based on the failed component and the failure mode: for example there can be different AOTs for a valve depending on if it has failed to open or failed to close. There can also be several AOTs for a single component depending on whether other systems are available to substitute the failed component. Conversely, if multiple redundancies of a system are taken down by a common cause failure (CCF), the AOT can be significantly shorter.

2.2 Risk-informed AOT analysis of Loviisa NPP

Technical specifications of NPPs have traditionally been created based on deterministic analysis (Samanta et al., 1994). However, as more operational experience of NPPs has become available, some of the requirements specified in the TS have been found to be unnecessarily restrictive. After the development and application of probabilistic risk assessment methods for NPPs, a risk-informed approach has been suggested to be used to evaluate and balance these requirements since the end of 1980s (e.g. Laakso et al., 1991; Mankamo et al., 1992). A risk-informed development of TS is nowadays also suggested in the Regulatory Guides on nuclear safety and security (YVL) by Radiation and Nuclear Safety Authority (STUK) in Finland.

The risk-informed analysis of AOTs of Loviisa NPP was started by Kivirinta (2005), which showed that there were some imbalance between the AOT and the importance of the corresponding components in the PRA model. Sirén (2007a) developed this work further and created a method for risk-informed optimization of AOTs. This work was later used to develop a method for risk-informed evaluation of the TS of Loviisa NPP (Jänkälä and Sirén, 2008) and later to evaluate the AOTs in 2013 (Sirén, 2013).

The risk-informed AOT optimization method by Sirén (2007a) uses a model for estimating realized repair times of components for each AOT class. The component repair time estimation model is presented in Sirén (2007b). The model assumes, that the realized repair times depend linearly on the AOT. Assumption that the AOT affects realized repair times is reasonable, as the AOT class of a component sets requirements for e.g. spare part availability, and generally the data used to fit the model also backs up the assumption. This assumption is also used to generalize the model for continuous AOT values.

The AOT optimization model by Sirén (2007a) estimates the risk increase of a given AOT value by dividing the risk into two parts. These are

1. the risk increase of component unavailability during AOT and
2. the risk increase of plant shutdown due to repair time exceeding AOT.

The sum of these risk increases has a minimum value for some AOT as illustrated in Figure 1. To calculate these risk increases, from the repair time estimation model we need three values, which are (Sirén, 2007a)

1. the expected repair time of a component given an AOT,
2. the probability that a repair cannot be completed within the AOT, and
3. the expected repair time given that the repair is completed within the AOT.

These requirements set some limitations to the repair time estimation model. To keep the model relatively simple and easy to interpret, Sirén (2007b) chooses to model the repair time as a random variable that follows the exponential distribution.

To assign an optimal AOT for each component, the AOT optimization model by Sirén (2007a) calculates the expected risk increase of each AOT class for every component. Thereafter the AOT class with the minimal expected risk increase is selected.

2.3 Component repair time estimation

Usually in parameter estimation for PRA modelling purposes, the focus has been in estimating component failure rate, i.e. modelling the lifetime of the component, as it usually has a greater impact on component unavailability. The reason for this is that generally mean time between critical failures of a component can be measured in years, whereas mean repair times are measured in hours or days. However, to estimate the risk increase given that a component has failed, there is a need for a method to accurately estimate component repair times.

Typical assumptions for estimating a random time in reliability analysis are that the random times are independent and follow the same probability distribution. Typical distributions that are used to model random times are lognormal, exponential, Weibull and gamma distributions (Atwood et al., 2003). However, exponential distribution is probably the most used distribution to model random times due to its simplicity. It is used, for example, in the T-book by The TUD Office (2015) simply using the arithmetic mean for the component repair time estimate.

In recent years, the repairability of failures and repair time estimation have been

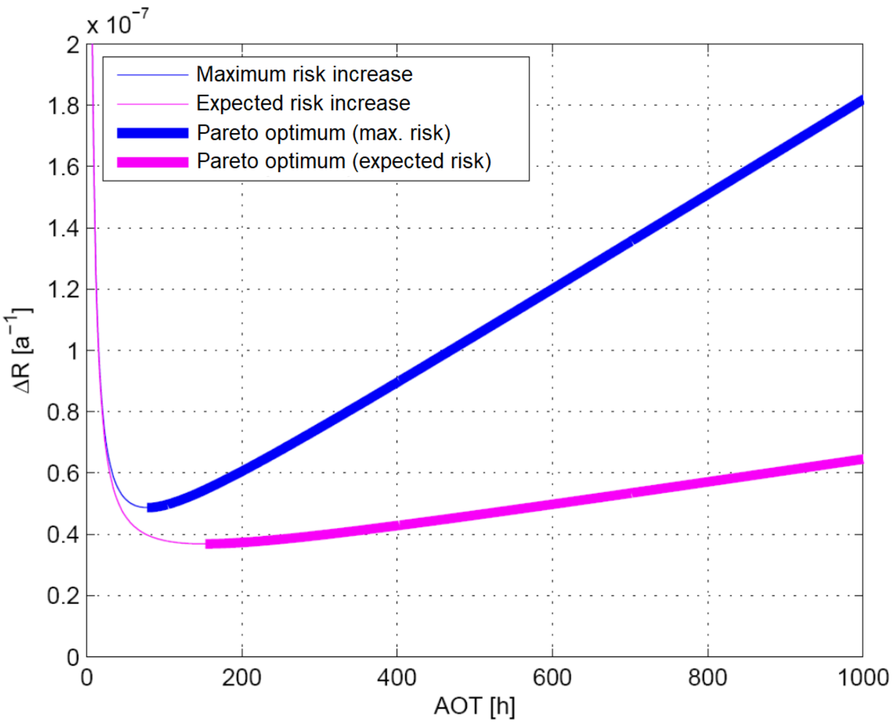

Figure 1: Risk increase as a function of AOT (Sirén, 2007a). The highlighted lines represent pareto optimal points, where risk cannot be decreased without compromising plant availability.

studied more extensively. While in traditional PRA models component repairs in an accident scenario are not considered because of limited time frame, in some long-term accident scenarios component repairs are possible and they could be incorporated into corresponding PRA models. For example, in a study by Sparre et al. (2022), the repair time of failures is investigated by dividing it into repair waiting time and active repair time. The repair waiting time is then assumed to be 8 h based on personnel availability and active repair times are estimated using both lognormal and exponential distributions. While lognormal distribution fits the data better, Sparre et al. (2022) state that exponential distribution will be preferred in future modelling.

Component repair time should not be confounded with component unavailability time, which in some cases cannot be directly measured. For example, a fault of a stand-by component observed in a periodic test may have occurred anywhere in the periodic test interval. Thus the component latent unavailability time is on average half of the periodic test interval, and the whole unavailability time is latent unavailability time and repair time combined.

In this study the component repair time is considered to begin from the failure observation and to end when the failed component is restored back to operation. An estimate for mean repair time is calculated by fitting exponential distribution to data collected from Loviisa NPP using method described in the next section.

3 Method and data

3.1 Data

The data used in this study is collected from maintenance work orders created at Loviisa NPP. For every maintenance task performed at the plant, a work order is created, so they have traditionally been used to estimate plant-spesific component failure and repair rates. This is also the approach recommended by Atwood et al. (2003). For each work order, it is considered whether there are LCOs that limit the AOT of the component. In this study, work orders created between 2006–2022 that had an LCO were analyzed.

In the dataset, we have approximately 8000 work orders with AOT. However, we are only interested in component renovations and repairs, and consequently periodic maintenance and test work orders can be filtered out. Moreover, the AOT can start either from the start of the repair (renovation of non-critical failure) or immediately after observing a failure. In the scope of this study, we are only interested in the latter type of work orders, since the repair time of a random occurring critical failure should also include the planning of the repair, which is not the case when AOT starts at the start of the repair. The data is not filtered in any way by the type of the failed component. Thus, the dataset contains, for example, valves, pumps, blowers, and measurement devices. With these limitations there are 1050 observations in the data.

For each work order in the dataset, the AOT that is defined by the TS is known. The realized repair time of each work order is also available in the dataset. From these repair times, the expected repair time given the AOT can be estimated.

Some studies (e.g. Himanen et al., 2008) suggest screening out observations with short, less than one hour realized repair times. However, in this study no justification for such approach was found.

3.2 Estimation method

The model and data used in the AOT optimization of Loviisa NPP sets specific conditions for the estimation of realized repair times. In this section we present the method used in this study, which is a similar approach to the one used by Sirén (2007b).

Let n denote the number of observations, that is, the number of work orders in the analysis. If we order the observations in decreasing order by the realized repair time, we can let $T_i, i \in \{1, 2, \ldots n\}$ denote the realized repair time of observation i. We assume that the repair times are exponentially distributed such that

$$T_i \sim \mathrm{Exp}(\mu),$$

where μ is the repair intensity of the exponential distribution. The expected value for the realized repair time is $E[T_i] = 1/\mu$.

The maximum likelihood estimate for parameter μ is the inverse of arithmetic mean of realized repair times, that is

$$\hat{\mu} = \frac{1}{\mathrm{MTTR}} = \left(\frac{\sum_{i=1}^{n} T_i}{n} \right)^{-1},$$

where MTTR stands for mean time to repair. However, this is not a suitable approach due to the nature of the data. If a repair cannot be executed within the AOT, the realized repair time will probably not have the same repair intensity anymore. This is because the plant either has to be driven into safer operation state or the supervisory authority grants a permission to extend repair time over AOT. Thus, when taking observations that exceed AOT into the average, the estimate for repair intensity is too low. However, if we only consider mean repair time of observations that are repaired within AOT (denoted by $\mathrm{MTTR}_{T_i<\mathrm{AOT}}$), the estimate for repair intensity is too high.

We can mitigate these biases by giving each observation i a cumulative probability $p_i = P(X \leq T_i)$ such that

$$p_i = \frac{n - i + 0.5}{n}.$$

That way p_i is the probability that a random repair time is shorter than T_i. If the realized repair times are exponentially distributed, from the cumulative distribution function (CDF) of the exponential distribution (Atwood et al., 2003) we have

$$p_i = 1 - e^{-\mu T_i},$$

from which by solving for T_i we have

$$T_i = -\ln(1 - p_i)\mu^{-1}.$$

Thus points $(-\ln(1 - p_i), T_i)$ should lie on a straight line through the origin with a slope of μ^{-1} . We can then use least squares regression to find this slope. However, in this approach we only fit the line through points where $T_i < \mathrm{AOT}$; that way the observations where AOT is exceeded only affect the cumulative probabilities p_i and our estimate for μ corresponds to situation where the realized repair times exceeding AOT would follow same distribution as other observations.

4 Results

4.1 Estimates for realized repair times

The estimation method described in Section 3.2 was used to fit exponential distributions to the work order data from Loviisa NPP. The fitting was done in three parts: first, exponential distributions were fitted for the whole dataset from 2006 to 2022, and then for two time periods of 2006–2012 and 2013–2022 that contain roughly same amount of work orders. The AOTs for which the estimation was done were selected to be 8 h, 24 h, 72 h and 504 h, since these are the most common in the data and cover about 95% of all work orders. For these also the arithmetic mean repair times were calculated. Results of these estimations are presented in Table 1.

From values in Table 1, it can be seen that the AOT of a component generally seems to have an effect on the realized repair times. Furthermore, it can be seen that fitting exponential distribution generally seems to give an estimate between MTTR and $\mathrm{MTTR}_{T_i<\mathrm{AOT}}$, as hypothesized in Section 3.2. However, this does not seem to be the case for the long 504 h AOT, where the exponential distribution seems to overestimate the realized repair time.

To analyze the exception in 504 h AOT class. we plot the exponential distribution fits presented in Figure 2. In this figure the fits for other AOT classes seem to follow the data pretty neatly, but the fit for the AOT class of 504 h is not as good. One possible explanation for this is that there are numerous possible fault types for the components. For example, a fault of a pump that has AOT of 504 h can be a blown fuse, which is reasonably quick to repair, or it can be a more severe fault that requires

Table 1: Results of realized repair time estimations for different AOTs and time periods.

		AOT			
Time period	Parameter	8 h	24 h	72 h	504 h
Whole dataset	n	67	35	522	368
	μ^{-1}	4.29	15.16	23.00	105.33
	MTTR	6.94	27.20	50.46	95.35
	$\mathrm{MTTR}_{T_i<\mathrm{AOT}}$	4.09	9.72	20.32	86.70
2006–2012	n	22	23	260	162
	μ^{-1}	4.81	12.84	28.43	141.81
	MTTR	11.31	27.44	46.19	133.48
	$\mathrm{MTTR}_{T_i<\mathrm{AOT}}$	3.89	8.40	25.13	127.79
2013–2022	n	45	12	262	206
	μ^{-1}	3.95	17.52	17.21	67.39
	MTTR	4.80	23.73	54.70	65.32
	$\mathrm{MTTR}_{T_i<\mathrm{AOT}}$	4.18	12.09	15.69	54.47

isolating the pump from the process, building scaffolds or waiting for spare parts. Thus the repair intensity for all fault types may not be the same. However, the exponential distribution seems to fit the data well enough that the usage of it can be justified. The plots also suggest that the repairs that exceed AOT clearly follow a different distribution, which justifies the proposed estimation method. Plots similar to Figure 2 for the different data periods are presented in Appendix A.

In Table 1, the realized repair times seem to have shortened on the latter time period. This is especially noticeable in longer AOTs of 72 h and 504 h. One explanation for this change is that realized repair times for the 72 h AOT are nowadays monitored and they affect employee incentives if the mean repair time in a calendar year is under 15 hours (Rinkinen, V. and Kirkinen, A-P., 2023). Presently the TS of Loviisa NPP also require that all repairs have to be started without delay and to be completed as fast as possible.

From the values in Table 1 and the plots in Figure 2 and Appendix A, we conclude that estimates are uncertain for the 24 h AOT class due to the small number of observations. For example, in the newer data period our estimate for repair time of components with 24 h AOT is longer than for components with 72 h AOT. This can also result from the fact, that most of the components in the data with 24 h AOT are containment isolation valves, which may require longer repair times.

4.2 Continuous AOT model

From the estimates for realized repair times, we next generalize the model for a continuous AOT, as required by the AOT optimization model (Sirén, 2013). We assume, as described in Section 3.2, that the component repair time depends linearly on AOT. This allows us to estimate the realized repair time of arbitrary AOT by fitting a linear model to the estimates of repair time for each AOT class.

Since the data suggests that there is a significant change in the realized component repair times between the two analyzed time periods, to get a contemporary model only the data from 2013–2022 is used in the linear model. By using data from Table 1 and simple linear regression, we estimate the exponential distribution parameter μ for continuous AOT to be

$$\mu = \frac{1}{0.12 \cdot \mathrm{AOT} + 8.8}.$$

A plot of the fitted model is presented in Figure 3. The coefficient of determination of the model is about $R^2 \approx 0.97$, which indicates a good fit, even though there are only a few data points. This indicates a clear relation between AOT and realized repair time.

We compare this new relation to the previous estimate used in Sirén (2013), which is

$$\mu^{-1} = 0.15 \cdot \mathrm{AOT} + 2.5.$$

The term dependent of AOT is about 20% smaller in the new estimate, which reflects that the change in realized repair times is larger in the longer AOT classes. The

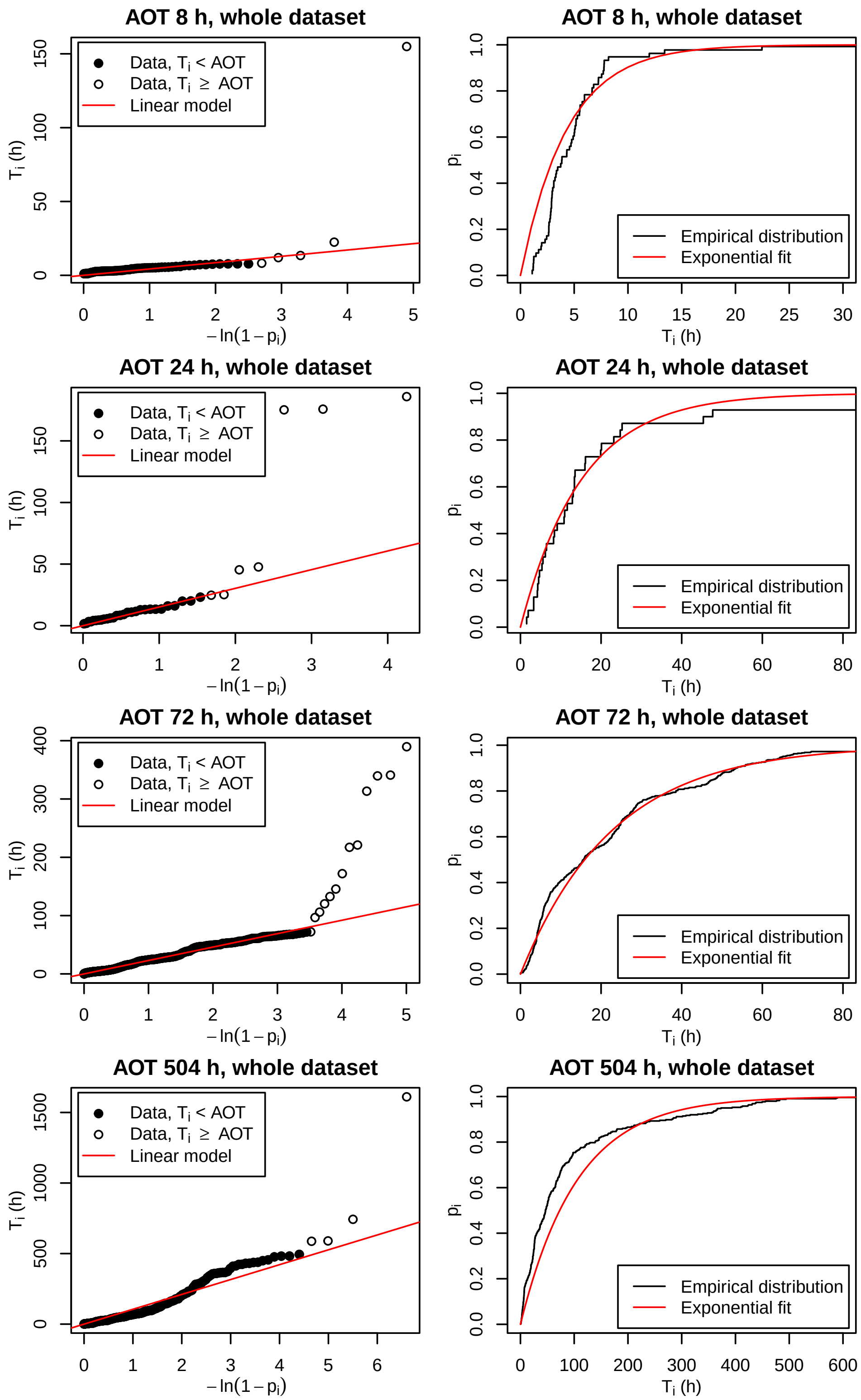

Figure 2: Exponential distribution fits to the whole dataset for each AOT class. In the left pane there are plots of points $(-\ln(1-p_i), T_i)$ and the fitted linear model, highlighting the points that are used for the fitting. In the right, there are empirical distribution functions plotted from the data, along with CDF of the exponential distribution with the fitted parameter μ.

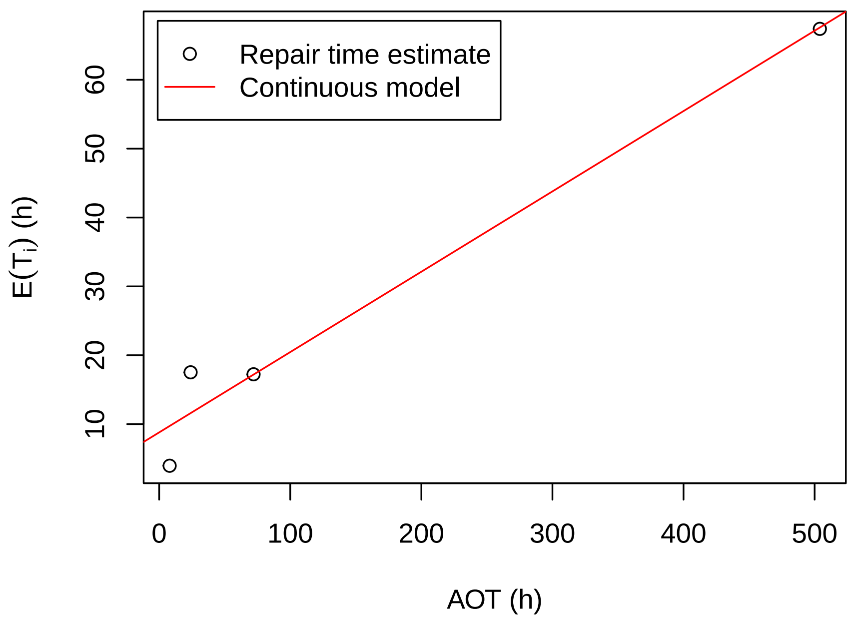

Figure 3: Linear regression model fitted to the estimated repair times for each AOT class.

constant term has increased from 2.5 hours to about 8.8 hours. However, this can be somewhat expected, because the old repair time model had an identified weakness in that it appears to have predicted too optimistic repair times for shorter AOT classes. The difference in the constant term can also result from including all component types in the data.

4.3 Preliminary analysis on effects of the new repair time model

The effects of the new parameters for the continuous AOT model were tested by inputting the formula into the AOT optimization model by Sirén (2013). The results of this test are in Table 2. In the table, AOT class of 2 hours is used to describe the AOT class for immediate shutdown, as described in Section 2.1. Similarly, AOT class of 8200 h is used to describe unrestricted AOT, i.e. that the component repair can wait for the yearly refuelling outage. Furthermore, $P(T_i < \text{AOT})$ denotes the probability that the repair time is shorter than AOT, $E[T_i|T_i < \text{AOT}]$ denotes the expected repair time given that the repair is completed within AOT and #Components denotes the number of components assigned to the AOT class by the model with the method in Section 2.2.

The results in Table 2 suggest that, in general, the model tends to assign more

Table 2: Effects of new realized repair time model on the AOT optimization model.

	AOT	μ^{-1}	$P(T_i < \text{AOT})$	$E[T_i \mid T_i < \text{AOT}]$	#Components
Old model	2 h	2.8	0.510	0.9	3
	8 h	3.7	0.885	2.7	115
	72 h	13.3	0.996	13.0	1677
	504 h	78.1	0.998	77.3	521
	8200 h	1232.5	0.999	1221.9	4956
New model	2 h	9.0	0.198	1.0	4
	8 h	9.7	0.559	3.5	38
	72 h	17.2	0.984	16.1	1221
	504 h	67.6	0.999	67.3	1053
	8200 h	965.7	1.000	964.1	4956

components to the longer AOT classes with the new realized repair time model. This suggests that there are possibilities to give longer AOT classes for some components to reduce the risk induced by unnecessary plant shutdowns. This is plausible, as shortening the expected component repair time also reduces the expected risk increase of the repair.

However, as the optimization model by Sirén (2013) uses risk measures from a 10 year old PRA model, these results should only be seen as indicative. More research should be conducted by updating the AOT optimization model with importance measures from the newer PRA model. Also, the model for unscheduled plant shutdowns is under development, so it should be incorporated to the AOT optimization model after new results are available.

5 Discussion

The results in Section 4 indicate that the selected model seems reasonable for estimating component repair times for a given AOT. There is a clear dependence between AOT of a repair and the realized repair time. While the amount of data collected at Loviisa NPP continues to grow every year, the number of observations in 8 h and 24 h AOT classes are very low compared to 3 day and 3 week AOTs. However, by using the linear model for a continuous AOT, we can use data from the more common AOT classes to predict repair times of shorter AOTs. The model gives a realistic minimum estimated repair time of about 9 hours.

We also test our assumption of AOT affecting the repair rate by fitting exponential distribution to data from all AOT classes. A plot of such fit for the 2013–2022 data is shown in Figure 4. Clearly, the plot shows that that the exponential distribution does not fit the data as well as when fitted to data from single AOT.

In the newer data, the realized repair times have shortened compared to data between 2006–2012. However, the fact that mean realized repair time of 72 h AOT class affects employee incentives probably adds some bias to the data. It could be considered whether the 72 h class should be analyzed separately from other AOT classes. However, as that AOT class has most work orders, it would reduce the amount of data for fitting the linear model for continuous AOT.

To increase the accuracy of the repair time model model for a given component, we could consider the type of the component. This would require fitting different models for different types of components, such as pumps, valves, blowers, and switches. This was studied by Sirén (2007b), and some differences between repair time estimates of different component types were found. However, there is also a trade-off between modeling accuracy and data availability, which is why the component type information is not used in the AOT optimization model. That is also why in this study all component types were selected for the model fitting.

Generally, exponential distribution seems to fit the data pretty well. While other probability distributions such as Weibull or lognormal distributions could produce better fits, they are not that easy to incorporate into the model as the generalization for continuous AOT is not trivial for distributions with two or more parameters.

If we would consider discrete AOT classes without extending the model for a continuous AOT, we would not have to make any assumptions about the underlying probability distribution. That is because all the parameters used in the AOT optimization model in Section 2.2 could then be estimated directly from the data. However, with AOT classes that only have a few observed failures, this approach is more prone to random errors. This topic could be studied more in the future as the risk-informed assessment of the TS of Loviisa NPP is continued.

Other uses of the repair time estimation model in addition to AOT optimization could also be investigated. For example, the model could be used to incorporate component repairs into PRA modelling using for example the I&AB (Initiators and

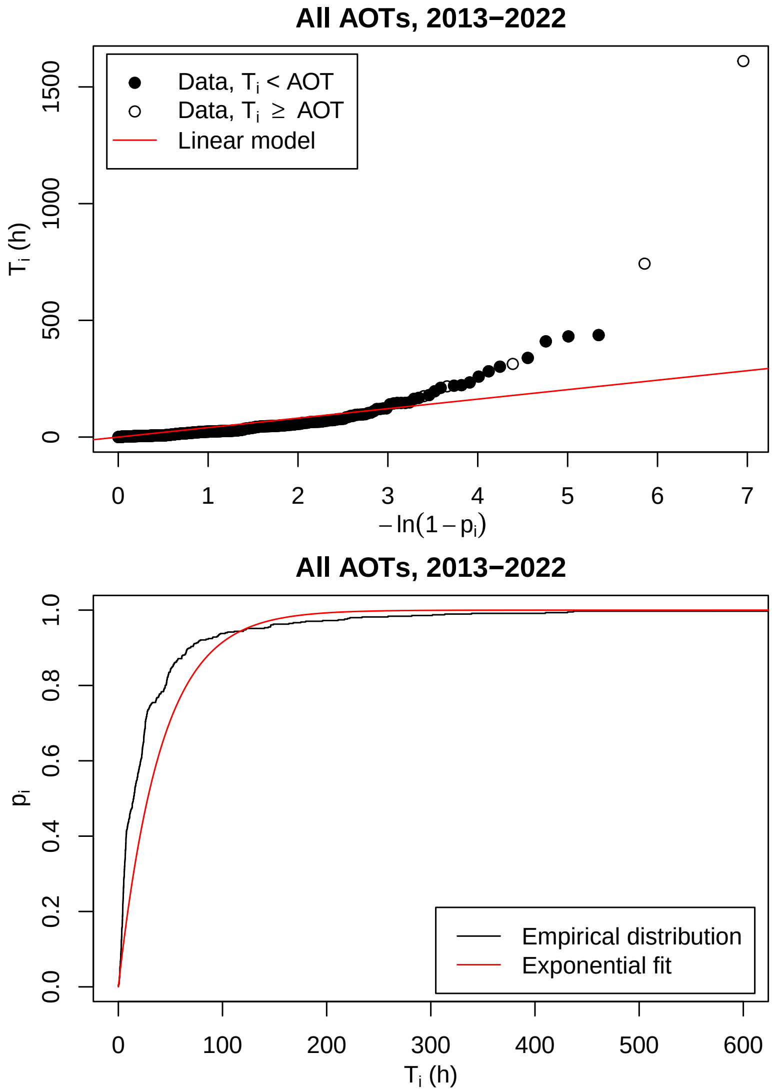

Figure 4: Exponential distribution fitted to all AOT classes of the 2013–2022 data.

All Barriers) quantification method proposed by Bouissou and Hernu (2016).

6 Conclusion

This special assignment study updated a component repair time estimation model used to optimize allowed outage times of the TS of Loviisa NPP by using new plant data. The results show that generally the repair times of components have shortened during the past decade due to changes in maintenance practices, but the AOT of a component still affects its repair time. Preliminary testing with AOT optimization model indicates that shorter realized repair times justify the assignment of longer AOTs for a larger number of components.

This study is a part of the continual process of risk-informed evaluation of the TS of Loviisa NPP. As there have been safety-improving plant modifications in Loviisa and the PRA model of the plant has been developed significantly since the last risk-informed evaluation, these changes should be incorporated to the AOT optimization model to get a timely assessment of the TS.

References

C. L. Atwood, LaChance J. L., H. F. Martz, D. J. Anderson, M. Englehardt, D. Whitehead, and T. Wheeler. Handbook of Parameter Estimation for Probabilistic Risk Assessment. Technical Report NUREG/CR-6823, US.NRC, 2003.

M. Bouissou and O. Hernu. Boolean approximation for calculating the reliability of a very large repairable system with dependencies among components. In *Proceedings of the 25th European Safety and Reliability Conference (ESREL)*, 2016.

R. Himanen, J. Pesonen, P. Pyy, M. Tupala, and J-E. Holmberg. Evaluation of Olkiluoto BWR TechSpecs by using plant specific PSA. In *ANS PSA 2008 Topical Meeting*. American Nuclear Society, 2008.

K. Jänkälä and S. Sirén. TTKE:n riskitietoinen arviointi. Technical Report LO1-T84307-00159, Loviisa Nuclear Power Plant, 2008.

T. Kivirinta. Risk-Informed Balancing of Allowed Outage Times of a Nuclear Power Plant. Master's thesis, Helsinki University of Technology, 2005.

K. Laakso, A. Engqvist, M. Knochenhauer, M. Kosonen, B. Liwang, T. Mankamo, and K. Pörn. Optimization of technical specifications by use of probabilistic methods — a Nordic perspective. *Use of probabilistic safety assessment*, page 63, 1991.

T. Mankamo, I. S. Kim, and P. K. Samanta. Risk-based evaluation of Allowed Outage Times (AOTs) considering risk of shutdown. 1992. URL `https://www.osti.gov/biblio/10126559`.

Radiation and Nuclear Safety Authority (STUK). Probabilistic risk assessment and risk management of a nuclear power plant (YVL A.7). Available at `https://www.stuklex.fi/en/ohje/YVLA-7`, 2019.

Rinkinen, V. and Kirkinen, A-P. Ydinturvallisuusindeksin mittaamiseen liittyvät kuvaukset. Memorandum LO1-B31-00013, Loviisa Nuclear Power Plant, 2023.

T. Ronkainen. Loviisa 1 turvallisuustekniset käyttöehdot. Technical Report LO1-K857-00277, Loviisa Nuclear Power Plant, 2023.

T. Ronkainen and S. Sirén. Turvallisuusteknisten käyttöehtojen riskitietoisen (RI-TTKE:n) päivitystarpeen arviointi. Technical Report LO1-K857-00523, Loviisa Nuclear Power Plant, 2023.

P. K. Samanta, I. S. Kim, T. Mankamo, and W. E. Vesely. Handbook of methods for risk-based analyses of technical specifications. Technical Report NUREG/CR-6141, US.NRC, 1994.

S. Sirén. Risk-Informed Optimization of Allowed Outage Times of a Nuclear Power Plant. Master's thesis, Helsinki University of Technology, 2007a.

S. Sirén. Ydinvoimalaitoksen turvatärkeiden laitteiden korjausajan mallinnus. Special assignment, Helsinki University of Technology, 2007b.

S. Sirén. TTKE:n riskitietoinen tarkastus - sallitut korjausajat. Technical Report LO1-T84307-00231, Loviisa Nuclear Power Plant, 2013.

E. Sparre, M. Håkansson, C. Eriksson, and G. Johanson. Investigation of Repairability of Failures in PRA (Project DIOR). In *Probabilistic Safety Assessment and Management PSAM 16*, 2022.

The TUD Office. *T-book: Reliability Data of Components in Nordic Nuclear Power Plants (8th edition)*. Vattenfall AB, 2015.

A Plots of exponential distribution fits to the data

Plots of exponential distribution fits to the data for the data period 2006–2012 are in Figure A1 and similarly for the data period 2013–2022 in Figure A2.

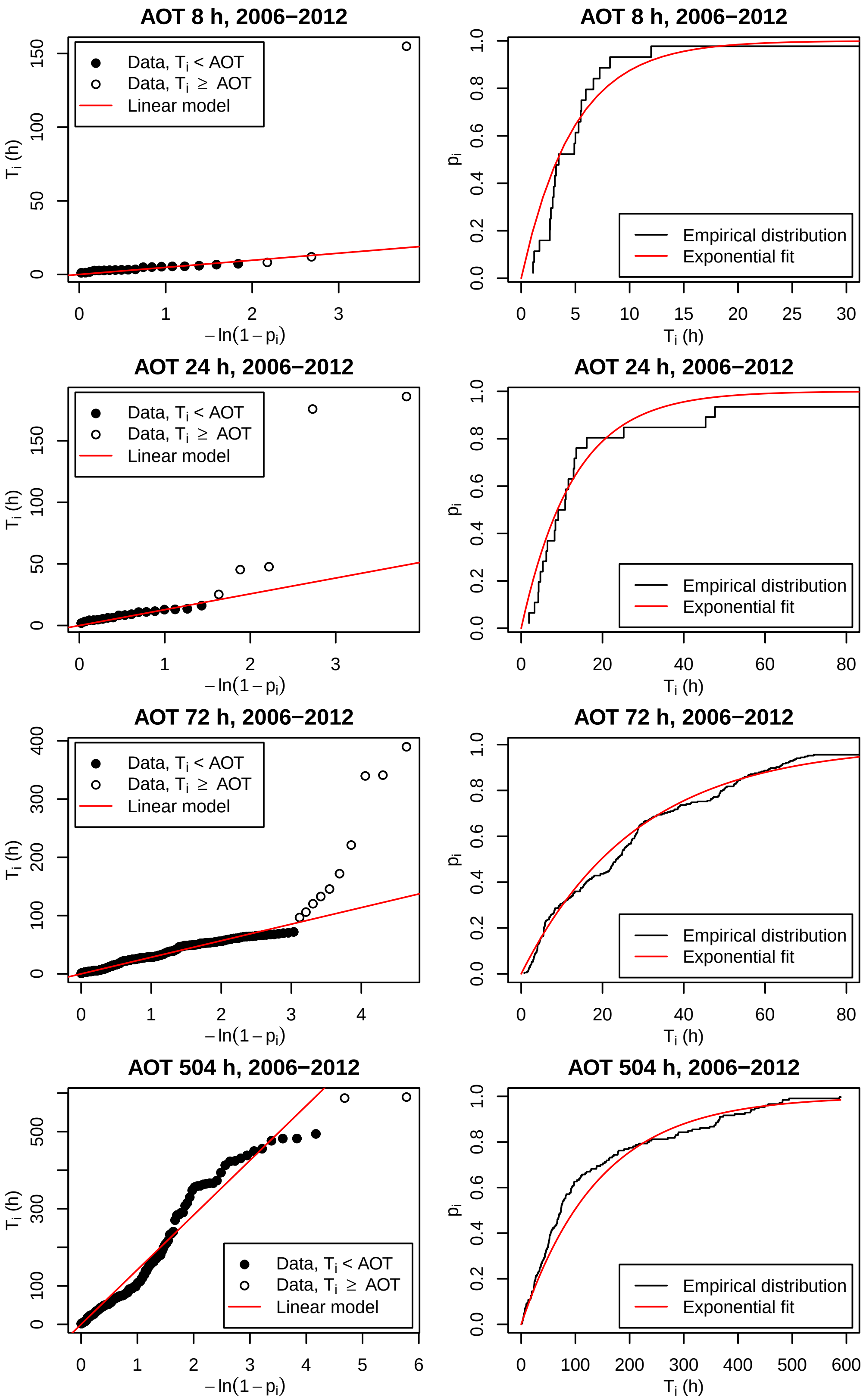

Figure A1: Exponential distribution fits to the data from 2006 to 2012.

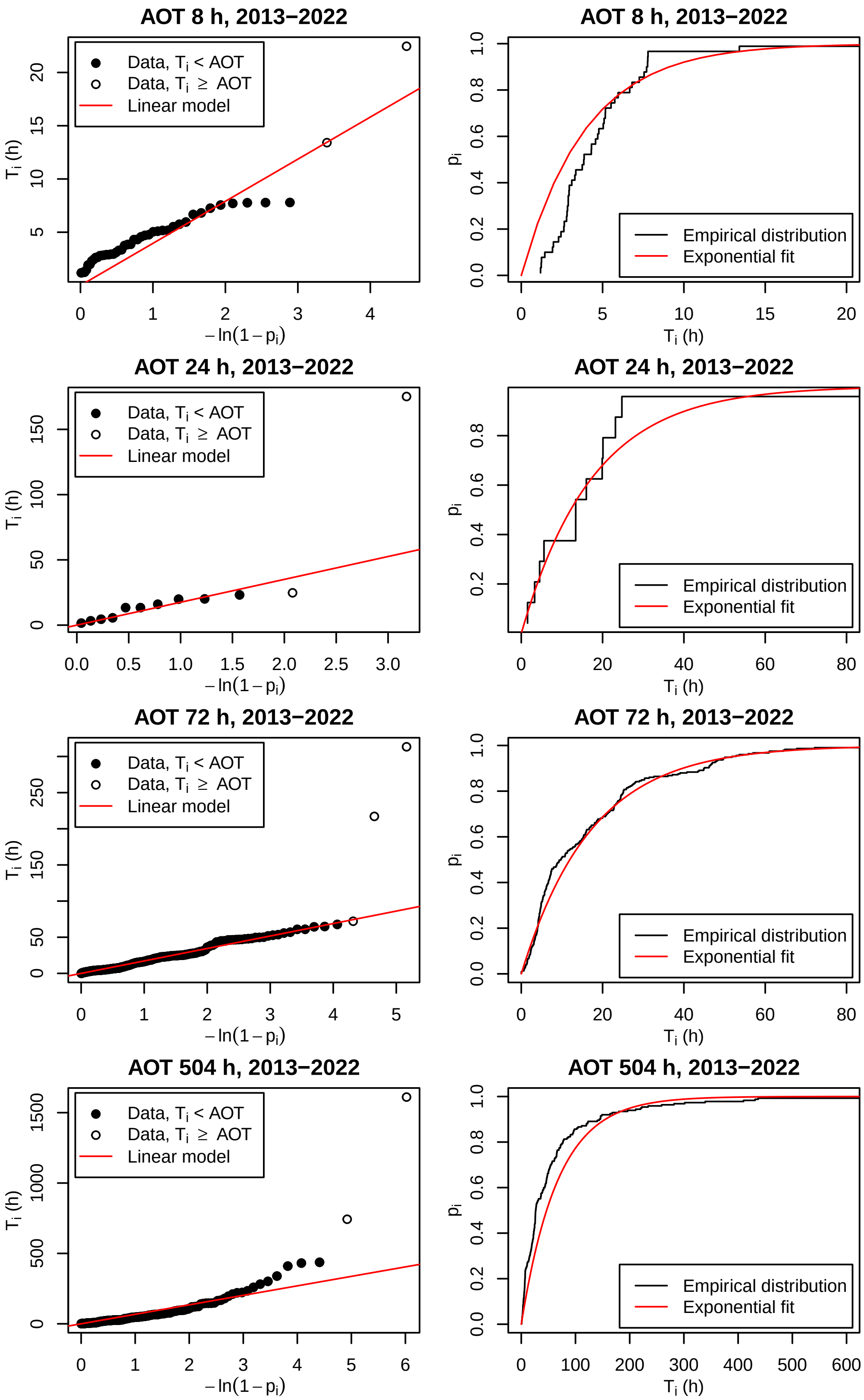

Figure A2: Exponential distribution fits to the data from 2013 to 2022.