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# Value of information of repair times for offshore wind farm maintenance planning

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**Abstract.** A large contribution to the total cost of energy in offshore wind farms is due to maintenance costs. In recent years research has focused therefore on lowering the maintenance costs using different approaches. Decision support models for scheduling the maintenance exist already, dealing with different factors influencing the scheduling. Our contribution deals with the uncertainty in the repair times. Given the mean repair times for different turbine components we make some assumptions regarding the underlying repair time distribution. We compare the results of a decision support model for the mean times to repair and those repair time distributions. Additionally, distributions with the same mean but different variances are compared under the same conditions. The value of lowering the uncertainty in the repair time is calculated and we find that using distributions significantly decreases the availability, when scheduling maintenance for multiple turbines in a wind park. Having detailed information about the repair time distribution may influence the results of maintenance modeling and might help identify cost factors.

## 1. Introduction

In the offshore wind industry, cost of energy is a lot higher than in its onshore counterpart. This is partly due to high operations and maintenance cost, accounting for up to 30 % of the cost of energy [1]. Several approaches to lowering these costs are being pursued by current research. Specifically, four maintenance cost models for offshore wind farms have been actively developed recently [2, 3, 4, 5, 6, 7]. These models incorporate different factors influencing the maintenance cost, like weather, failures and resources. The uncertainty in the weather forecasts used when planning the maintenance is a commonly known factor that needs to be addressed by the models. Also the occurrence of a failure is associated with uncertainties and addressed by using annual failure rates [8] or Markov models. The models cited above however, do not include uncertainties in the repair time information and instead assume constant repair times for the occurring failures. Very recently a study on the sensitivity of one of the models to changes in model inputs has been conducted [9]. In this study, different values for constant repair times have been investigated. The question we address here is whether it makes a difference to include the uncertainties in the repair time in the analysis. The success of a maintenance task depends on whether the given weather window is as long or longer than the time needed to complete the repair. Therefore the interaction between uncertainties in weather and repair times is the point of interest. A first approach to variable repair times and their influence on the production loss due to weather delays has been conducted [17]. The novelty here is to investigate not only the interaction between



weather and repair times, but additionally include the influence of the maintenance scheduling in the cost model. Our hypothesis was that including probabilistic variations of the repair time significantly changes the results observed in the deterministic analysis of the maintenance cost model and, in particular, leads to less availability compared to using the simplification of a constant repair time.

## 2. Methodology

To conduct this analysis we used a simulation model to model the sea states and wind speed. Three main methods for simulating sea states can be found in the literature. These can be based on Gaussian statistics, ARMA processes or stochastic processes satisfying the Markov property [10], where the latter is the most used. We use the model developed by Scheu et al. [2, 11, 12]. It simulates wave-height time series using discrete time Markov chains. Wind speeds are then calculated with a wave-wind correlation matrix. The transition probabilities for the Markov chains and the wave-wind correlations are calculated based on 37 year ERA-Interim reanalysis data from the European Centre for Medium-Range Weather Forecasts (ECMWF) for the site of the Dogger Bank wind farm (54°N 2°E). To process the weather data, generate the Markov matrices and wind wave correlation matrix, we used the software R [13].

For the mean repair times, we use the repair time data presented by Carroll et al. [14]. From these mean repair times we calibrated an exponential distribution such that it has the same mean. Subsequently we fit a log-normal distribution that has the same mean and variance as the exponential distribution and a log-normal distribution with the same mean and a larger/smaller variance, in order to investigate how changes in the repair time variability influence the results. The repair times of the turbine components based on these distributions are drawn randomly for each simulation step with the integrated functions in MATLAB [15]. The different distributions for the duration of a major blade repair can be seen in Figure 1. The exponential function is used as it is the simplest model for a random time to an event, but its variance is fixed. The log-normal distribution depends on two parameters and is a natural candidate for modeling non-negative random processes where the variance is known (or assumed).

To simulate the maintenance of the wind farm we use a maintenance cost model based on Scheu's model [2]. The simulation models an offshore wind farm with a given number of turbines in steps of 6 hours, due to the limited resolution of the weather data. The changes in wave height are calculated according to the Markov matrices, which in turn are based on the site data. The wind speed is then simulated according to the wind wave correlation matrix as explained in [2]. The wave height and time series data generated by the weather simulation tool is then further used in the maintenance model. The inputs for the scheduling simulation include failure rates [14], different wind turbine parameters [16], the assumed number of available crew transport vessels and cranes, the assumed number of persons needed for the repair of different components and a wave height restriction for access to the turbines. The information about the turbine, like rated power, cut in wind speed, wind speed at the rated power output and cut-out wind speed, is used in the model to calculate the production losses due to downtime based on an assumed power curve.

The information about the annual failure rate [14], is used to model the occurrence of a failure independently for each component in each turbine. If a failure occurs, the repair time of the specific component is set to the mean time to repair in the original model. Here, we draw random numbers according to the different distributions for each occurring failure. The scheduling of the repair crews and vessels is modeled according to the strategy presented by Scheu et al. in [2, Figure 2, p.284]. Apart from the production losses for each simulation run, the availability of the wind farm is also calculated.

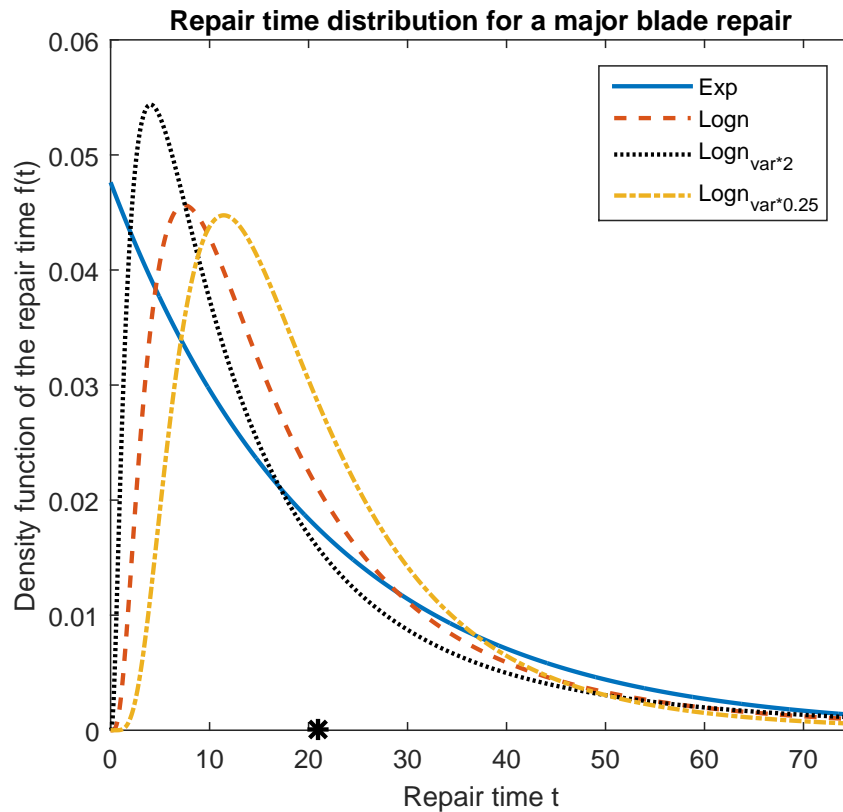


Figure 1: Density functions for different repair time distributions for a major blade repair. The mean time to repair of 21 hours is marked with a black asterisk.

### 3. Value of information of repair time

The repair time data used in this study was presented for 19 different turbine components and three different repair types each in Carroll et al. [14]. For modeling the failures in the maintenance cost model, we use the annual failure rates for the same 19 components. We assumed a wind farm with 100 turbines of the NREL 5 MW type [16] and two different access vessels. For both minor and major repair actions, we assume a repair crew size of 2 persons and the transport with a crew transport vessel (CTV). For major replacements, which constitute the third repair type in [14], we assume a crew size of 10 persons and the need for a crane. The transit time for the CTV is assumed to be 6 hours, which corresponds to a maximal speed of 18 knots for a distance to shore of 200 km. Most crew transport vessels (CTVs) can reach a speed between 20 and 25 knots. The transition time for the crane is assumed to be 12 h, corresponding to a speed of 9 knots at the same distance from shore. The coordinates of the location used for the weather model are 132 km from Withernsea on the English coast and thus assuming a distance to shore of 200 km already includes some conservatism. For our simulation, we first consider a fleet of 20 CTVs and 5 crane vessels and a maximum wave height restriction of 1.5 m for both vessel types in a first run. We use these high numbers of vessels, to separate the influence of the repair time from effects due to different scheduling strategies. In a second step, we reduce the analysis to 5 CTVs and 1 crane vessel. This does not significantly change the results and we present the results for the case with only 5 CTVs and 1 crane here, as a more realistic scenario. The results presented here are based on 25 simulations of one year of wind

Table 1: This table shows the mean annual lost production in MWh per turbine for 13 different scenarios of repair time distributions. In all scenarios, the mean is equal to the mean time to repair. The variance of the log-normal distribution is set equal to the variance of the exponential distribution ( $\sigma^2 = (1/\text{MTTR})^2$ ). For the log-normal distributions with increased and decreased variances, the variance is doubled for the increased variance and halved for the decreased variance.

Repair time distribution for CTV components	Repair time distribution for crane components	Mean lost production in MWh
Deterministic	Deterministic	139.5
Exponential	Exponential	323.4
Log-normal	Log-normal	289.9
Log-normal, increased variance	Log-normal, increased variance	340.7
Log-normal, decreased variance	Log-normal, decreased variance	249.6
Deterministic	Exponential	134.3
Deterministic	Log-normal	131.0
Deterministic	Log-normal, increased variance	136.6
Deterministic	Log-normal, decreased variance	138.1
Exponential	Deterministic	325.1
Log-normal	Deterministic	296.5
Log-normal, increased variance	Deterministic	333.7
Log-normal, decreased variance	Deterministic	262.5

farm operation, resulting in a total of 36500 time steps for each scenario.

Table 1 shows the mean values for the annual lost production in MWh per turbine over 25 simulation years for different simulation scenarios. The most important observation is that the production losses increase, when uncertainty in the repair times is included. The leading cause seem to be those turbine components, where the repair does not require a crane vessel. It can be seen, that the production losses increase for an increase in the variance of the repair times, and analogously decrease for a decrease in repair time variance. Similar observations can be made for the mean annual availability of the wind farm as shown in Table 2. Again, the main influence comes from the components with higher failure rates (that can be repaired by a maintenance crew accessing the turbine with a CTV). This result differs from the analysis presented in [17], where the largest influence on the delay was shown to come from the components with the longest repair times (which correspond to components with low annual failure rates). It can therefore be assumed, that the influence of delay in scheduled maintenance outweighs the delays due to sea state in this model.

Figure 2 shows the distributions of production losses for the scenarios presented in Table 1. Here, the influence of the different distributions of the repair time on the distribution of the production losses can be seen in (a). The repair times follow the presented distributions for all turbine components, both components that require a crane vessel for a repair and those components that can be repaired by a repair team alone. In (b), the effect of the stochastic variations for repair times of different component types on the total production loss can be seen. As mentioned previously, the components requiring only a CTV access dominate the production losses. This is most likely due to the higher annual failure rates in these turbine components and the resulting higher number of necessary repair actions.

In order to investigate how the size of a wind farm influences the production losses and availability, we additionally used the model to simulate a wind farm with one single turbine. The distribution of the production losses per turbine are shown in Figure 3 for a wind farm with

Table 2: This table shows the mean wind farm availability in percent for 13 different scenarios of repair time distributions. In all scenarios, the mean is equal to the mean time to repair. The variance of the log-normal distribution is set equal to the variance of the exponential distribution ( $\sigma^2 = (1/MTTR)^2$ ). For the log-normal distributions with increased and decreased variances, the variance is doubled for the increased variance and halved for the decreased variance.

Repair time distribution for CTV components	Repair time distribution for crane components	Mean wind farm availability in percent
Deterministic	Deterministic	76.7
Exponential	Exponential	43.7
Log-normal	Log-normal	49.1
Log-normal, increased variance	Log-normal, increased variance	40.7
Log-normal, decreased variance	Log-normal, decreased variance	57.8
Deterministic	Exponential	77.6
Deterministic	Log-normal	78.2
Deterministic	Log-normal, increased variance	76.9
Deterministic	Log-normal, decreased variance	76.8
Exponential	Deterministic	42.6
Log-normal	Deterministic	47.9
Log-normal, increased variance	Deterministic	40.8
Log-normal, decreased variance	Deterministic	55.1

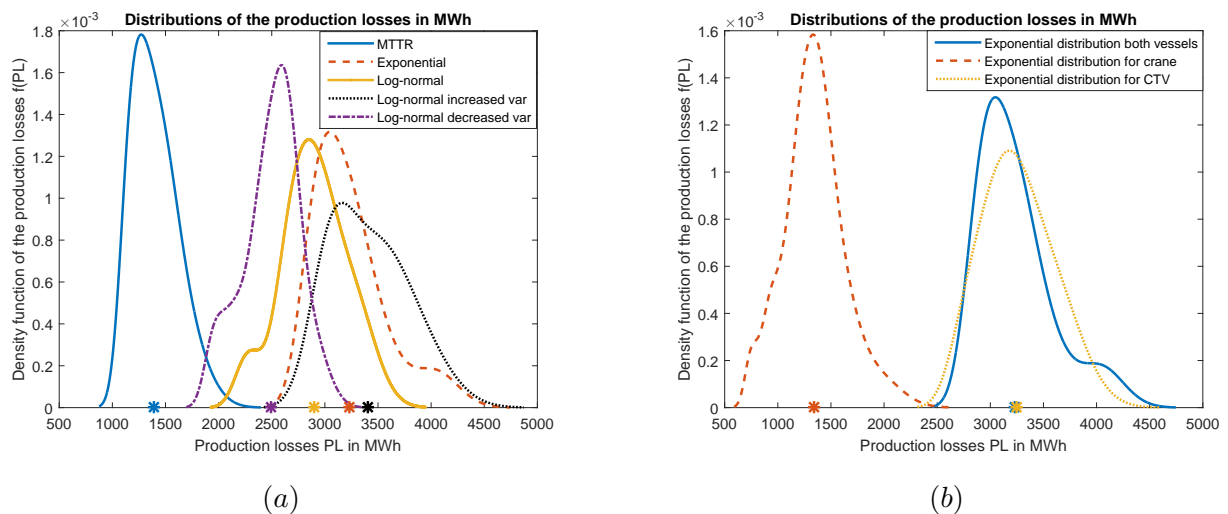


Figure 2: The distribution of the annual production loss per turbine in MWh for different distributions for the repair time. (a) shows the production loss for stochastic distributed repair times for both CTV and crane components. (b) shows the production loss due to exponentially distributed repair times and the effect of the ship and crane components.

100 turbines and for a wind farm with 1 turbine. In both simulations, we assume 5 CTVs and 1 crane. For the mean repair time, the larger wind farm has higher average production losses, which might be due to the limitations of vessels or due to the lack of sufficient weather conditions. In the case of a single turbine, the influence of the variation in repair times is more pronounced than in the wind farm with 100 turbines. This shows the influence of the maintenance scheduling on the production losses and availability. For the exponentially distributed repair times, having multiple turbines in the wind farm reduces the mean production losses as well as the variance

in the losses. This is probably due to the possibility to group repairs. Maintenance crews that are already offshore in order to repair one component of one turbine in the wind farm can stay offshore and conduct repairs on other turbines in the wind farm. This can reduce the downtime of the second turbine, since the transit to the park drops out of the analysis and will be especially pronounced for short repair times.

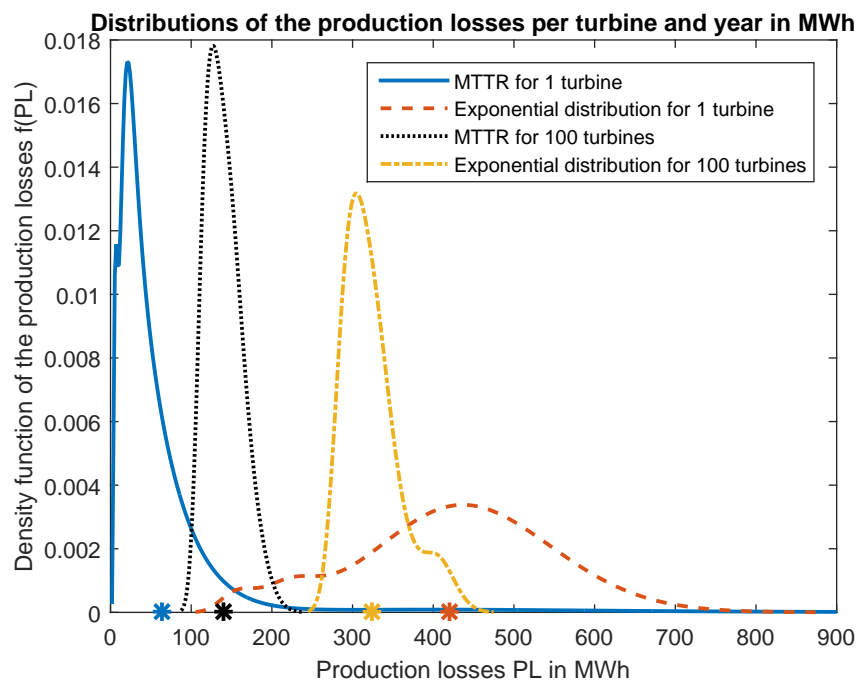


Figure 3: The distribution of the production losses per turbine for a wind farm with 100 turbines, and for a wind farm with one single turbine.

#### 4. Conclusion

The presented analysis shows the influence of uncertainties in the repair time on both the wind farm availability and on the production losses due to down time. This effect is significant. In order to schedule the corrective maintenance of a wind farm optimally, accurate information about the real repair times is a crucial factor. Here, the repair times for turbine components that can be repaired by a small repair team accessing the turbine from a crew transport vessel should be addressed first, since a variation in these repair times has more influence on the outcome than the repair time of other components, where a crane vessel and larger crew is necessary. Further analysis of the interaction of repair times, annual failure rates, uncertain weather conditions and scheduling of tasks is highly recommended. One goal of this analysis will be to investigate the difference between the analysis presented here and the previously presented analysis on the weather delays. The analyses use different methods and include a different number of factors into the models. However, both show the significant influence of a variable repair time on the production losses and suggest that maintenance costs can be lowered if these are investigated further.

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