Probabilistic decision support for offshore wind operations: a Bayesian Network approach to include the dependence of the installation activities

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Abstract: Offshore wind operations are logistical challenges and require improved management of the installation and maintenance processes. For this reason, numerous models have been developed concerning different aspects of these operations. Most of these models assume constant durations for the installation or maintenance activities or employ probability distributions to describe the associated uncertainty. However, these two approaches do not take into account the dependence between the activities. This paper proposes a method to describe the dependence between the main installation activities of offshore wind turbines (WTGs) by the use of a non-parametric Bayesian Network (NPBN). To achieve this, different tests were performed and the NPBN was quantified based on real data from a realized project. To illustrate the impact of neglecting the dependence between the activities, a hypothetical case regarding the installation of 150 WTGs was simulated for all three aforementioned approaches (non-dependent: deterministic and probabilistic vs. dependent). It was found that the proposed approach allows for a proper representation of the dependence between the installation activities. Moreover, it can lead to more accurate and reliable estimated installation duration. Hence, this NPBN model can effectively support decision makers in optimizing the work planning of offshore wind processes.

Keywords: Offshore Wind Installation, Probabilistic Decision Support, Uncertainty Representation, Activities Dependence, Non-parametric Bayesian Network.

1. INTRODUCTION

During the last years, it became apparent that offshore wind energy can significantly contribute to the essential transition from conventional energy sources to renewables [1], [2]. Moreover, this transition can already be observed in the European offshore industry; offshore wind energy has recently become financially competitive, attracting more investments from major Oil and Gas (O&G) companies. However, certain aspects, related to the management of the construction process of offshore wind farms, should be improved in order to tackle the logistical challenges caused by the necessity to move farther offshore in coming years.

Construction activities of offshore wind farms are complex and capital intensive. On top of that, these activities are subject to various uncertainties such as environmental conditions, supply disruptions and failures or crew mistakes which may occur during the installation process. However, most of these uncertainties are often neglected or described superficially, resulting in significant budget and schedule overruns. To avoid these undesirable outcomes, probabilistic risk analysis methods should be utilized in the planning phase to support optimal decision making under uncertainty.

During the last years, various models have been developed concerning different aspects of the installation process of offshore wind farms [3]–[10]. However, the majority of the available models either assume constant values for the duration of the activities, neglecting the associated uncertainty, or make use of distributions (such as triangular or normal probability distributions many times

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quantified with informal procedures and not adequately validated) to describe the uncertainty of these variables. In both cases, the dependence between the durations of subsequent construction activities is ignored. The construction activities of offshore wind farms are operations that are usually performed sequentially, by the same set of installation vessels and crew. Hence, the assumption of independence could lead to miss-estimations of total cost and time, which may result in decisions which will prove to be far from optimal during the installation phase.

Therefore, the purpose of this paper is to investigate the impact of neglecting the dependence between the duration of the offshore construction activities and propose a method to incorporate this dependence into the estimates of the cost and time of the project. For this purpose, in the proposed method, the durations of the offshore construction activities of the wind turbine generators (WTG) are calculated using a Bayesian network (BN). This represents the dependence relationship between the activities and was populated using historical data of a past project. To investigate the impact of this approach, a test case concerning the installation of 150 wind turbines in the North Sea is simulated for three different approaches. The first and second approach are those currently used in practice (i.e *Approach 1*: independent constant values for the activities duration and *Approach 2*: durations described by a triangular distributions) while the third scenario utilize the developed BN. The cumulative distributions of cost and time for project completion are compared and the impact of neglecting dependence is presented.

2. BAYESIAN NETWORK FOR ACTIVITY DURATION

2.1 Theoretical background

Bayesian networks (BNs) are graphical, probabilistic models which consist of nodes and directed arrows (or arcs). Each node represents a continuous or discrete random variable, while the arrows connect the nodes to describe the dependence between the random variables. Each arc connects a predecessor (or parent) node with a successor (or child) node and represents the dependence between these two. The arcs of the BN should connect the nodes in a way such that there are no directed cycles in the graph. Moreover, the graphical structure of BNs allows the visualization of conditional independencies as well as conditional dependencies. Summarizing, the BNs are directed acyclical graphs (DAGs) which represent the joint probability distribution of random variables in an intuitive way.

There are different classes of BNs depending on the type of random variables that constitute the network. Namely discrete BNs which consist of discrete random variables and hybrid BNs (HBNs) which can involve both discrete and/or continuous variables. For the formalization of discrete BNs the reader is referred to [11]. In this study, since the variables of interest (i.e. duration of installation activities) are continuous, a class of HBNs, the so called non-parametric BNs (NPBNs) were used. The main characteristic of NPBNs is that the dependence is described by copulas. Copulas are multivariate distribution functions whose one-dimensional margins are uniform on the [0,1] interval [12]. Hence, for NPBNs it is only required to specify the empirical marginal distribution for each variable and a (conditional) rank correlation for each arc [13]. A complete description of NPBNs is out of the scope of this paper. For a complete overview, the reader is referred to [14] and [13].

There are different families of copulas. A detailed description of these can be found in [15]. For the purpose of this study, we limit the analysis to one-parameter copula families for which the dependence structure can be written as function of the rank correlation coefficient between pairs of random variables. The Spearman's rank correlation for the ranks of two random variables X and Y is given by eq. 1, where $\mathrm{F_X(x)}$ is the rank of variable X.

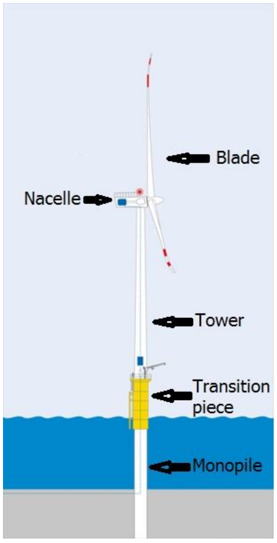
$$r(X,Y) = \frac{E\big(F_X(x)F_Y(y)\big) - E\big(F_X(x)\big)\,E(F_X(x))}{\sigma_{F_X(x)}\sigma_{F_Y(y)}} \tag{1}$$

2.2. BN model for duration of installation activities

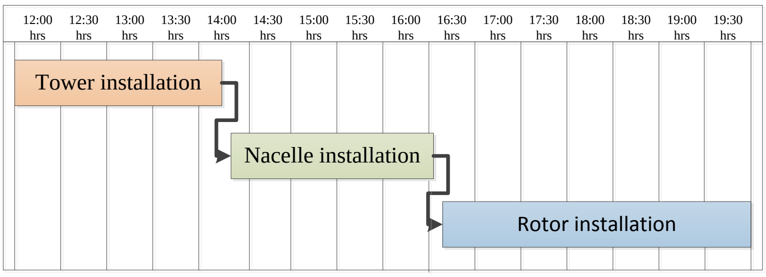
2.2.1. Historical data

As it was mentioned before, the purpose of this study is to investigate the impact of including the dependence between sequential installation activities of offshore WTGs. Figure 1.a. presents the different parts of a typical WTG. In general, the installation of offshore WTGs consists of multiple activities, including activities for positioning of the vessel, preparation for the construction activities and testing the mechanical systems after the completion of the installation. Since our goal is to investigate whether the dependence between these activities is important or not, it was chosen to focus on the "main" activities of the installation. Therefore, in our case, the installation of the WTGs concerns the installation of tower, nacelle and rotor (i.e. 3 blades). These are sequential activities which are usually performed from the installation vessel that has all the required components on board. In Figure 1.b., a hypothetical simple Gantt chart illustrates the order of the installation activities for one WTG.

Historical data from an installation project performed by the Dutch marine contractor Van Oord were used. This project concerns the installation of 150 WTGs in an OWF located in the North Sea. The provided database concerns a detailed register of the durations of all the operations which were performed by two installation vessels (vessel V1 and vessel V2), as well as the delays that occurred for different reasons. The database was divided per vessel and the durations of the installation activities were analyzed. From the analysis of the database, it was found that the duration of the installation activities under investigation presents noticeable fluctuations. More precisely, the average duration of the rotor installation was 255 min and 367 min, while the standard deviation was 78 min and 95.4 min, for vessel V1 and V2 respectively (see also Figure 4.a. and 4.b.). In the calculation of these durations the delays due to weather conditions were not included.



(a) Parts of WTG



(b) Order of installation activities of WTGs

Figure 1: Details of offshore WTGs installation

2.2.2. Identifying the appropriate copula

Two different tests were performed to identify the appropriate bivariate copula that describes the dependence between pairs of installation activities. Three of the most popular one-parameter copulas which represent different tail dependencies were investigated. Namely, the Gaussian copula, the Gumbel copula and the Clayton copula. The different characteristics of these copulas are summarized in Table 1, where $\mathbf{\Phi}$ denotes the standard normal cumulative distribution and $\mathbf{\Phi}_\rho$ denotes the standard bivariate normal distribution with Pearson correlation ρ.

Table 1: Characteristics of investigated copulas

Copula	Definition	Tail dependence
Gaussian	$C(u,v) = \Phi_\rho\left(\Phi^{-1}(u), \Phi^{-1}(v)\right)$	none
Gumbel	$C(u,v;\theta) = \exp\{-\left[(-\ln(u))^\theta + (-\ln(v))^\theta\right]^{1/\theta}\}$	upper
Clayton	$C(u,v;\beta) = (u^{-\beta} + v^{-\beta} - 1)^{-1/\beta}$	lower

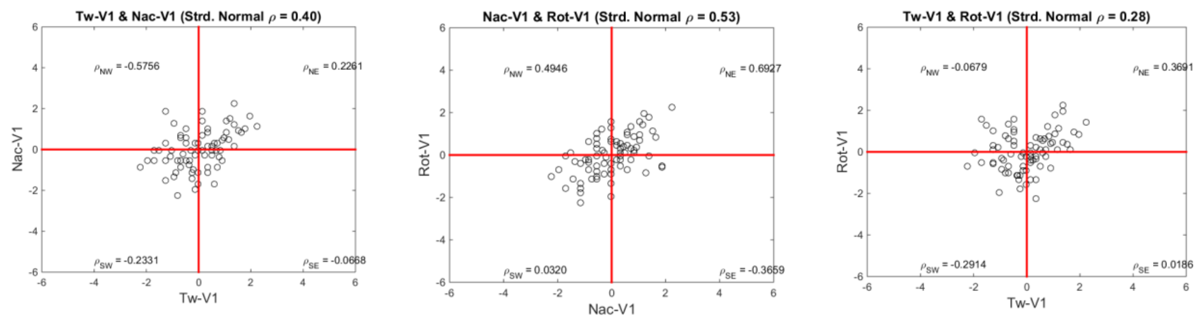
The performed tests concern: i) the computation of semi-correlations introduced in [15] and ii) the Cramér-von Mises statistic presented in the “blanket test” described in [16], for every pair of installation activities for each vessel. These tests have also been used to identify the best fitting copulas in a variety of applications such as [10], [17], [18].

The first test concerns the semi-correlations which are the Pearson correlation coefficients for each quadrant (i.e. NE, SE, SW and NW) computed on the standard normal transforms of the original data. If the values of semi-correlations are larger than the overall Pearson correlation coefficient ρ, then there is indication of tail dependence. The calculated semi-correlations for vessel V1 are presented in Table 2 and the results are visualized together with the normal transforms in Figure 2. For vessel V1, the semi-correlations of different pairs of activities indicate that there might be asymmetry, however the semi-correlations of the quadrants are not significantly different than the overall Pearson correlation. Regarding vessel V2, the calculated semi-correlations are presented in Table 3 and the normal transforms are presented in Figure 3. For vessel V2, the semi-correlations regarding the installation activity pairs of Tower – Rotor and Nacelle - Rotor have a larger value compared to the overall correlations. Therefore, the second diagnostic test (i.e. “blanket test”) was used.

The second test is based on the Cramér-von Mises statistic and describes the sum of square differences between the empirical copula $C_n(\boldsymbol{u})$ (given by: $C_n(\boldsymbol{u}) = \frac{1}{n}\sum_{i=1}^{n} \mathbf{1}(U_1 \le u_1, U_2 \le u_2),\ \boldsymbol{u} = (u_1, u_2) \in [0,1]^2$) and the parametric copula $C_{\theta_n}(\boldsymbol{u})$, as presented in eq. 2. This shows which copula family fits better the empirical copula of each pair of activities. In Table 2 and Table 3 the results of the Cramér – von Mises statistic for every pair of activities are presented for vessel V1 and V2 respectively. The best fitting copulas for every pair can be seen in bold. However, the values of the statistic for every copula are low and the differences between the different copulas are not significant. Hence, the parametric bootstrap procedure described in [16] was also performed, with a sample size equal 1000 and grid space equal to 300, resulting in the p-values presented in Table 4.

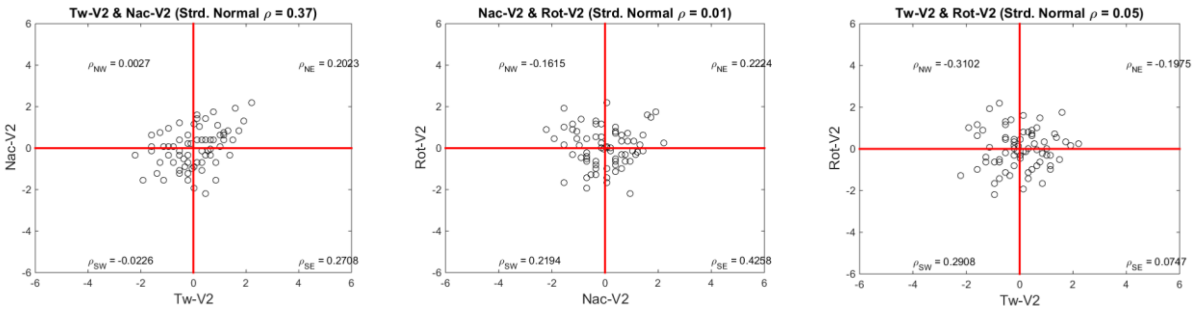
$$S_n = \sum \{C_n(\boldsymbol{u}) - C_{\theta_n}(\boldsymbol{u})\}^2 \tag{2}$$

Based on the computed p-values, it is not possible to reject any of the investigated copulas. Based on the analysis described above, it was decided to use the Gaussian copula as a fair representation for all bivariate pairs of installation activities. This copula family will be used in the BN to represent the dependence structure of each pair of activity durations.



(a) Tower – Nacelle installation duration (b) Nacelle – Rotor installation duration (c) Tower – Rotor installation duration

Figure 2: Semi-correlations and normal transforms for pairs of activities performed by V1



(a) Tower – Nacelle installation duration | (b) Nacelle – Rotor installation duration | (c) Tower – Rotor installation duration

Figure 3: Semi-correlations and normal transforms for pairs of activities performed by V2

Table 2: Summary of performed tests for vessel V1

	ρ	ρ_{NE}	ρ_{SE}	ρ_{SW}	ρ_{NW}	S_{gauss}	S_{gumbel}	$S_{clayton}$
Twr - Nac	0,40	0,2261	-0,0668	-0,2331	-0,5756	0,453161	0,**396868**	0,674134
Twr - Rot	0,28	0,3691	0,0186	-0,2914	-0,0679	0,642832	0,**586493**	0,864018
Nac - Rot	0,53	0,6927	-0,3659	0,0320	0,4946	0,**297208**	0,336712	0,357019

Table 3: Summary of performed tests for vessel V2

	ρ	ρ_{NE}	ρ_{SE}	ρ_{SW}	ρ_{NW}	S_{gauss}	S_{gumbel}	$S_{clayton}$
Twr -Nac	0,37	0,2023	0,2708	-0,0226	0,0027	0,43700	0,**363020**	0,75536
Twr - Rot	0,05	-0,1975	0,0747	0,2908	-0,3102	0,36516	**0,358885**	0,381857
Nac - Rot	0,01	0,2224	0,4258	0,2194	-0,1615	0,53070	0,522695	**0,480592**

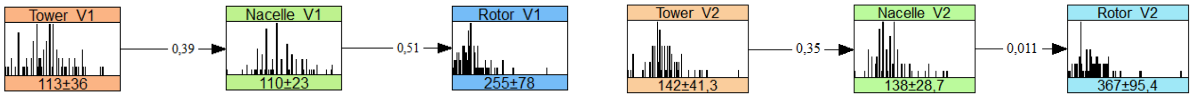
Table 4: P-values from bootstrap

	Vessel V1			Vessel V2		
	Gauss	Gumbel	Clayton	Gauss	Gumbel	Clayton
Twr - Nac	0,758	0,841	0,484	0,768	0,859	0,417
Twr - Rot	0,503	0,603	0,33	0,847	0,889	0,838
Nac - Rot	0,949	0,889	0,869	0,639	0,653	0,709

2.2.3. Building the BN model(s)

In order to build the BN model that describes the dependence between the WTG installation activities, the Uninet software for non-parametric BNs was used [19]. Different configurations were tested to build the model for each vessel. To decide which configuration describes better the dependence of the WTG installation activities the empirical rank correlation matrices were compared to those of the developed BN models using the normal copula. The rank correlation matrices were constructed by calculating the rank correlation between every possible pair of the installation activities.

For both vessels, models with serial connection were chosen (Figure 4.a. and 4.b. for vessel V1 and V2 respectively). The nodes are represented as histograms of the duration of every activity and the average and standard deviation of those samples are also shown. The comparison of the BN rank correlation matrices to the empirical ones are presented in Tables 5 and 6. As it can be seen, these do not present significant differences. The chosen configuration (i.e. serial connection) is also an intuitive representation of the dependence between the sequential installation activities of the WTG.



(a) BN model for V1 (b) BN model for V2

Figure 4: Developed BN models for WTG installation activities

Table 5: Empirical and BN rank correlation matrices regarding vessel V1

	Empirical rank correlation			BN rank correlation		
	Tower_V1	Nacelle_V1	Rotor_V1	Tower_V1	Nacelle_V1	Rotor_V1
Tower_V1	1	0.403	0.285	1	0.386	0.203
Nacelle_V1	0.403	1	0.517	0.386	1	0.51
Rotor_V1	0.285	0.517	1	0.203	0.51	1

Table 6: Empirical and BN rank correlation matrices regarding vessel V2

	Empirical rank correlation			BN rank correlation matrix		
	Tower_V2	Nacelle_V2	Rotor_V2	Tower_V2	Nacelle_V2	Rotor_V2
Tower_V2	1	0.342	0.0379	1	0.353	0.00394
Nacelle_V2	0.342	1	-0.00981	0.353	1	0.0107
Rotor_V2	0.0379	-0.00981	1	0.00394	0.0107	1

As it was mentioned in section 2.2.2, the Gaussian copula was assumed to describe the bivariate dependence between the installation activities. In order to verify this assumption, the determinants of the rank correlation matrices were used as described in [13]. The determinant takes values between zero (if there is linear dependence between the normal transforms of the variables) and one (if all variables are independent). Three different determinants of rank correlation matrices were calculated using Uninet. Namely, the determinant of the empirical rank correlation (DER), the determinant of the empirical normal rank correlation (DNR) and the determinant of the rank correlation matrix of the developed BN using the Gaussian copula (DBN). To clarify, DER and DBN of vessel V1 are the determinants of the correlation matrices presented in Table 7 while DNR is the determinant of the rank correlation matrix that is obtained by transforming the marginals to standard normals.

Table 7: Values of determinants for models validation.

	Model for V1	Model for V2
DER	0.60777	0.88103
DNR	0.62483	0.87358
DBN	0.62964	0.87514

The calculated determinants are expected to differ since the empirical copula would be different than the Gaussian copula. Hence, for each model it was tested: i) whether the DER is within the 90% confidence bound of the DNR and ii) whether the DNR is within the 90% confidence bound of the DBN. For both models, it was found that DER was within 90% bound of DNR and DNR was within 90% bound of DBN, for 150000 samples. This means that the Gaussian copula is a valid assumption for both models and these can be used to represent the dependence of the offshore WTG installation activities.

3. CASE STUDY

3.1. Simulation algorithm

To investigate the impact of the developed BN models into the estimated duration of the OWF installation process, a simulation model was developed in MATLAB, regarding the installation of offshore WTGs. A flowchart of the developed simulation algorithm is presented in Figure 5. First the details of a particular installation scenario (i.e. details of OWF and vessels, available environmental time series, environmental limits etc.) are loaded.

This scenario is simulated $\boldsymbol{N\_ts}$ times for every available environmental time series to introduce the weather risk and $\boldsymbol{N\_sims}$ times for every available time series to introduce the uncertainty of the activities duration. The activities for the installation of every WTG are treated as uninterruptable, thus each activity starts only if there is enough time remaining in the weather window. If this condition is satisfied, then the time of completion of this particular activity is saved and the next activity is examined, otherwise the subsequent weather window is examined. This procedure is repeated until all the required $\boldsymbol{N\_WTG}$ are installed. Ultimately, the cumulative distribution of the duration of the WTGs installation is computed and plotted.

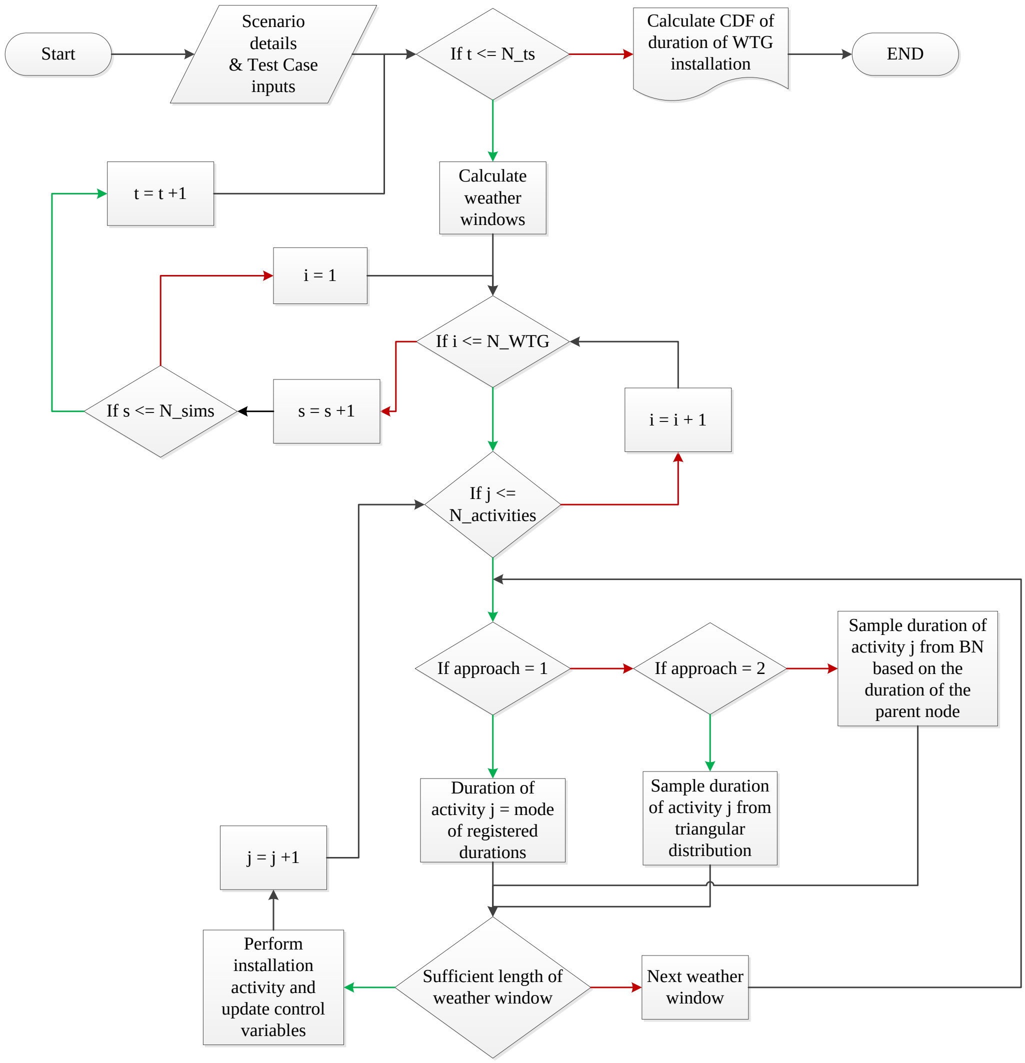


Figure 5: Flowchart of developed simulation algorithm

3.2. Inputs of test case

The developed simulation model was used to simulate a hypothetical case concerning the installation of 150 WTGs in the North Sea. Time series consisting of ten years of measurements concerning significant wave height (H_s) and wind speed U_W in the North Sea were used, to incorporate environmental uncertainty similarly to [10], [20]. The environmental limits, above which the activities cannot be performed were set equal to 1.5 m for significant wave height and 8 m/s wind velocity according to [8]. For this test case, the analyzed 2 vessels (V1 and V2) were used to install 75 WTG each. It should be mentioned that one of the main assumptions of this simulation model is that the support structures and the TPs are already installed when the vessel is positioned and ready to start the installation of the WTGs.

Three different approaches were used to calculate the duration of the activities in order to investigate the impact on the cumulative distribution of the total duration of the installation. *Approach 1* made use of the mode (i.e. most frequent value) of the registered durations for every activity performed by each vessel. *Approach 2* employed a triangular distribution for every activity using as parameters the minimum, mode and maximum of the registered durations. Finally, *Approach 3* made use of the developed BN models to incorporate the dependence between the installation activities. The reasoning for choosing to compare these three approaches is that *Approach 1* is a logical and simple approach that could often be used in current practice, *Approach 2* is commonly used for introducing uncertainty regarding the durations of project activities and *Approach 3* is the proposed way to introduce the dependence of activities duration in a stochastic simulation framework. A summary of the details of the simulated scenario can be found in Table 8.

Table 8: Details of simulated scenario.

<table>
<tr><th>Details</th><th colspan="8">Value</th></tr>
<tr><td>Number of WTGs</td><td colspan="8">150</td></tr>
<tr><td>Number of vessels</td><td colspan="8">2 (vessel V1 and V2)</td></tr>
<tr><td>Location</td><td colspan="8">North Sea</td></tr>
<tr><td>Environmental time series</td><td colspan="8">10 years of measurements for H_s and U_W</td></tr>
<tr><td>Environmental limits</td><td colspan="8">$H_s = 1.5\,m$ and $U_W = 8\,m/s$ [8]</td></tr>
<tr><td>Approach 1 (independent deterministic durations)</td><td colspan="4">Tower_V1 = 115 min
Nacelle_V1 = 105 min
Rotor_V1 = 230 min</td><td colspan="4">Tower_V2 = 125 min
Nacelle_V2 = 125 min
Rotor_V2 = 305 min</td></tr>
<tr><td rowspan="5">Approach 2 (independent stochastic durations)</td><td colspan="4">Triangular distribution for V1 with parameters</td><td colspan="4">Triangular distribution for V2 with parameters</td></tr>
<tr><td></td><td>a</td><td>b</td><td>c</td><td></td><td>a</td><td>b</td><td>c</td></tr>
<tr><td>Twr</td><td>45</td><td>115</td><td>226</td><td>Twr</td><td>65</td><td>125</td><td>310</td></tr>
<tr><td>Nac</td><td>55</td><td>105</td><td>170</td><td>Nac</td><td>85</td><td>125</td><td>255</td></tr>
<tr><td>Rot</td><td>165</td><td>230</td><td>653</td><td>Rot</td><td>245</td><td>305</td><td>795</td></tr>
<tr><td>Approach 3 (dependent stochastic durations)</td><td colspan="4">Developed BN model for V1 (Figure 4.a.)</td><td colspan="4">Developed BN model for V2 (Figure 4.b.)</td></tr>
</table>

3.2. Results

The results of the simulated scenario concerning the CDFs of the total installation duration are presented in Figure 6. When the samples from the triangular distributions (*Approach 2*) and the developed BNs (*Approach 3*) are obtained beforehand, the simulation algorithm needs less than 2 min to produce and plot the results. From the obtained distributions one can notice significant differences in the estimates of the total duration of the WTGs installation. When *Approach 1* is used the estimated duration ranges from ≈1950 hours to ≈2700 hours due to the uncertainty of the environmental conditions. The estimated total duration for *Approach 2* ranges from ≈2450 hours to ≈3350 hours while for *Approach 3* ranges from ≈2150 hours to ≈2900 hours. These results indicate that when the uncertainty regarding the duration of the activities is introduced without taking into account the dependence between these (*Approach 2*), then the overall uncertainty of the estimated duration increases. In other words, it is shown that the proposed BN models allow a more a realistic representation of the installation process that leads to reduction of the uncertainty of the estimated installation's duration.

In practice, similar computations are used in the planning process of OWF installation projects and constant values such as the mode (*Approach 1*) or the mean of the registered activities are used. By comparing the 80th percentile (P80) of the CDF of *Approach 1* with that of the CDF of *Approach 3* a difference equal to ≈200 hours (≈ 9 days) is observed. Considering the fact that the day rates of the installation vessels approximate hundreds of thousands of Euros, an underestimation of that level can lead to a miss-estimation of millions of Euros. Hence, the appropriate representation of the dependence between the installation activities can assist the decision makers to more accurate estimates which can be profitable for all the involved parties.

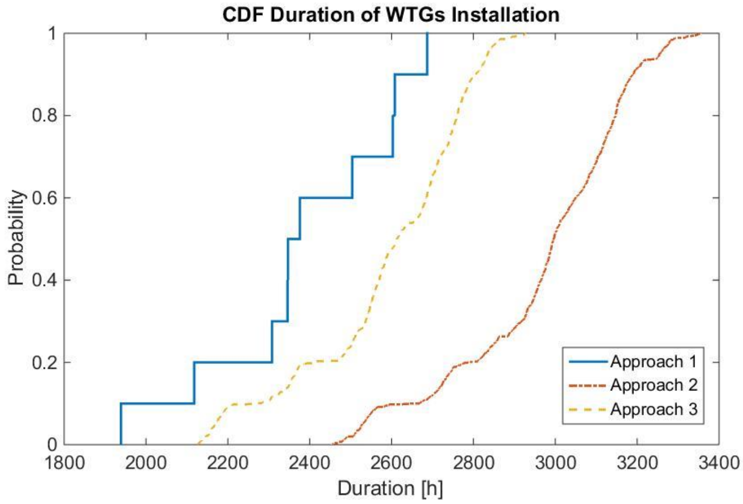


Figure 6: Obtained distribution of the simulated test case for the different approaches.

4. CONCLUSION

One way to further reduce the costs and improve the competitiveness of offshore wind energy is by improving the management of the logistics of the installation process. To achieve this, simulation models that take into account the predominant uncertainties can prove useful. In this paper, a method utilizing the theory of Bayesian Networks was used to build models that represent the dependence between the installation activities of offshore wind turbines.

It was shown that a NPBN with serial connection can be used to represent the sequential nature of the installation activities performed by a vessel. To illustrate the impact of incorporating the dependence of the installation activities, a simulation algorithm was developed and a hypothetical case was simulated for three approaches concerning the duration of the activities. It was found that the proposed approach (i.e. dependent, stochastic activity durations) results in estimates with reduced uncertainty compared to the approach where independent stochastic activity durations were considered. Furthermore, it provides more realistic and accurate representation of the installation process that can lead to more reliable estimates of the total duration compared to a simple approach that is used in practice. More precisely, the simplest approach (independent, constant activity duration) resulted in an underestimation of the total duration up to 9 day for the P80 value, compared to the proposed approach.

Concluding, the proposed approach allow proper representation of the dependence between the installation activities that can assist decision makers in the planning of the installation process. This approach can lead to reduction of the uncertainty of the estimated installation duration and subsequently its cost. However, it must be mentioned that for this study, it was decided to focus only on the "main" activities of the installation of WTGs based on data from one past project. In order to obtain a widely applicable general representation of the dependence between the installation activities further research is required. Furthermore, there are many more activities that are required for the installation of OWFs and their dependence should be investigated and described appropriately. These will result in a more complex model and acquiring sufficient data to quantify the BN model might be very challenging or impossible. A potential solution would be to quantify the BN based on formal expert judgment methods.

Acknowledgements

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