energies

*Supplementary Materials (S2)*

# Supplementary results for "Integration of Degradation Processes in a Strategic Offshore Wind Farm O&M Simulation Model"

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This note describes supplementary simulation results associated with the paper "Integration of Degradation Processes in a Strategic Offshore Wind Farm O&M Simulation Model", henceforth referred to as *the paper*. Section 1 illustrates how the time dependence of the wind farm availability estimates differ between full and loose integration of a degradation process. Section 2 investigates more closely the difference between full and loose integration for the variation of the case study including failure categories for multiple components. Section 3 presents results considering an alternative jack-up vessel charter strategy and thus illustrates how the interactions between the maintenance logistics strategy and the inspection strategy are captures by the two integration approaches. Section 4 considers the impact of treating the pre-warning time $T_{det}$ as a stochastic variable in the O&M model.

## 1. Time dependence of wind farm availability

Although loose and full integration of degradation processes were shown to result in very similar wind farm availability estimates, the time dependence of the availability is not necessarily very similar for the two approaches. In other words, how the availability depends on the time of the year or the year of the operational lifetime of the wind farm may differ. Figure 1 shows an example of how the availability varies with the operational year of the wind farm and Figure 2 shows an example of how the availability varies with the month of the year. The results for both figures are based on the case study considering only blade failures and the West Gabbard data set using 100 Monte Carlo iterations.

For loose integration, Figure 1 illustrates the effect where CBM task can be "shifted" to occur at earlier points in time during the simulation, as discussed in the paper in Section 5. This leads to a lower availability during the first year of operation than for the full integration approach, which exhibits a more somewhat more realistic decrease of the availability from the point where all turbines are operational after the commissioning of the wind farm. Nevertheless, on average the availability is very similar for full and loose integration both in Figure 1 and Figure 2.

Much of the variation in availability over the year shown in Figure 2 can be explained by the time of inspections as simulated in the O&M model. In the full integration approach, the interaction between the degradation process, failures, corrective and condition-based maintenance and inspections is fully captured in the simulations in the O&M model. Accordingly, the simulated time of inspections varies relatively much over the time of the year: Although inspections are initially scheduled once a year (each January), over the operational lifetime the actual inspections are being shifted in time both due to logistics delays and due to failures and maintenance. This can be seen in Figure 3, which shows how the contribution from inspections to the unavailability varies with the month of the year. This contribution to the unavailability corresponds to the turbine downtime due to inspections.

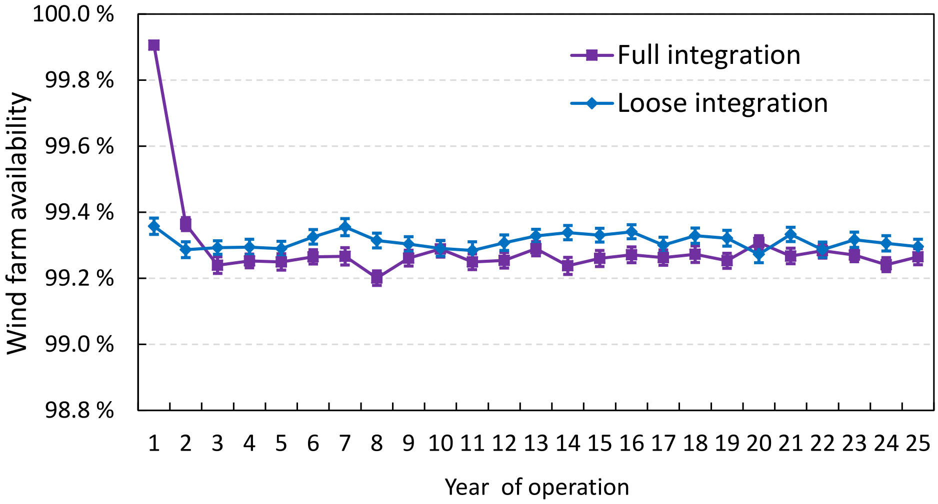



**Figure 1.** Time dependence of wind farm availability: Variation over the operational lifetime of the wind farm.

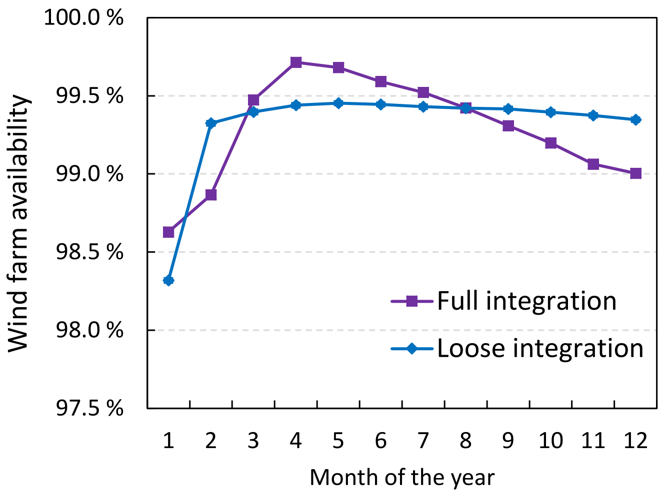



**Figure 2.** Time dependence of wind farm availability: Variation over the year.

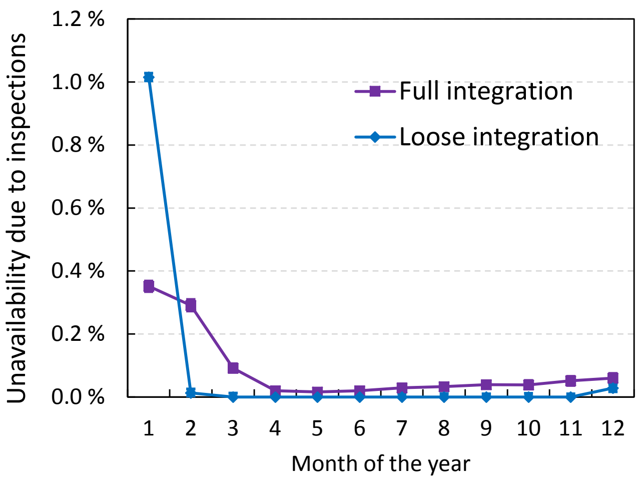



**Figure 3.** The contribution to unavailability (downtime relative to the lifetime of the wind farm) from inspections: Variation over the year.

In the simplified loose integration approach, on the other hand, the inspections are represented in the O&M model by predetermined preventive maintenance tasks scheduled to take place once a year (each January). The interaction between these tasks and degradation, failures and maintenance is not captured explicitly in the O&M model, and the actual time of inspections is not shifted in time the same way as in the full integration approach. This is shown in Figure 3, where the majority of the inspections are seen to take place in January. A similar trend was seen also for the other weather data sets (not shown), but the downtime is being distributed more evenly across the year when harsher weather conditions cause turbines to become less accessible during the winter months.

Because wind power production varies over the year, downtime e.g. in a winter month has a greater impact on the annual electric energy production and thus the energy-based availability than downtime in a summer month. Therefore, the differences in the time dependence of (time-based) availability for loose and full integration implies a difference in energy-based availability that is greater than the difference in average time-based availability. Figure 4 shows results for the energy-based availability corresponding to the time-based availability results presented in Figure 6 of the paper. It can be seen that the difference between loose and full integration for energy-based availability depends more strongly on the weather conditions.

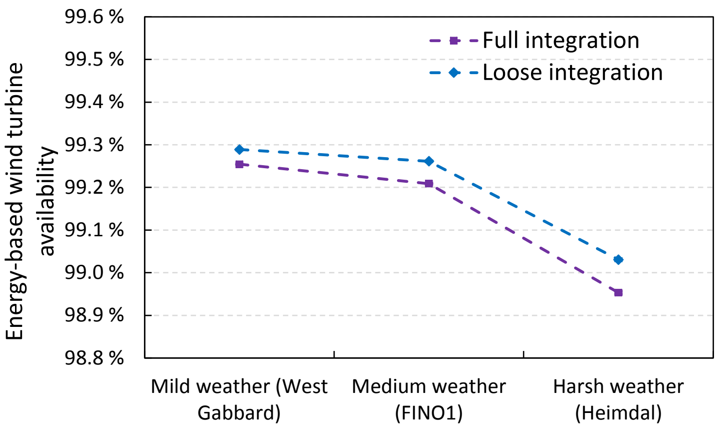
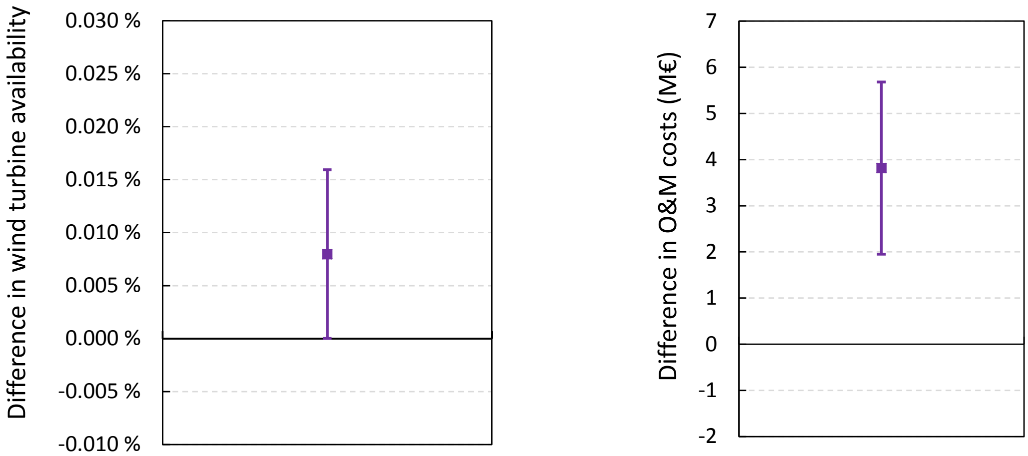



**Figure 4.** Results for energy-based wind turbine availability under different weather conditions.

## 2. Difference between full and loose integration considering multiple components

For the variant of the case study in the paper considering failure categories representing multiple components, differences between full and loose integration are smaller and the statistical uncertainty is larger than for the results only considering blade failures. To investigates more closely the relatively small difference between full and loose integration, we employ the following variance reduction technique based on common random numbers: Since simulations for both full and loose integration are based on the same set of synthetic weather time series, there are correlations between the results for a Monte Carlo iteration for full integration ($z_{\text{full}}^{(i)}$) and the results for the corresponding Monte Carlo iteration for loose integration ($z_{\text{loose}}^{(i)}$). Therefore, the variance in the difference $z_{\text{loose}} - z_{\text{full}}$ between the means for full and loose integration is smaller than one would estimate from the variance of the means themselves (of $z_{\text{loose}}$ and of $z_{\text{full}}$), if one assumed no correlations. On this basis one can partially overcome the challenges due to the relatively limited number of Monte Carlo iterations (500) in the case study.

Figure 5 shows the differences in results between loose and full integration for a failure data set including all wind turbine components. The uncertainty estimates here are calculated by first calculating the difference $z_{\text{loose}}^{(i)} - z_{\text{full}}^{(i)}$ for all Monte Carlo iterations $i$ and then calculating the standard error based on these differences. For the wind farm availability, the difference is almost identical to the uncertainty estimate (i.e. 0.008 %). This means that although the availability for loose integration most likely is higher than for full integration, the difference is unlikely to be larger than when only blade failures were considered (0.02–0.03 %). This implies that the difference between full and loose integration is relatively small also when more failure categories representing multiple components are considered.




(**a**) (**b**)

**Figure 5.** Difference in results between loose and full integration for a failure data set including all wind turbine components: (**a**) Wind farm availability; (**b**) O&M costs.

## 3. Alternative jack-up vessel charter strategy

The paper is primarily concerned with the most typical applications of O&M models, such as assessing the economic viability of a wind farm project and optimizing the logistics strategy for transferring technicians to the turbines to carry out O&M. This section illustrates an application of an O&M model where the advantages of full integration of a degradation process may be somewhat greater than those considered in the paper, namely optimizing the jack-up vessel charter strategy.

Different strategies for chartering jack-up vessel strategies are described [1]. In the paper, a conventional "fix-on-failure" chartering strategy was assumed. An alternative that was investigated in [1] is a pre-determined campaign period strategy, where one pre-charters the jack-up vessels long in advance (at reduced day rates) for certain fixed campaign periods throughout the year. Optimizing this strategy amounts to selecting the periods of the year that gives an optimal trade-off between vessel charter costs and downtime costs. In [1], campaign periods in March, July and October was shown to be a cost-effective charter strategy. The wind farm scenario considered in [1] is similar to that considered in the paper for the case that multiple components are included (Section 4.2 in the paper). Therefore, the same jack-up vessel charter strategy is considered in this section.

Figure 6 shows results for the wind farm availability for a pre-determined jack-up vessel campaign period strategy (March, July and October), considering a failure data set including all wind turbine components in addition to only blade failures. These results are based on 200 Monte Carlo iterations. Comparing the results to Figure 8 in the paper, one notices that the pre-determined jack-up vessel campaign period strategy gives lower availability but also lower O&M costs than the fix-on-failure strategy assumed in the paper. The difference between full and loose integration are also higher in Figure 6 than in the paper. This is at least the case for the wind farm availability: The difference in Figure 6a is 0.18 %, and the differences in wind farm availability in the paper were in the range 0.01–0.03 %.

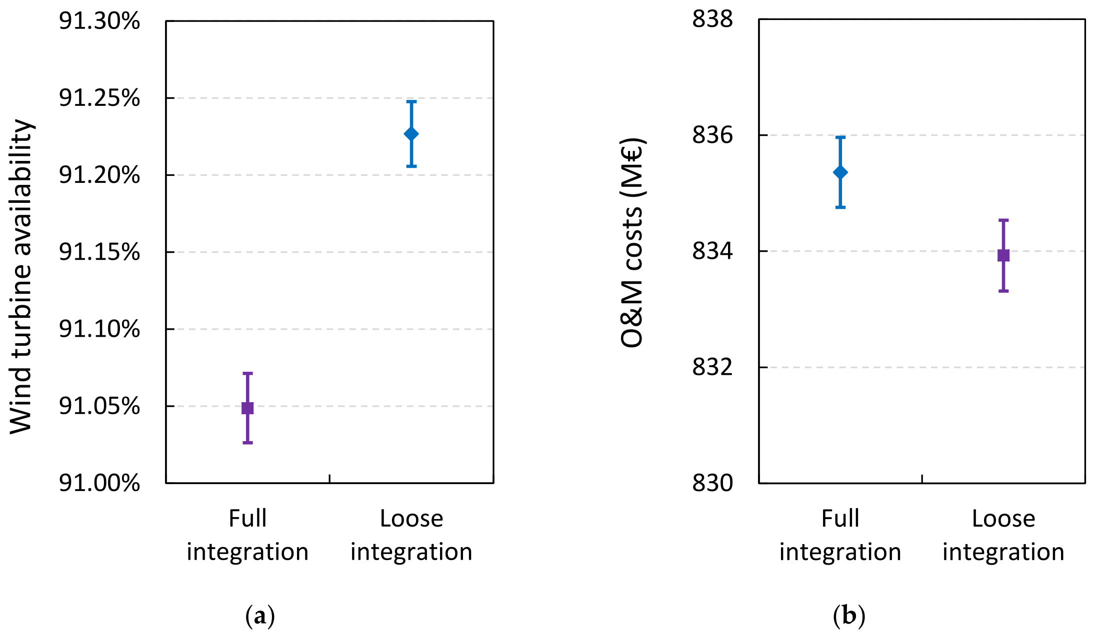



**Figure 6.** Results for a failure data set including all wind turbine components, assuming a pre-determined jack-up vessel campaign period strategy: (**a**) Wind farm availability; (**b**) O&M costs.

The reason why somewhat larger differences were observed for a pre-determined campaign period strategy most likely is that the distribution of inspections, corrective and condition-based maintenance tasks throughout the year is somewhat different for full integration and loose integration. This effect was also illustrated in Section 1. This time dependence can impact the results more strongly when jack-up vessels only are available certain pre-determined months of the year than when jack-up vessels are chartered on demand, independently of the time of the year (i.e. "fix-on-failure").

## 4. Stochasticity of the pre-warning time

In case study the paper, for the loose integration approach a "translator" was used to estimate the pre-warning time $T_{det}$ to use as input to the condition-based maintenance module of the O&M model (NOWIcob). The translator is based on Monte Carlo simulations, and can be used to estimate the probability distribution of $T_{det}$. However, only the mean value of $T_{det}$ was used in the case study in the paper in order to consider an as simple input data representation as possible for the loose integration. The black curve in Figure 7 shows the estimate of the probability distribution of produced by the translator $T_{det}$ for the case study in the paper.

NOWIcob has the capability to treat $T_{det}$ as a stochastic variable in the simulations by drawing values from a probability distribution. Currently only a triangular distribution and a normal distribution are implemented as two simple but convenient models for representing some measure of stochasticity in different parameters. (The vessel mobilization time, spare part lead time and active maintenance time can also be treated as stochastic variables.) Although one in principle could implement an arbitrary probability density function in NOWIcob, the existing option with a triangular distribution was chosen to test the impact of treating $T_{det}$ as a stochastic variable in the case study considered in the paper. Denoting henceforth the mean value as $\bar{T}_{\mathrm{det}}$, an "equivalent" triangular probability density function $f(T_{\mathrm{det}}) = 2/3\bar{T}_{\mathrm{det}}\,(1 - T_{\mathrm{det}}/3\bar{T}_{\mathrm{det}})$ can be constructed that has the mean as the probability density function estimated using the translator. This triangular distribution is also shown in Figure 7. Although it is a very crude approximation of the real distribution, and for instance does not capture the rather fat tail of the real distribution, it suffices for testing the impact of using stochastic versus deterministic variables.

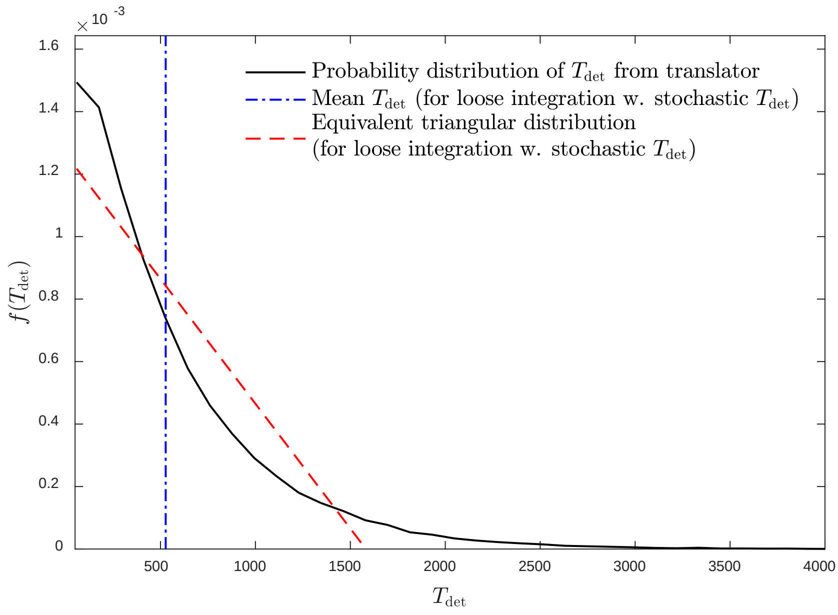



**Figure 7.** Probability density functions for the pre-warning time $T_{\mathrm{det}}$.

Figure 8 shows how the stochasticity of $T_{\mathrm{det}}$ in the loose integration approach may influence the results of the O&M model. Here the case study with only blade failures is considered, using the West Gabbard weather data set and 1000 Monte Carlo iterations. Results for the wind farm availability with loose integration and stochastic $T_{\mathrm{det}}$ (assuming a triangular distribution) is compared with both full integration and loose integration assuming a deterministic $T_{\mathrm{det}}$ (i.e. using just the mean value). (Note that $T_{\mathrm{det}}$ naturally is treated as a stochastic variable also in the full integration approach.)

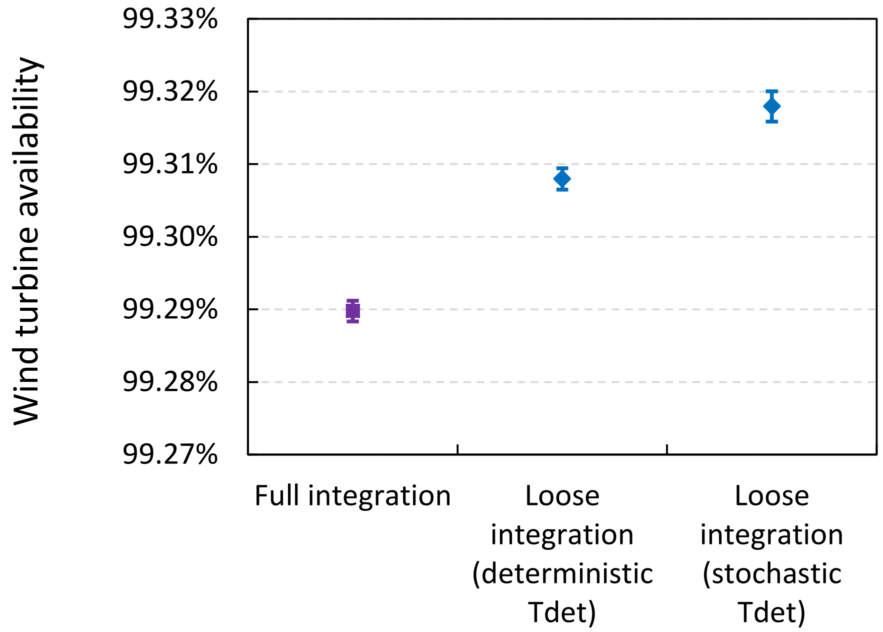



**Figure 8.** The effect of treating the pre-warning time $T_{\mathrm{det}}$ as a stochastic or a deterministic variable in the O&M model.

For the two variants of loose integration, the difference of 0.01 % between the results for deterministic and stochastic $T_{det}$ is relatively small, also when compared to the difference between results for full integration and loose integration (i.e. with deterministic $T_{det}$). However, treating $T_{det}$ as a stochastic variable in the loose integration approach results in a wind farm availability that is farther away from the result for full integration than when treating $T_{det}$ as a deterministic variable. This may appear somewhat counterintuitive, but one should keep in mind that, 1) not only is the triangular distribution in Figure 8 a rather crude approximation, but 2) loose integration also implies a number of other approximations that may cause subtle discrepancies in the results that partly cancel each other out. It has not been possible to disentangle all these effects from the simulation results, but Figure 8 implies that the differences between full and loose integration could be slightly larger than indicated by the case study presented in the paper. Similar results as in Figure 8 were also found for the other weather data sets and for other variants of the probability distribution for $T_{det}$. Nevertheless, the conclusion from these tests remains that treating $T_{det}$ as a deterministic variable in the case study in the paper was of minor consequence for the results and is of no consequence for the main conclusions of the paper.

## References

1. Sperstad, I.B.; McAuliffe, F.D.; Kolstad, M.; Sjømark, S. Investigating key decision problems to optimise the operation and maintenance strategy of offshore wind farms. *Energy Proc.* **2016**, *94*, 261–268.