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Decision Making under Uncertainty for Construction Management of Offshore Wind Assets

DECISION MAKING UNDER UNCERTAINTY FOR CONSTRUCTION MANAGEMENT OF OFFSHORE WIND ASSETS

Proefschrift

ter verkrijging van de graad van doctor
aan de Technische Universiteit Delft,
op gezag van de Rector Magnificus Prof.dr.ir. T.H.J.J. van der Hagen,
voorzitter van het College voor Promoties,
in het openbaar te verdedigen op dinsdag 16 November 2021 om 15:00 uur

door

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Dit proefschrift is goedgekeurd door de promotoren.

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It is the mark of an educated mind to rest satisfied
with the degree of precision which the nature of the subject admits
and not to seek exactness where only an approximation is possible.

Aristotle

CONTENTS

SUMMARY

Offshore wind is expected to be one of the important contributors to the energy transition towards a more renewable and sustainable energy future. This can be clearly seen from the amount of investments over the past years as well as from the substantial upcoming offshore wind projects in the years to come. Many technological implementation challenges have already been addressed, but the number of new challenges will continue to increase. Especially, as the industry continues moving further offshore with larger wind turbines and as the existing offshore wind farms will approach the end of their service lives. Therefore, the need for improved asset management modelling over the entire service life from design towards decommissioning will continue increasing to support better data driven decision making under uncertainty.

For this and in particular for the construction management of offshore wind assets, in this thesis new models and methods have been developed to support this enhanced decision making. These decisions are subject to various types of risks and uncertainties, varying from environmental uncertainties, supply chain disruptions and stochasticity of construction activities' durations. Therefore, these should be properly taken into account in construction management models using performance and/or expert data from past construction projects.

In this thesis two types of data availability have been distinguished: (i) where sufficient relevant performance data is available and (ii) where relevant past performance data is rather limited. In the first case, statistical methods are used, such as Copula functions to model the dependence between metocean variables and Bayesian Networks to model the dependence between subsequent construction activities. In the second case, expert knowledge and data are used to quantify the uncertainty using a mathematical aggregation method for expert judgments (i.e. Cooke's classical modelling). The different methods have been applied to several test cases to investigate the associated cost and time impact. As a result of this research, different tools and an open-source software were developed. These also can be used in different fields of application using this proper mathematical expert judgment aggregation modelling.

Finally, it can be concluded that the state-of the art developments within this thesis substantially contribute to decision making under uncertainty, so that construction management strategies are optimised and thereby the offshore wind energy assets life cycle value is maximised.

SAMENVATTING

Wind op zee zal naar verwachting één van de belangrijke bijdragen leveren aan de toekomstige energietransitie naar meer hernieuwbare en duurzame energie. Dat blijkt duidelijk uit de hoeveelheid investeringen van de afgelopen jaren en uit het omvangrijke aantal offshore windprojecten voor de komende jaren. Veel technologische implementatie uitdagingen zijn al aangepakt, maar het aantal nieuwe uitdagingen zal nog steeds verder toenemen. Dit komt vooral omdat de industrie steeds grotere windturbines en steeds verder uit de kust installeert en omdat de bestaande offshore windparken het einde van hun levensduur zullen naderen. Daarom zal de behoefte aan verbeterde asset management modellering gedurende de gehele levensduur -van ontwerp tot ontmanteling - blijven toenemen om hiermee betere en data gedreven besluitvorming onder onzekerheid te ondersteunen.

Hiervoor, en in het bijzonder voor het constructiemanagement van offshore windparken, zijn in dit proefschrift nieuwe modellen en methoden ontwikkeld om deze verbeterde besluitvorming te ondersteunen. Deze beslissingen zijn onderhevig aan verschillende soorten risico's en onzekerheden, variërend van omgevingsonzekerheden, verstoringen in de bouwstroom en onzekerheid van de duur van de constructieactiviteiten. Daarom moet hier goed rekening mee worden gehouden in constructiemanagement modellen welke gebruik maken van prestatie- en/of expertgegevens van eerdere constructie projecten.

In dit proefschrift worden twee soorten gegevensbeschikbaarheid onderscheiden: (i) daar waar er voldoende relevante prestatiegegevens beschikbaar zijn, en (ii) daar waar relevante historische prestatiegegevens te beperkt zijn. In het eerste geval worden statistische methoden gebruikt, zoals Copula-functies, om de afhankelijkheid tussen metocean variabelen te modelleren en Bayesiaanse netwerken om de afhankelijkheid tussen opeenvolgende constructieactiviteiten te modelleren. In het tweede geval worden expertkennis en gegevens gebruikt om de onzekerheid te kwantificeren met behulp van een wiskundige aggregatiemethode voor expertbeoordelingen (i.e., de klassieke Cooke's modellering). De verschillende methoden zijn toegepast op verschillende testgevallen om de impact op de bijbehorende kosten- en tijdimpact te onderzoeken. Als resultaat van dit onderzoek zijn verschillende tools en een open-source software ontwikkeld. Deze kunnen ook in verschillende andere toepassingsgebieden worden gebruikt met behulp van deze juiste wiskundige aggregatiemethode voor expertbeoordelingen.

Ten slotte kan worden geconcludeerd dat de 'state-of-the-art' ontwikkelingen binnen dit proefschrift substantieel bijdragen aan besluitvorming onder onzekerheid, zodat constructiemanagement strategieën worden geoptimaliseerd en daarmee de levenscycluswaarde van offshore windenergie-assets wordt gemaximaliseerd.

I

INTRODUCTION

1

RESEARCH CONTEXT

By failing to prepare you are preparing to fail.

Benjamin Franklin

1.1. DECISION MAKING UNDER UNCERTAINTY

UNCERTAINTIES have been impacting the decisions of humans since the start of early civilizations and will *almost certainly* continue impacting the lives of everyone in the future.

But what is uncertainty? Uncertainty can be defined as the lack of certainty and it disappears when one becomes certain about a declarative sentence, when truth conditions about this sentence exist and the conditions for the value “true" hold [1]. In practical applications uncertainty is usually removed by observation. A clear distinction should be made between uncertainty and ambiguity. Ambiguity can be removed to a certain extent by increasing the clarity of linguistic conventions. On the other hand, uncertainty can be quantified or represented mathematically. This can be expressed in terms of probability which has the formal properties of a measure of area on a surface with total area equal to 1[1]. For example the initial statement of this section can be rewritten as follows: “Uncertainties have been impacting the decisions of humans since the start of early civilizations and with *probability almost equal to 1* uncertainty will continue impacting the lives of people in the future".

Quantifying uncertainty can be particularly useful in decision making. By properly quantifying the uncertainty it is possible to compare different scenarios and choose the most adequate one with a certain level of confidence. This can be particularly useful for taking decisions concerning topics with high impact. These can vary from global policies to management decisions concerning large offshore wind energy infrastructure assets (as in this thesis). These topics usually have many different risk factors that increase their complexity. Moreover, these are often dependent on each other. Hence, proper representation of the associated uncertainties, their dependence as well as the aggregated effect of all these factors should be taken into account by the analysts and the decision makers to ensure that the problem under investigation is adequately informed.

1.2. ENERGY SITUATION

THE world energy consumption has been steadily increasing during the past decades. Projections from the US Energy Information Administration show an increase of 28% between 2015 and 2040 in their international energy outlook reference case IEO2017[2] [3]. As it can also be seen in Figure 1.1 more than half of the increase is attributed to countries (including China and India) which are not members of the Economic Cooperation and Development (OECD). This expected increase in demand for energy is driven mainly by the economic growth.

Another more recent study, from the International Energy Agency, investigated two different scenarios [4]. Namely the Current Policies Scenario (CPS) and the Stated Policies Scenario (SPS). The CPS assumes there will be no additional changes in the existing

[1] More precise and formal definition of probability can be given by the axioms of Kolmogorov [2].

[2] According to US Energy Information Administration: “The used reference case assumes continual improvement in known technologies based on current trends and relies on the views of leading economic forecasters and demographers related to economic and demographic trends for 16 world regions based on OECD membership status. The IEO2017 considers current policies—as reflected in current laws, regulations, and stated targets that are judged to reflect an actual policy commitment—for major countries with the goal of realistically capturing their effects in the projection"

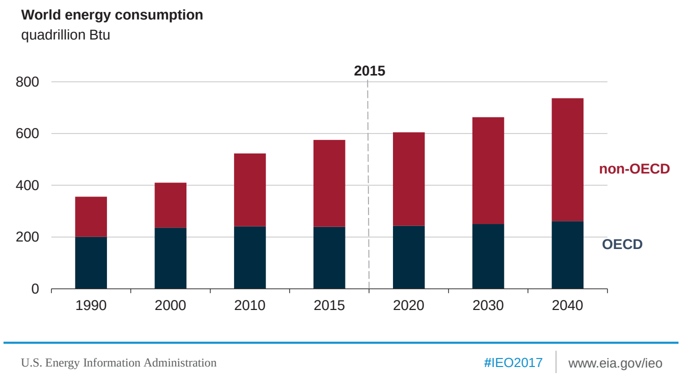

Figure 1.1: International energy outlook [3].

policy, while the SPS considers intended policy initiatives and targets that have been announced. In CPS, the energy demand rises by 1.3% annually until 2040. Despite the fact that this estimate is lower than the 2.3% increase that was observed in 2018, it would still lead to an important increase in energy-related emissions and need for energy security. In SPS, an increase by 1% per year until 2040 is estimated. In this Scenario, low-carbon sources cover more than half this demand and liquefied natural gas (LNG) accounts for another third. Also, it is estimated that oil demand will slow down by 2030s and coal use will also decrease. It is estimated that the electricity sector will be subjected to rapid transformations and especially those countries with “net zero aspirations" will reshape their supply and consumption. However, one of the findings of this analysis is that the growth of “clean energies" will not be sufficient to balance the effects of an expanding global economy and population. This leads to the conclusion that *the world falls far short of shared sustainability goals*

During the past years a lot of attention has been drawn towards the development of clear energy or renewable energy technologies due to the expected depletion of fossil fuels and respective consequences [5] [6] [7]. According to the World Bank renewables in a global scale, have contributed a growing share of electric capacity every year reaching $\approx$ 22.8% of total global power generating capacity in 2015 [8]. It is expected that this share will continue increasing by 2.3% per year on average reaching 31% in 2040 [3].

Among the different renewable energy technologies offshore wind has showed impressive growth in the last years, especially in Europe. Although offshore wind energy technology was less mature than onshore wind [9], the advantages of offshore wind energy such as the higher-quality of wind resources at sea; the ability to use larger wind turbines and the ability to build larger wind farms than onshore attracted major developers.

Figure 1.2: Sandbank OWF of Vattenfall[3].

According to [10], the global offshore wind market grew approximately 30% between 2010 and 2018. United Kingdom, Germany and Denmark are the leaders in Europe. United Kingdom and Germany have currently the largest offshore wind capacity in operation while Denmark in 2018 produced 15% of its electricity from offshore wind. It is worth mentioning that China also added more capacity than any other in 2018. In the coming years, approximately 150 new offshore wind projects are scheduled to be completed worldwide.

According to the energy outlook report of International Energy Agency [4], the "Cost reductions and experience gained in Europe's North Sea are opening up a huge renewable resource. Offshore wind energy has the technical potential to meet today's electricity demand many times over". One of the main reasons is the advancements in offshore wind technology which allows for larger turbines which lead to higher electricity production. Further improvements and innovations such as floating wind turbines and energy storage (e.g. hydrogen storage) are expected in the future. These will allow to move farther offshore and make use of higher and more reliable wind speeds as well as enabling new markets. Offshore wind projects are expected to attract investment up to a trillion dollars to 2040 [4]. In the Sustainable Development Scenario, presented in [4] offshore wind energy together with onshore wind energy become the leading source of electricity generation in the European Union. In this way the full decarbonisation of Europe's power sector can become possible.

1.3. DEVELOPMENT GAP

OFFSHORE wind energy is considered one of the most promising renewable energy sources and it is expected to grow even more during the upcoming years. However,

[3]Source: https://powerplants.vattenfall.com/sandbank.

the high costs of offshore wind farms (OWF) should reduce further in order to achieve the set goals and make them more competitive compared to the conventional energy sources. For these reasons, a lot of research has been funded in the last years. EUROS (Excellence in Uncertainty Reduction of Offshore wind Systems) research programme was funded by the Dutch government and industry partners and aimed to combine excellence in expertise areas from universities, knowledge institutes and industry in an integral approach of cost reduction in wind energy, unprecedented in the sector. EUROS focuses on major factors in the total cost of energy of an OWF: design and construction, and the logistics of installation and maintenance. Despite the fact that there are various uncertainties and risks in design and logistics, present evaluation approaches are fragmented, focusing on single issues. Therefore, in order to avoid obstructive conclusions, methods for integral models should be developed that will assist in understanding and treating properly the aggregated effects of the risks and uncertainties concerning the entire offshore wind project. This leads to better risk and uncertainty assessment.

Installation and maintenance services of OWF are capital intensive activities which can be further optimized in terms of cost and time by investigating possible alternatives and making decisions concerning the assets involved. Towards that direction, this PhD thesis (funded by EUROS and its respective work package entitled “Smart service logistics”) concerns the development of stochastic models in order to include and quantify uncertainties to enable the improvement of the entire OWF installation process.

Construction activities of OWFs are not only expensive, but also complex. Their complexity stems from the fact that these are subject to various uncertainties such as environmental offshore conditions, supply disruptions and failures which may occur during the construction process. All these uncertainties should be taken into account especially during the planning phase. Otherwise, planning based on inaccurate estimates, may lead to decisions which will cause significant schedule and budget overruns during the construction phase. To avoid these undesirable outcomes, probabilistic decision support tools should be utilized in the planning phase to support optimal construction management given these uncertainties. Thus, reliable tools that take into account various uncertainties during the entire OWF supply chain, would be essential for achieving cost reduction.

For the aforementioned reasons, during the last years, various models have been developed concerning different aspects of OWFs decision support. A thorough review of the developed models until 2011 is presented in [11]. The majority of these models were focused on the maintenance strategies. Since then, more studies were conducted and various models concerning the construction (or installation) process of OWFs were developed. For example, Kaiser and Snyder in [12] developed a model of the installation costs of offshore wind projects on the U.S. Outer Continental Shelf. While Sarker and Faiz in [13] proposed a method to identify the characteristics of OWFs installation processes that minimize the total time requirement for transportation and installation, without taking into account the uncertainties. Moreover, most of the developed models use a simulation-based approach and focus on developing different approaches to better describe the environmental condition uncertainty. In particular, Vis and Ursavas in [14] developed a simulation-based decision support tool to investigate different logistical approaches within the installation phase of OWFs while taking into account the external influence of weather by the use of a Markov chain with three states. Paterson et al. in [15] developed a software tool that relies on Monte Carlo methods to simulate multiple independent scenarios of the defined installation strategy for an offshore wind farm, while considers the risk imposed by adverse weather conditions by using a hidden Markov model (HMM). Morandeau et al. in [16] presented the MERMAID (Marine Economic Risk Management Aid) simulation software package that was used for the analysis and optimization of marine energy installations and the investigation of a vessel designed for installation of OWFs. Leontaris et al. in [17] proposed a methodology to produce realistic synthetic time series of wind speed and wave height in order to incorporate the environmental risk into the estimates of the duration of cable installation of OWFs. Also, Guo et al. in [18] proposed a fuzzy duration forecast model for the construction of onshore wind turbines which are only subject to the impact of wind uncertainty.

Other researchers focused on investigating optimization techniques concerning the installation of OWFs. Irawan et al. in [19] developed an integer linear programming (ILP) model to determine the optimal installation schedule considering constraints regarding weather conditions and the availability of vessels. Kerkhove et al. in [20] proposed a Markovian model to describe the weather component and an approach that uses both general meta-heuristic optimization approaches and dedicated heuristics to optimize the project planning. Ursavas et al. in [21] proposed a two-stage stochastic integer program that considers disruptions arising from uncertain weather conditions and the solution approach of the planning problem of wind farms is based on partial Benders decomposition strategy. Barlow et al. in [22] proposed a decision-support tool in a combined framework of an optimization and simulation model which improves the capabilities of both models to provide a mechanism to address current OWF installation projects while taking into account the seasonal uncertainties. Scholz-Reiter et al. in [23] have developed an optimization model for OWF installation scheduling using mixed-integer linear programming (MILP). Particularly, Scholz-Reiter et al. [23] recommended to develop a simulation model that takes into account possible supply disruptions and to integrate this with their model, in order to have a robust design for planning of offshore installation.

1.3.1. RESEARCH OBJECTIVES

In order to contribute to the essential energy transition towards sustainable energy technologies in the upcoming years, the goal of this research is to investigate probabilistic risk analysis methods and develop models to allow for proper quantification of the predominant uncertainties concerning the construction management of offshore wind energy assets.

More specifically, this objective is split into the following:

1. Identify appropriate methods that can properly describe the predominant uncertainties for the construction management of offshore wind assets. These predominant uncertainties concern the following:
    - Environmental uncertainties, which hinder the offshore operations
    - Risk of supply disruption during the construction
    - Durations of construction activities and their dependence

2. Enable comparisons of realistic scenarios and mitigation measures to aid decision making.

3. Enable the quantification of the aggregated effect of the aforementioned uncertainties on the scheduling and budgeting of offshore wind asset projects.

1.4. THESIS OUTLINE

The outline of this thesis is presented in Figure 1.3. The main body of the thesis (excluding Part I: Introduction and Part IV: Epilogue) is divided into two main parts (i.e. Part II and Part III) which present methods and applications for decision making under uncertainty regarding the construction management of offshore wind assets. Part II concerns methods that can be used for representing uncertainty in cases where there are sufficient available data. On the other hand, Part III discuss methods and applications concerning the representation of uncertainty in cases where only limited relevant data are available. Part II and III comprises of two and three chapters respectively, which are based on several scientific publications where the author of this thesis was the main author.

More specifically, Chapter 2 is based on [17] and presents a method to create synthetic time series of the most important metocean conditions that hinder the construction operations. It also discusses shortly an extension to this model that takes into account current velocity that was particularly interesting for an application on the O&M of tidal energy converters.

Chapter 3 is based on [24] and presents a novel model allowing for investigating the effect of the dependence of the installation activities of OWFs.

Chapter 4 is based on [25] and presents a newly developed MATLAB toolbox that can be used for the analysis and synthesis of expert judgments using Cooke's classical model.

Chapter 5 is based on [26] and presents a methodology to assess the supply disruption risk during the construction of OWFs using expert judgments and its incorporation into the estimates of duration and cost of the project.

Chapter 6 is based on [27] and presents a method to improve the uncertainty representation of the reliability of OWFs in order to enable comparison and selection of operation and maintenance (O&M) strategies.

The Chapters of this dissertation do not include the full research output of the author related to this research project. The remaining research output, in which the author was also involved, is summarized in a list of publications in section Publications.

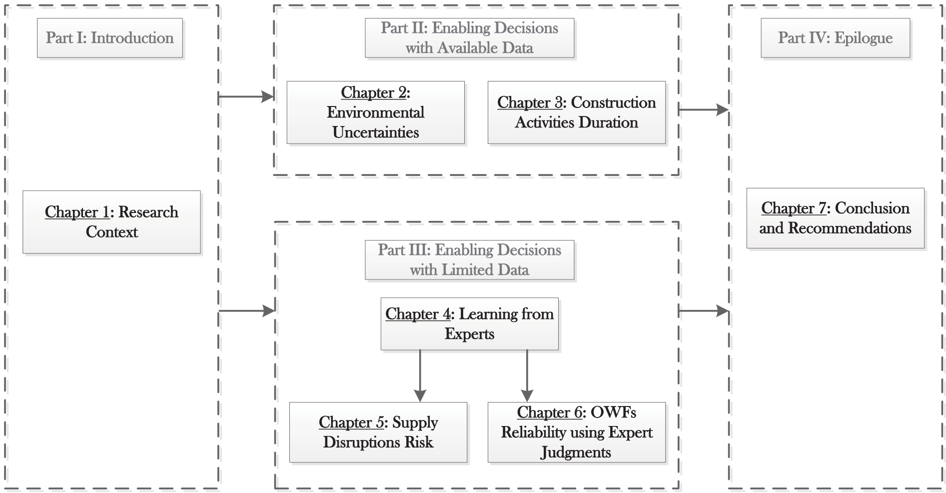

Figure 1.3: Visual representation of the outline of this thesis.

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II

Enabling Decisions with Available Data

2

ENVIROMENTAL UNCERTAINTIES

Remember to get the weather in your damn book
weather is very important.

Ernest Hemingway

Environmental uncertainties concerning variables such as wave height and wind speed are crucial because these may affect installation and maintenance operations with potential delays and financial consequences. In order to include these uncertainties into the estimation, adequate models should be developed to simulate an installation scenario for a large number of historical environmental data. Data regarding environmental time series are usually scarce and limited, therefore they should be modelled. Since the environmental variables are in reality dependent, a probabilistic method is proposed for their construction using copulas. To demonstrate the effectiveness of this method compared to the cases where observed or independently constructed environmental time series are used, a realistic cable installation scenario for an offshore wind farm was simulated. It was found that the proposed method should be followed to acquire more reliable and accurate estimates of the installation's duration.

Parts of this chapter have been published verbatim in Ocean Engineering , (2018) [1].

THIS chapter proposes an alternative method to produce large number of realistic time series of wind speed and significant wave height, which can be valuable for planning and scheduling more efficiently offshore installation operations. In order to plan the sequence of complex offshore installation operations and decide the optimal combination of vessels and equipment required for a particular operation, different scenarios should be simulated and compared. Therefore, large number of environmental time series is needed to account for uncertainties regarding the environmental conditions that limit the operations. Usually it is difficult, expensive and sometimes impossible to acquire a large data set of environmental time series and when it is possible there are often missing values due to failures in the measuring equipment [2], which can influence the estimation of the duration of offshore operations. For these reasons it is important to create realistic environmental time series by taking into account the dependence between the environmental characteristics.

2.1. AVAILABLE METHODS

OFFSHORE construction operations, are subject to a variety of uncertainties such as environmental conditions, failure of vessels and/or equipment, variation in the duration of operations, availability of the required components etc. However one of the main cause of miss-estimations of project duration and delays is the miss-estimation of environmental parameters, such as the wind speed and the significant wave height, which are difficult to predict in the planning phase. For those reasons, project schedulers may use buffers in the planning phase which can lead to overestimation of the duration of a project and subsequently the cost of the installation. Therefore it is essential to find a method which will assist schedulers in acquiring more accurate and reliable estimation of the duration of offshore installation operations by incorporating these uncertainties.

A lot of research has been conducted in the past regarding forecasting of environmental time series. Zounemat-Kermani et al. in [3] mention the following methods to model wind - wave characteristics: statistical techniques, discrete spectral approach, stochastic simulation, numerical methods and data driven models (such as artificial neural networks, fuzzy wavelet model, genetic programming and fuzzy logic). Moreover, a survey regarding the stochastic models for wind and wave state time series was conducted by Monbet et al. in [2] and categorizes these models into: non-parametric models, models based on Gaussian approximations and other parametric models. Also, Zounemat-Kermani et al. in [3] propose an analysis of wind-wave time series using chaos theory. These methods however do not always explain the underlying physical properties attached to a joint probability distribution. Hence nothing or little may be said in terms of joint probabilities of environmental random variables that are described by a non-normal joint distribution.

Univariate distributions are used frequently in order to estimate the design parameters of wind speed and wave characteristics without considering their dependence [4]. Some studies were focused on estimating the joint distribution of wave characteristics such as significant wave height and wave period. Particularly, Salvadori et al. in [5] used Copulas, Athanassoulis et al. in [6] used applications of Placket model and Galiatsatou and Prinos in [7] investigated different bivariate distributions, in order to find the dependence between significant wave height and wave period. However only a few studies investigate the joint distribution of the wind speed and the significant wave height. Particularly, Fouques et al. in [8] propose one method using only the correlation matrix and another method based on multivariate Hermite polynomials expansion of the multi-normal distribution, in order to model the joint occurrence of those variables including the wave period. Moreover Bitner-Gregensen and Haver in [9] and [10] developed a joint environmental model which is based on conditional modelling approach (CMA) which concerns wind, waves, current and sea water level. This model was also applied for design and operations of marine structures by calculating the joint distribution based on parametric fits for each one dimensional marginal [11]. Also the Nataf model [12] is used in many applications in literature for modelling metocean variables. Nevertheless in [13], it is noted that Nataf model may lead to bias results, when the transformation to standard normal variates deviates from a multi normal distribution. Finally, Yang and Zhang in [4] followed a similar approach as the one described in this article, using Copulas to estimate the joint distribution of wind speed and significant wave height without taking into account the autocorrelation which is essential when time series are required.

In the following sections a method using copulas is proposed in order to produce time series of environmental characteristics that limit the operations (i.e. wind speed and significant wave height) by taking into account their dependence and the observed autocorrelation. Copulas provide a way of studying scale free measures of dependence and a starting point for constructing families of bivariate distribution [14]. Also, copulas allow the construction of models which go beyond the standard ones at the level of dependence [15] and they avoid the restriction that presents the traditionally used method which describes the pairwise dependence using families of bivariate distribution characterized by the same parametric family of univariate distributions [16]. Following the copula approach, it is possible in many cases to construct the joint distribution requiring only the marginal distributions of the variables and measures of their dependence [17]. Also, in our case, the characterization of the joint distribution of the environmental variables of interest is semi-parametric. In other words, the one dimensional margins are modelled by non-parametric estimators while the underlying dependence structure are described by one parameter copulas. Moreover the use of copulas has made the investigation of asymmetries in the joint distribution relatively easier since they satisfy different types of tail behaviour [18]. These asymmetries are, as it shall be demonstrated in this chapter, crucial for offshore operations which are mainly influenced by extreme environmental conditions. Finally, in order to investigate the effect of this approach, an application of the proposed method concerning the estimation of the duration of the cable installation of an offshore wind farm was conducted.

2.2. PRELIMINARY CONCEPTS

BEFORE continuing to the method proposed for the construction of time series for significant wave height and wind speed, the main concepts and definitions to be used in the remainder of this chapter are introduced. Copulas are defined as functions that join or "couple" multivariate distribution functions to their one-dimensional marginals. In particular, they are multivariate distribution functions whose one-dimensional margins are uniform on the interval [0,1] [14]. The most important theorem of copulas theory is Sklar's theorem [19] which states that any multivariate joint distribution can be

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written in terms of the univariate marginal distribution functions and a copula which describes the dependence between the random variables. For the two dimensional case, let $H_{XY}(x, y)$ be a joint distribution function with marginal distribution $F_X(x)$ and $G_Y(y)$ which lie in the interval $[0, 1]$. Then there is a copula C on the unit square I^2 such that for all x, y satisfies equation 2.1 [16].

$$H_{XY}(x, y) = C(F_X(x), G_Y(y)), \quad x, y \in \Re \tag{2.1}$$

There is a large variety of copulas which can be used to model joint distributions with different characteristics. Three of the most common families of copulas are: the Gaussian, Gumbel and Clayton copulas. These copulas can model different tail asymmetries of the joint distributions and have been used in many financial applications(e.g.see [20]).These were also investigated in the application that is presented in section 2.4. The Gaussian copula is given by equation 2.2

$$C(u, v) = \Phi_\rho(\Phi^{-1}(u), \Phi^{-1}(v)) \tag{2.2}$$

where Φ denotes the standard normal distribution function and Φ_ρ the standard bivariate normal distribution function with linear correlation coefficient ρ. The Gumbel and Clayton copulas are two of the most used one-parameter Archimedean copulas. For the bivariate case, Archimedean copulas are defined as $C(u, v) = \phi^{-1}(\phi(u) + \phi(v))$. The generator function of Gumbel copula is $\phi(u) = [-ln(u)]^\theta, \quad \theta \in [1, \infty)$ while the generator of Clayton copula is $\phi(u) = (u^{-\beta} - 1)/\beta, \quad \beta \in [-1, \infty)$ [14]. The Gumbel copula is defined in equation 2.2 and the Clayton copula is defined in equation 2.2.

$$C(u, v; \theta) = exp(-[(-ln(u))^\theta + (-ln(v))^\theta]^{1/\theta}) \tag{2.3}$$

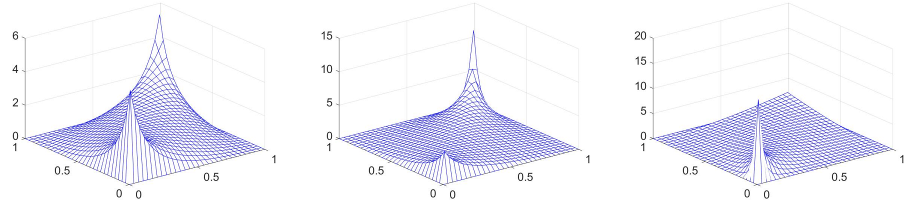
$$C(u, v; \beta) = (u^{-\beta} + v^{-\beta} - 1)^{-1/\beta} \tag{2.4}$$

A way of fitting copulas to data concerns the use of correlation estimators (which are measures of dependence) such as Spearman's rho r_S and/or Kendall's τ. These important measures of dependence refer to the ranks of the data achieving scale-invariant estimates [21]. In equation 2.5, Spearman's rho r_S is presented in terms of copulas.

$$r_S(X, Y) = 12 \int\int_{I^2} uv dC(u, v) - 3 = 12 \int\int_{I^2} C(u, v) du dv - 3 \tag{2.5}$$

Another important concept that should be introduced for our analysis, is tail dependence. Tail dependence allows the study of dependence between extreme values, because (for positive dependence) shows the amount of dependence in the upper right quadrant tail or lower left quadrant tail of a bivariate distributions [15]. The upper tail dependence coefficient is defined in equation 2.6.

$$\lambda_U = \lim_{q \to 1} P(Y > G^{-1}(q) | X > F^{-1}(q)) \tag{2.6}$$



(a) Gaussian copula ($\rho = 0.7$)

(b) Gumbel copula ($\theta = 2, r_S = 0.7$)

(c) Clayton copula ($\beta = 2.1, r_S = 0.7$)

Figure 2.1: Density functions of Gaussian, Gumbel and Clayton copulas.

One can characterize X and Y as asymptotically dependent in the upper tail when $\lambda_U \in (0, 1]$ or as asymptotically independent in the upper tail if $\lambda = 0$. The coefficient of lower tail dependence can be defined analogously for the lower tail. The three parametric models of interest have been selected precisely because they capture lower, upper or no-tail dependence. Usually, the density of bivariate copulas defined as: $c(\mathbf{u}) = (\partial^2 C(u_1, u_2))/(\partial u_1 \partial u_2)$ is used to illustrate copulas' distributions.

Plots of the density function of the three copulas of interest in this chapter (for Spearman's rank correlation r_S equal to 0.7) are presented in Figure 2.1. Intuitively the reader may see that for positive correlation the mass in the upper tail of the Gumbel copula is significantly larger than that in the lower tail, which is indication of upper tail dependence. Analogously for the Clayton copula the mass in the lower tail is larger than that in the upper tail, which indicates lower tail dependence. Having described briefly the main concepts to be used in the rest of the article, we proceed to describe the data of interest.

2.3. PROPOSED METHOD

HISTORICAL metocean time series should be analyzed to find the best fitting model that can be used to construct synthetic time series with similar statistical characteristics. The steps that are proposed for this analysis are presented in section 2.3.1. After the procedure of the analysis, the algorithm for the construction of synthetic time series is presented in section 2.3.2. Finally, the methods to validate the synthetic time series are presented in Section 2.3.3. The proposed method is summarized in the following steps:

1. Analysis of Historical Data (Section 2.3.1)
2. Construction of synthetic time series (Section 2.3.2)
3. Validation of synthetic times series (Section 2.3.3)

2.3.1. ANALYSIS OF HISTORICAL DATA

The analysis of historical environmental data is consisted of the following steps

1. Data pre-processing
2. Transforming observations in pseudo-observations

3. Performing different statistical tests:
    - Sum of square differences based on Cramér-von Mises statistics
    - Calculation of semi-correlations
    - Calculation of exceedance probabilities of different percentiles

DATA PRE-PROCESSING

For all datasets that the author has analyzed during this research project, there was the need of data pre-processing. The purpose of this is to remove missing, unfeasible or unrealistic values and put data in the required format for further analysis. Particularly, several values were observed in the environmental datasets that were used for the analysis in section 2.4.1. These values were probably occurred due to failures in the measuring or recording equipment. Although the number of these values was comparatively small to the size of the set, their exclusion was required. The importance of this process is usually underrated. However it is self-evident that including unrealistic/wrong values will probably lead to miss-estimation of the best fitting copula and its parameter and subsequently to the synthetic time series.

DATA TRANSFORMATION

Because the marginal distributions of random variables are usually unknown, it is often recommended to estimate the parameters of the copula of interest using pseudo-observations. These may be interpreted as a sample of the underlying copula [16, 22]. The underlying copula of a random vector is invariant by continuous, strictly increasing transformations. Therefore the observations X_j, when j refers to the random variable, can be safely transformed to pseudo-observations, using the ranks. The pseudo-observations are defined as [16]: $U_j = R_j/(n+1) = n\hat{F}_j(X_j)/(n+1)$, where n refers to the number of the observations and $\hat{F}_j$ the empirical cumulative distribution function defined as:

$$\hat{F}_j(t) = \frac{1}{n}\sum_{i=1}^{n} \mathbf{1}(X_j \leqslant t) \tag{2.7}$$

where $\mathbf{1}()$ is the indicator function, which is defined as follows for a set E:

$$\mathbf{1}_E(\omega) = \begin{cases} 1, & \omega \in E \\ 0, & \omega \notin E \end{cases} \tag{2.8}$$

STATISTICAL TESTS

The following different statistical tests are proposed in order to find the goodness of fit of the copulas under investigation.

Sum of square differences based on Crámer-von Mises statistic. In order to find which copula fits the data best, "blanket tests" are usually used. The "blanket tests" are favoured compared to other methodologies due to the fact that they do not involve parameter tuning or other strategic choices [16]. There are various types of "blanket tests" nevertheless in our study the test that concerns the calculation of the sum of square differences between the empirical C_n and the parametric copula $C_{(\theta_n)}$, based on Crámer-von Mises statistic was performed. The empirical copula is a non-parametric estimator of the true copula and it summarizes the information of pseudo-observations. For the bivariate case with two random variables (u_1, u_2) the empirical copula is defined as in equation 2.3.1.

$$C_n(\mathbf{u}) = \frac{1}{n}\sum_{i=1}^{n}\mathbf{1}(U_1 \leqslant u_1, U_2 \leqslant u_2), \quad \mathbf{u} = (u_1, u_2) \in [0,1]^2 \tag{2.9}$$

Moreover, the sum of square differences based on Crámer - von Mises statistic for an empirical process $A_n = \sqrt{n}(C_n - C_{\theta_n})$, is defined as in [23] by equation 2.10

$$S_n = \int_{[0,1]^d} {A_n}^2(u)\,dC_n(u) = \sum_{i=1}^{n}(C_n(U_n) - C_{\theta_n}(U_n))^2 \tag{2.10}$$

The sum of the square difference between the empirical and the parametric copula is calculated for every copula under consideration (e.g. S_N for Gaussian, S_{Gum} for Gumbel and S_{Cl} for Clayton) and the copula for which the smallest value is obtained should be preferred.

Calculation of semi-correlations. Another approach to investigate which copula describes better the dependence between significant wave height and wind speed, concerns the calculation of Pearson correlation for upper and lower quadrant of the actual observations transformed to standard normal N(0,1) margins. Let Φ denote the standard normal cumulative distribution function, then $Z_j = \Phi^{-1}(U_j)$, for $j = 1,\ldots,d$ are the standard normal transforms of the pseudo-observations [18]. After dividing the standard normal transforms of observations into four quadrants, for positive correlation the upper semi-correlation is defined as: $\rho_{ne} = \rho(Z_1, Z_2 | Z_1 > 0, Z_2 > 0)$ and the lower semi-correlation is defined as: $\rho_{sw} = \rho(Z_1, Z_2 | Z_1 < 0, Z_2 < 0)$. The upper and lower quadrant correlations indicate whether or not there is tail asymmetry. When there is tail asymmetry, the two semi-correlations present an obvious difference [18]. Also, these values could be compared to the product moment correlation of all quadrants . This procedure has been exemplified in the context of traffic load measurements before, for example in [24]. If the values of semi-correlation are larger than the overall Pearson correlation or there is big difference between the upper and lower semi correlation, then there is indication of tail dependence.

Calculation of exceedance probabilities for different percentiles. The third test concerns the calculation of conditional exceedance probability for different percentiles concerning the observations as well as the investigated copulas. The calculation of the joint exceedance probabilities for each copula under consideration is described by equation 2.11 where u_p is the percentile of interest.

$$P(U > u_p, V > u_p) = 1 - 2u_p + C(u_p, u_p) \tag{2.11}$$

Therefore the calculation of the joint conditional exceedance probabilities for each copula under consideration is given by equation 2.12.

$$P(U > u_p | V > u_p) = P(U > u_p, V > u_p)/P(V > u_p) = (1 - 2u_p + C(u_p, u_p))/(1 - u_p) \tag{2.12}$$

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The calculated exceedance probabilities of the observations, which were computed based on the empirical version of equation 2.12, were plotted along with the conditional exceedance probabilities for each different copula under investigation, in order to evaluate which copula describes better the extreme cases of large wind speeds occurring together with large wave heights. The purpose of this study is to find the right copula that will be used to produce environmental time series which will show whether or not certain operations can be performed during the time intervals. Hence, the percentiles u_p that are investigated should correspond to values close to the environmental limits of the operations. For that reason, it was decided to conduct this analysis for values of u_p larger than 80^{th} percentile. Following this approach it is safe to assume that these percentiles include the values that address the limits of the vessels.

2.3.2. ALGORITHM FOR SYNTHETIC TIME SERIES

Knowing the copula among the investigated families, that describes best the dependence between wind speed and significant wave height, it is possible to produce couples that take into account the dependence between the variables by using the estimated parameter for each month. However, in order to produce realistic environmental time series the autocorrelation should also be taken into account. Similar analysis as the one presented in section 2.3.1 was performed in order to investigate which copula describes the dependence of the wind speed with lagged versions of itself and it was found that the Gaussian copula describes it best.

After the copulas that describe the dependence of the environmental variables and the autocorrelation are both known, random environmental (synthetic) time series can be produced. In our case, the procedure of random time series generation was conducted for each month separately in order to include seasonality. The generation of time series for each month could be represented by simple vine or a dependence tree, as it is defined by Kurowicka and Cooke [25], consisting of three nodes and two edges. The nodes are associated with marginal densities while the first edge specifies the autocorrelation of wind speed and the second edge specifies the dependence between wind speed and wave height, using the copula families that were determined by the analysis. The procedure consists of the following steps:

1. Generate the first wind speed value $u_t \sim U[0,1]$, using a uniform random number generator.

2. Calculate the subsequent value(s) of wind speed in $[0,1]$ based on the previous value (u_t) by solving the inverse conditional Gaussian copula [18] in equation 2.13.

$$C^{-1}(u_{t+1}|u_t;\rho) = \Phi(\Phi^{-1}(u_{t+1})\sqrt{1-\rho^2} + \rho\Phi^{-1}(u_t))) \tag{2.13}$$

   where Pearson correlation $\rho = 2\sin(\frac{\pi}{6} r_S)$ and r_S is the Spearman's rank correlation coefficient.

3. Next, the inverse conditional Gumbel copula function written in Matlab by Andrew Patton[1] provides the value of wave height $v_t \in [0,1]$ for each of the generated

[1] http://public.econ.duke.edu/ ap172/

wind speed values u_t. The conditional Gumbel copula is described by the equation 2.14 [18]:

$$C(v_t|u_t;\theta) = u_t^{-1} exp(-[x^\theta + y^\theta]^{1/\theta})[1 + (\frac{y}{x})^\theta]^{1/\theta-1} \tag{2.14}$$

where $x = -ln(u_t)$ and $y = -ln(v_t)$. Using the calculated parameter θ of the Gumbel copula the inverse conditional Gumbel copula is found numerically using a bisection method.

4. The values of wind speed and wave height are transformed back to the original units through the inverse cumulative distribution function of each separate variable.

5. Combine the generated time series of each month to acquire time series for the whole year.

It should be noted that the proposed method will cause a discontinuity between the values occurring at the last hour of the month and those at the first hour of the following month. However, this discontinuity is considered acceptable for the scope of this research, since our main focus lies on the environmental behaviour over a long period of time. Also, based on the method proposed by [18] time series were also generated by taking into account more than one lag (by using a D-Vine for the time series process of the wind speed U_t. However it was found that this approach does not improve the persistence of the synthetic time series and therefore it was decided to proceed with the proposed method based on a first order lag.

2.3.3. VALIDATION OF SYNTHETIC TIME SERIES

Besides the visual comparison between the scatter plots of the observed and generated time series, two additional characteristics of the time series is advised to be compared in order to validate the synthetic time series. These are the monthly workability and the persistence of weather windows.

The monthly workability concerns the percentage of the time steps during which an operation, limited by certain environmental thresholds, can be performed for every month. “The persistence of an environmental parameter above (below) some threshold level is defined as the time interval between an up-crossing (down-crossing) of that threshold level and the first subsequent level down crossing (up-crossing) of the same level” [26]. Similarly, the persistence of weather windows can be defined as the amount of hours that the environmental parameters (i.e. wind speed and wave height) do not exceed the environmental thresholds (or limits) of an operation.

2.4. APPLICATION OF PROPOSED METHOD

THIS section presents the application of the methods described in 2.3 as well as a test case concerning the estimation of the duration of the cable installation of an OWF.

2.4.1. ENVIRONMENTAL DATA ANALYSIS

Two different environmental data sets concerning average wind speed (m/s), that is the average of the wind speeds observed in the time interval of interest, and significant wave height (m) which is the mean values over the upper third of the observed wave heights during the time interval [27], were analysed in order to find which of the three copulas families introduced in section 2 describes best the dependence between those two variables. The first environmental data set concerns 21 years (1990-2011) of measurements in one-hour intervals from an offshore station (41010) located east of Cape Canaveral in Florida, available on National Oceanic and Atmospheric Administration (NOAA)[2] web site. The second environmental data set concerns 3 years (2010-2013) of observations from an offshore station located in the North Sea and it was provided by Deltares. Deltares' environmental data were provided in 10-min intervals and they were transformed into one-hour intervals by taking the maximum value observed during one hour. It was decided to take the maximum values of the means observed during one hour; however it must be noted that the results would not be different concerning which copula fits better the data if the mean of the mean values was used. Both available environmental data sets were analysed following the same procedure.

The described (in Section 2.3.1) historical environmental data analysis was conducted for every month in order to ensure that seasonality will be taken into account in the estimation of the copula parameter and subsequently in the produced time series. Concerning data from Deltares and NOAA, Tables 2.1 and 2.2 present the calculated values of the sum of square differences and the semi-correlations for February, June and for the entire data sets. For both environmental data sets the Gumbel copula had the smaller square difference compared to Gaussian and Clayton copula; meaning that the Gumbel copula has the smallest "distance" between empirical copula and the estimate represented by the parametric copula. Moreover, the calculated values of semi-correlations clearly show that there is tail asymmetry. It can be seen that the upper quadrant semi-correlation regarding Deltares' data is larger than the overall correlation while the upper quadrant semi-correlation regarding NOAA data are very close. This result suggests that a model with upper tail dependence is preferable. Considering the three copulas under investigation, only Gumbel copula has upper tail dependence. The results of these tests evidently indicated that the Gumbel copula is the copula that fits the data best among the copulas under consideration.

	ρ	ρ_{NE}	ρ_{SW}	S_N	S_{Gum}	S_{Cl}
Overall	0.6123	0.7092	0.1278	2.1420	0.9587	11.2876
February	0.6486	0.6479	0.2536	2.5932	1.3222	12.3801
June	0.6750	0.6431	0.3244	0.8740	0.3189	9.3321

Table 2.1: Semi-correlation and square differences of the environmental data provided by Deltares.

In Figures 2.2 and 2.3, the values of exceedance probability for percentiles larger than 80^{th} are presented for Gaussian, Gumbel and Clayton copula, while the dots indicate the exceedance probability of observations. Based on the presented plots, it was found that Gumbel copula underestimates the exceedance probability less than the other investigated families, as far as percentiles smaller than 90^{th} and 96^{th} are concerned for Deltares and NOAA entire data sets respectively. For higher percentiles, the size of the sample is

[2]https://www.noaa.gov/

	ρ	ρ_{NE}	ρ_{SW}	S_N	S_{Gum}	S_{Cl}
Overall	0.6412	0.6322	0.1531	1.2848	0.5084	9.7843
February	0.6542	0.6496	0.1442	1.1522	0.4223	9.7625
June	0.5595	0.5692	0.1232	1.0443	0.4731	6.8582

Table 2.2: Semi-correlation and square differences of the NOOA environmental data.

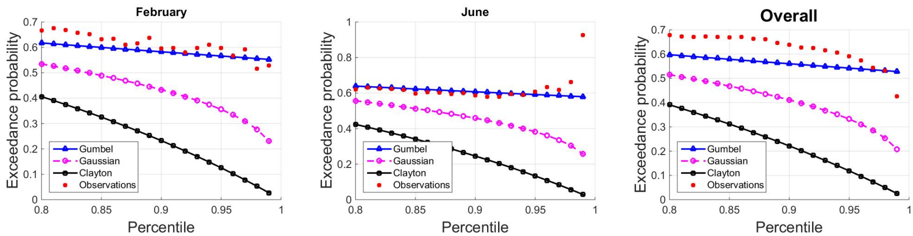

Figure 2.2: Conditional exceedance probabilities $P(U > u_p|V > u_p)$ for different percentiles u_p concerning environmental data provided by Deltares.

smaller and therefore the calculated exceedance probabilities of the observations tend to have larger distance from those of the Gumbel copula. However it is obvious that Gaussian copula, which was the second best among the investigated families, underestimates the probability of extreme environmental conditions in all cases. This is crucial in our case where the quality of the estimated duration of the operations is influenced by the quality of estimation regarding extreme environmental conditions that hinder the operability of the vessels and equipment. Therefore, based on the conducted tests on both available environmental data sets, one can safely conclude that among the one parameter copula families investigated Gumbel is the most appropriate to model the dependence between wind speed and significant wave height.

2.4.2. TEST CASE DESCRIPTION

A simulation algorithm, which performs Monte Carlo simulations concerning the in-field cable installation of an offshore wind farm, was developed in order to identify the influence of using synthetic time series instead of observations. The flowchart of this

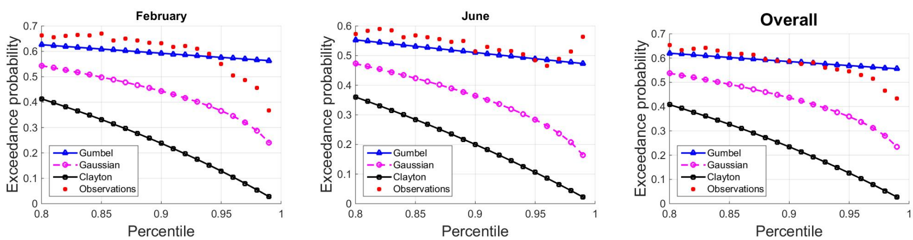

Figure 2.3: Conditional exceedance probabilities $P(U > u_p|V > u_p)$ for different percentiles u_p concerning environmental data from NOOA.

algorithm can be found in Figure 2.5 (in which green and red arrows denote respectively positive and negative response to associated decision boxes). The developed algorithm together with the copulas algorithm (described in Section 2.3.2) were combined into a decision support tool (Figure 2.4) which can be used by concept engineers to compare different cable installation scenarios.

The developed decision support tool works as follows: first historical environmental data observed in the installation site are fed into the copula analysis algorithm, which performs the presented statistical tests and calculate the parameters regarding the dependence of the wind speed and the significant wave height as well as the autocorrelation for each month. Then, as many random environmental time series as needed are produced. Through testing, it was found that 1000 randomly generated annual time series are sufficient since the resulted CDF curves of installation's duration do not present important differences with a larger number of time series. Following, the produced time series, along with the cable installation scenario details are fed into the cable installation algorithm which simulates the proposed installation scenario for every different set of time series. Finally a CDF curve of the duration of the cable installation is obtained as output and the user is able to estimate the duration of a cable installation scenario within a confidence level.

Operation	Wind	Wave
Pre-lay grapnel run	-	1.5 m
Crew transfer	12 m/s	1.25 m
Pull-in	12 m/s	1.25 m
Pre-lay survey	-	1.75 m
Cable laying	12 m/s	1.75 m
Pre-burial survey	-	1.5 m
Burying cable	-	1.5 m
Post-burial survey	-	1.5 m

Table 2.3: Details of the cable installation test case.

A realistic test case was provided by the internationally operating Dutch marine contractor Van Oord. This concerns the cable installation of an OWF consisting of 55 wind turbines in the North Sea. The layout of the OWF, consisting of nodes (i.e. wind turbines and ports) and edges (i.e. lines that connect different nodes and represent the cables) is presented in Figure 2.6. The infield cable installation of an offshore wind farm is a complex process consisting of different operations performed by different types of vessels. The cycle of installation operations that take place in every edge of the OWF when post lay burial (PLB) of the cable is concerned, are presented in a Gantt chart (Figure 2.7). Also, the environmental limits (Table 2.3) for the different operations of the cable installation, were provided. To clarify, it must be mentioned that the performance concerns the duration of each operation, and that the limiting environmental conditions may differ for various operations.

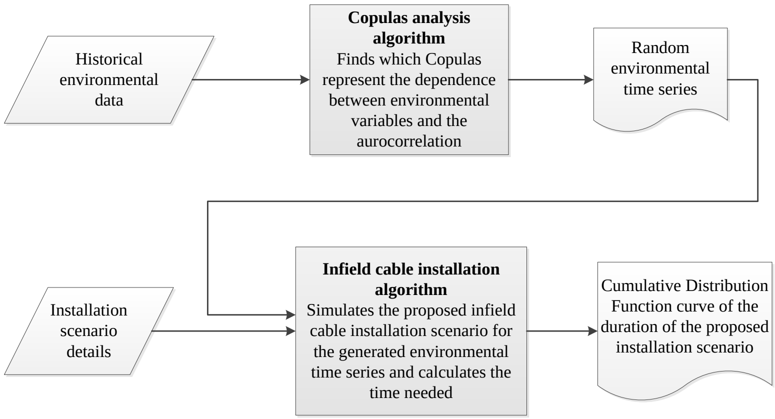

Figure 2.4: Developed decision support tool for cable installation.

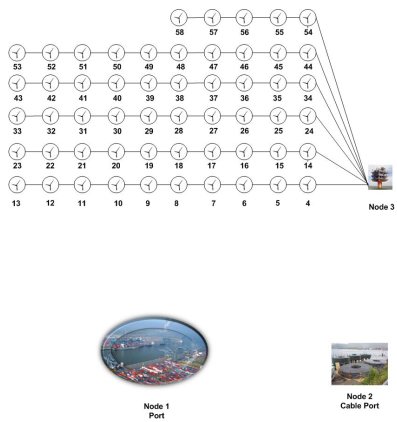

Figure 2.6: OWF and cable layout.

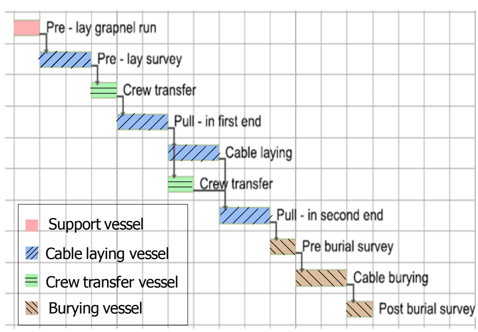

Figure 2.7: Gantt Chart for post burial scenario of cable installation.

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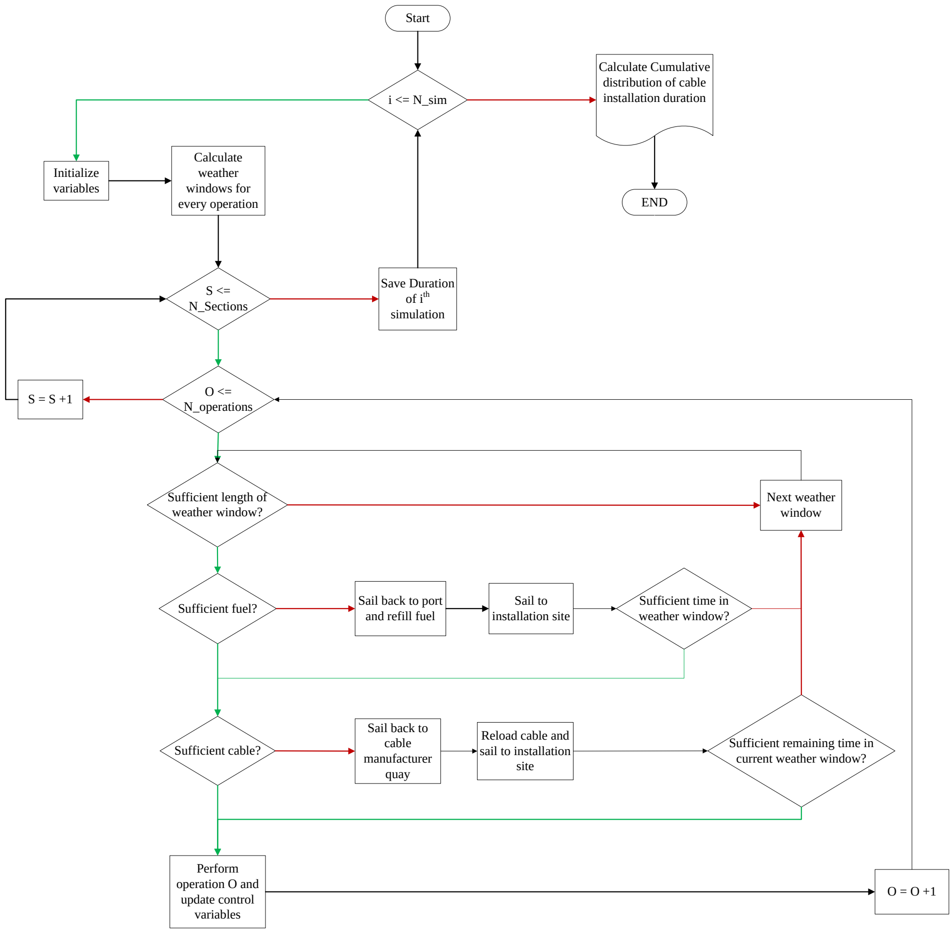

Figure 2.5: Algorithm for simulating the cable installation (green and red arrows denote respectively positive and negative response to associated decision boxes).

2.4.3. VALIDATION

Time series were also provided by Van Oord, concerning the wind speed and the significant wave height of a location in the North Sea, close to the site of the OWF. These time series concerned 10 years of corrected 6 hours intervals measurements. These environmental data were analyzed using the statistical analysis mentioned in section 2.3.1. It was found that the Gumbel copula describes the dependence of the wind speed and the significant wave height best for all months except November and December when the Gaussian copula was preferred. Therefore, the time series for these two months were produced, as it was described in section 2.3.2, by using the inverse h-function of Gaussian copula, instead of the inverse conditional Gumbel copula. Applying the proposed method, 1000 random annual time series of wind speed and wave height, considering 6h intervals, were constructed and their scatter plot is presented in Figure 2.8. While Figure 2.9 shows the scatter plot of the observed time series. It can be seen that the plots present similarities in terms of shape, marginal distributions and extreme values.

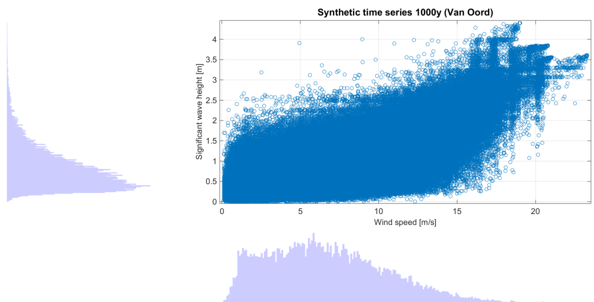

Figure 2.8: Scatter plot of 1000 constructed annual time series using copulas based on Van Oord's environmental data.

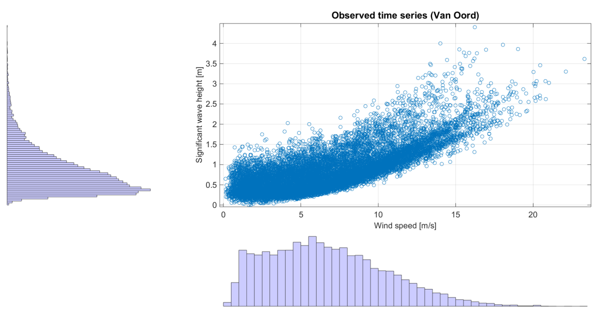

Figure 2.9: Scatter plot of 10 years of observed time series provided by Van Oord.

In order to validate the synthetic time series, the monthly workability and the persistence of weather windows were calculated for both synthetic and observed time series,

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considering an operation limited by values of significant wave height (X_2) larger than 1.5 m and values of wind speed (X_1) larger than 12 m/s. Moreover, different realistic environmental limits were tested, without resulting in significant differences from the presented case. In Figure 2.10, it can be seen that the mean workability of 1000 synthetic time series is very similar to the mean workability for 10 years of observed time series, for every month. This indicates that the proposed method captures sufficiently the dependence between wind speed and wave height, since it is possible to produce synthetic time series with similar workability to the observed.

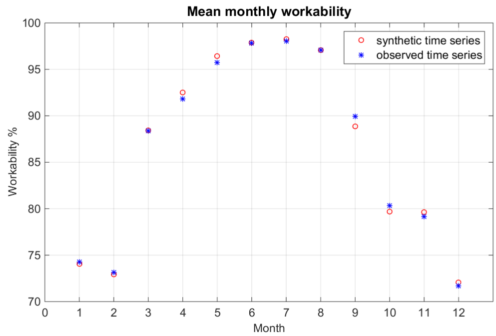
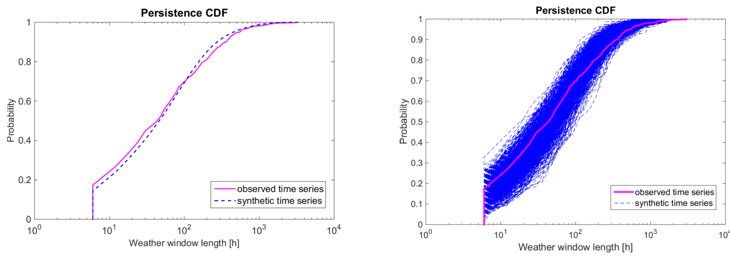


Figure 2.10: Mean monthly workability of observed and synthetic time series.

However, in order to ensure that the proposed method produces realistic time series that take into account the time dependence of the environmental variables, the persistence of the weather windows was also tested. The CDF of the persistence of the observed time series is compared to the CDF of the persistence of the synthetic time series and to every year's persistence of the synthetic time series, in Figure 2.11a and 2.11b respectively. As it can be seen in Figure 2.11a, the CDFs of the persistence of weather windows are very similar for both observed and synthetic time series. In Figure 2.11b, one may observe that the CDF of the persistence varies for different years of the generated time series. These results show that using the proposed method, it is possible to produce realistic time series that present similar characteristics to the observations avoiding overfitting of the model.

2.4.4. REQUIRED TRANSFORMATIONS

As it was mentioned before, cable installation consists of different sub-operations performed by various vessels with different operational limits. However some of these sub-operations may have durations smaller than six hours. Therefore it is needed to transform the time series from 6h intervals to 1h intervals. In this study we calculate the values for 1h interval using linear interpolation. After transforming both, observed and synthetic time series, to time series with 1h intervals, the workability and the weather windows' persistence was tested and ensured that the transformed time series (1h) have the same characteristics as their original (6h) time series. The workability plot concerning the interpolated synthetic time series was identical to the one concerning 6h synthetic time series (Figure 2.10). The plot showing the cumulative distribution of the per-



(a) Percistence CDF for observed and all synthetic time series
(b) Percistence CDF for observed and 1000 separate synthetic time series

Figure 2.11: Comparison of persistence between observed and synthetic times series.

sistence concerning the observed time series and the interpolated synthetic time series can be found in Figure 2.12. The resulting plot shows that the persistence of interpolated synthetic time series is similar to the persistence of observations. The main difference with Figure 2.11b is that there is a probability of having smaller weather windows than 6 hours since the resolution of the synthetic time series is 1 hour. However it must be mentioned that the probability of these cases is lower than the one of the 6h observations. This result supports the statement that it is possible to obtain higher resolution time series maintaining the characteristics of the observations.

To conclude this section, we call the reader's attention to two different cases in which 1h time series may be produced using the proposed method and 6h data available: (i) use linearly interpolated 1h historical data for the construction of synthetic time series; (ii) produce 1h synthetic time series directly from 6h available historical time series. It must be noted that both cases will lead to a wrong process as judged by persistence statistics. Hence, it is important to first produce synthetic time series with the same resolution as the available observed time series and then use interpolation to increase the resolution.

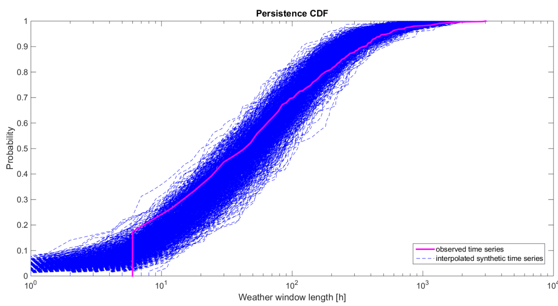


Figure 2.12: Comparison between CDF of the observed persistence and CDF of persistence for 1000 interpolated synthetic time series (1h).

2.4.5. RESULTS

The infield cable installation scenario under consideration was simulated for different sets of time series (1h),considering 1st of June as starting date of the operations and the obtained CDF curves were compared. Firstly, it is important to compare the CDF curves of the cases where the observed time series and the randomly constructed time series were considered for the simulation. Secondly, it is of interest to compare the same CDF curves when other types of uncertainties are also included. Thirdly, we compare the CDF curves of the cases where dependently and independently constructed time series are used. The last comparison is for illustration purposes, in order to emphasize why offshore operators should never consider environmental variables as independent.

Observed versus Synthetic time series One could say that it is sufficient to simulate the installation scenario for the available observed time series in order to acquire a good estimate of the duration. This statement was investigated by simulating the same cable installation scenario (PLB) for observed and synthetic time series without taking into account any other uncertainties (i.e. the durations of the operations were assumed constant and risks of failures were not considered).

In Figure 2.13, the CDF curves of these cases concerning the environmental data provided by Van Oord are presented. Usually project managers use CDF curves to estimate the duration of a project within a confidence interval. In practice experts often base their decisions on the 70th or 80th percentile (or P70, P80 value) of the CDF curve of the duration. Regarding the 70th percentile, it can be seen that when synthetic time series are used for the simulation, the estimated duration equals 1220 hours. However, the P70 value of the CDF of the duration when observed time series are considered, may range from 1190 – 1240 hours. Hence, when the scenario is simulated concerning dependently constructed time series instead of a limited number of observed time series, it is possible to acquire more accurate estimates of the total duration.

In general it can be said that the estimate of the duration using synthetic time series is similar to the estimate when observed time series are used. However, constructing a large number of time series includes more possible environmental realizations to the estimation of the duration. Thus, the obtained CDF curve presents a bigger range (from 1125 to 1390 hours), incorporating more environmental uncertainties into the estimation of the duration and can be used to acquire a more precise estimate of the distribution of duration.

Besides environmental conditions there are also other uncertainties that influence the total duration of an offshore operation. Some of these uncertainties could be potential failures of equipment or variation of performance value from the deterministic value that has been assigned. Selected uncertainties were also included in the developed tool after consultation with cable installation experts, using common features of Monte Carlo simulation models [28]. In particular it was decided to calculate the value of the most uncertain operation (i.e. crew transfer) from a triangular distribution and assign a failure probability equal to 2.5% and its impact in time regarding the pull-in operations. The results of the simulations for the same sets of observed and synthetic time series are presented in Figure 2.14. It is interesting to see that seven different runs of simulations concerning the observed time series present significant variations in the CDF of the duration of the installation. However, this is not observed for the CDF of the duration, concerning 1000 synthetic time series, which was almost identical for different runs. Hence, it can be stated that this outcome shows clearly the importance of having a

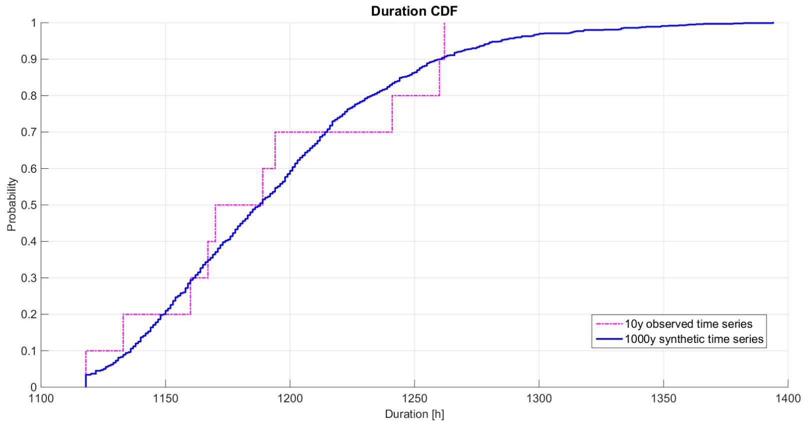


Figure 2.13: Comparison between observed and constructed time series based on Van Oord's environmental data without taking into account other uncertainties.

large number of realistic time series in order to acquire a reliable estimate of the duration of the installation, including uncertainties regarding the environment, the performance of the equipment and possible failures.

Dependently versus independently constructed synthetic times series For illustration purposes, the case was investigated where environmental time series are constructed independently by calculating random numbers in [0,1] and using the inverse empirical cumulative distribution of every month to transform them in the appropriate range. As it was expected, the scatter plot of the independently constructed time series (Figure 2.15) seems unrealistic compared to the observed time series. As it can be seen in Figure 2.16, the duration CDF curve of the independent case has larger values and bigger range than that of the dependent case. This result was anticipated for the independent case, due to the fact that the cases where at least one of the two values exceeds the environmental limits of an operation are more often, resulting in shorter weather windows and subsequently larger total duration. Therefore, the P70 value of the independent case overestimates the estimated duration in an order of 600 hours (i.e. 25 days) compared to the case of dependently constructed time series. An overestimation of that scale may lead to false decisions regarding the scheduling of the operations and the installation components (i.e. vessels and equipment), resulting in increase of the cost of the cable installation. All the above reasons indicate that constructed time series that take into account the dependence of the wind speed and the wave height should be used in order to safely estimate the time of the cable installation.

2.4.6. COMPARISON OF DIFFERENT CABLE INSTALLATION SCENARIOS

The developed tool can help project schedulers and researchers in comparing different installation scenarios based on the estimation of their duration, including environmental, performance and failure uncertainties. For that reason a different cable installation

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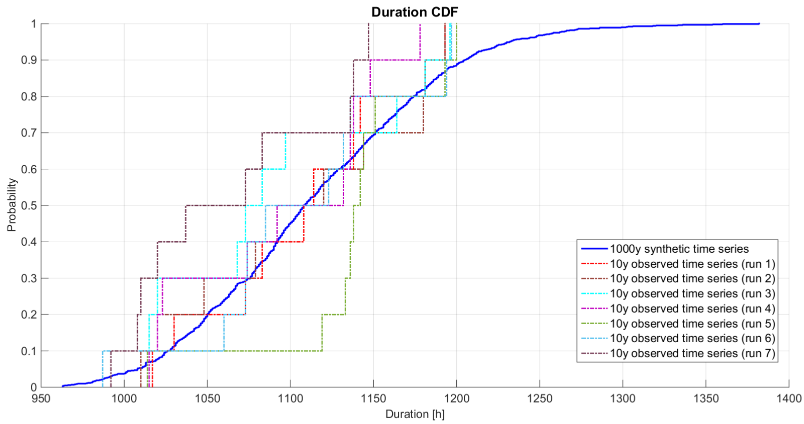

Figure 2.14: Comparison between CDF curves concerning synthetic time series and multiple runs for observed time series including performance and failure uncertainties.

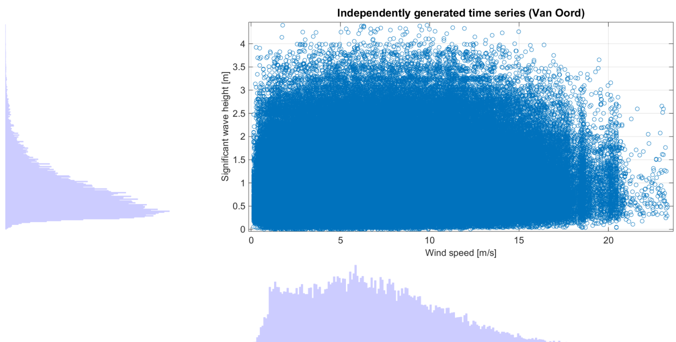

Figure 2.15: Scatter plot of independently constructed annual time series based on Van Oord's environmental data.

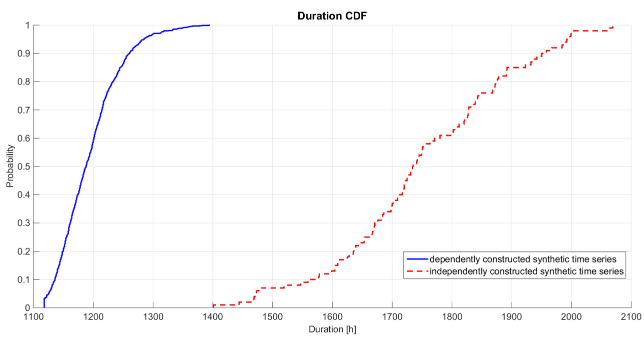

Figure 2.16: Comparison between dependently and independently constructed time series based on Van Oord's environmental data without taking into account other uncertainties.

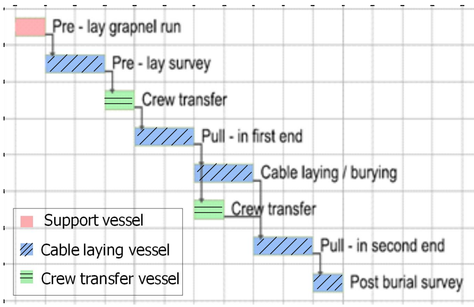

Figure 2.17: Gantt chart of SB scenario.

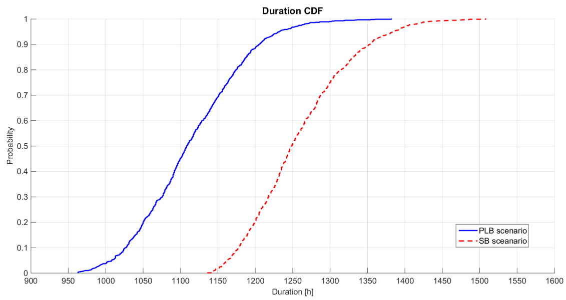

Figure 2.18: CDF curve of duration concerning PLB and SB scenarios including performance and failure uncertainties.

scenario was built and simulated. This scenario concerns the case of simultaneously burying (*SB*) which does not require a separate vessel for the burying of the cable but considers smaller performance regarding the cable laying/burying operation. The installation cycle of simultaneously burying scenario for every edge of the OWF, is presented in a Gantt chart (Figure 2.17). After simulating both cable installation scenarios, it can be seen from the obtained CDF curves (Figure 2.18) that it is more probable that the PLB scenario will result in smaller duration of the installation than the SB scenario. Hence, it is obvious that SB scenario would need more time to complete the installation and it should not be preferred over the PLB scenario. However, it must be mentioned that it could be possible that the SB scenario would be preferable in terms of costs, since it concerns three instead of four vessels, whose day rates are very expensive. Therefore, if one is interested in finding the overall optimal scenario, it is recommended to also investigate the cost.

2.5. CONCLUSIONS AND RECOMMENDATIONS

In this chapter a method is proposed in order to produce realistic random time series of the environmental conditions, such as wind speed and significant wave height, that usually hinder the operability of vessels for offshore operations. The proposed method uses copulas to take into account the autocorrelation and the dependence of wind speed and significant wave height. Usually observed time series are not available for many years. Therefore, being able to synthesize large number of realistic time series of wind speed and wave height can help project schedulers or researchers in simulating offshore operations including environmental uncertainties.

In order to evaluate the importance of using the proposed method in the estimation of the duration of offshore operations a decision support tool for the cable installation of offshore wind farm, was developed. A cable installation scenario as well as time series measured wind speed and wave height close to the installation site, were provided by Van Oord. Using the proposed method, 1000 synthetic time series were constructed and validated by comparing important characteristics such as workability and persistence with those of the observed time series. Then, the cable installation scenario was simulated for different sets of time series.

It was found that dependently constructed synthetic time series provide a better insight into the duration of the cable installation compared to the case where only observed time series are used. The main advantage has to do with the fact that more possible realizations of environmental conditions are taken into account. Concerning the case of independently constructed time series, the results show that not including the dependence between wind speed and significant wave height will lead to unrealistic time series which will result in miss-estimation of the duration of the offshore operations which are limited by these environmental characteristics. The presented method can help professionals and researchers who are interested in including uncertainties, concerning environmental conditions, performance of the equipment and possible failures, in the scheduling of offshore operations and the comparison of different scenarios, by acquiring more accurate and reliable estimations of their duration.

Besides wind speed and wave height, there are also other environmental variables such as wave period, wind direction, current speed etc., which limit or influence offshore operations. Extending the models which represent the bivariate joint probability distributions to models which represent multivariate joint probability distributions, adds significantly to the complexity of the models. As it was already mentioned in section 2.1, many studies have focused on describing the bivariate or multivariate joint distributions of metocean variables without aiming in constructing synthetic time series. Since nowadays it is possible to acquire historical environmental time series, it would be possible to extend the method proposed in this article in order to construct sufficient number of synthetic time series concerning more metocean variables. These synthetic time series can be used as input to stochastic simulation models in order to acquire better estimates of the duration of offshore construction activities. The use of Vine copulas, which have been used for time series in financial applications [29, 30], is suggested for future study. It is expected that different families of copulas with more than one parameter would be needed in order to describe the multivariate distributions. Attention should be paid though, because as the number of metocean variables increases, the dependence of these variables with each other and in time will become more complex. A good way to validate results is through persistence and workability as presented in Section 2.4.3. How much the persistence and workability computed from synthetic time series would differ from those computed from the observations, when more environmental variables are added, is to be investigated.

Finally, for future work, it is suggested to expand the features of the developed tool in order to be able to simulate the entire installation of an OWF including also uncertainties concerning the cost, the availability of components, the duration of operations and failure events. Incorporating these uncertainties will contribute significantly towards the reduction of their current high costs.

2.6. EXTENSION OF PROPOSED METHOD

It is worth mentioning that also in [31] similar approaches were followed using extended models of copulas that are named Vines. Vines are pairs of bi-variate copulas that are able to represent the dependence between multiple random variables. Previous studies on the application of vine copulas for describing sea states have already showed the relevance of modelling the dependence between wind and wave conditions [1, 31, 32].

In [33] a similar approach is proposed which can be seen as an extension of the method presented in this chapter. In this approach a Vine copula was used in order to produce multivariate synthetic time series including the wave period, the tidal velocity and the current velocity. This with the purpose of applying it on a topic concerning the O&M of tidal energy converters (TECs). The key findings from extending this method as shown in [33] are the following:

- Using a D-vine was possible to generate synthetic time series that incorporate the dependencies between wind speed, wave height, wave period and current velocity

- More possible realizations of the environmental conditions are possible to be represented while the persistence of the operational windows remains comparable to the original limited dataset

- It is possible to incorporate the dependent uncertainties of the offshore environmental conditions into the decision making processes for the replacement of tidal energy converters

- A replacement maintenance application case concerning a TEC concept from Damen Shipyards for a specific tidal location in Canada was examined to illustrate the impact of this approach on decision making.

- A decision support tool utilizing Semi-Markov Decision Process (SMDP) was used to determine “optimal" replacement maintenance policy (i.e. combination of failed TECs to initiate actions for replacement). This tool allowed the description of multiple failing TECs in different tidal platforms, ensuring the minimization of maintenance costs and revenue losses.

- The impact of using vine copula-based synthetic time series was also investigated. To achieve this the durations of certain activities were calculated and compared to the case where the original limited dataset was used. It was found that using the original limited dataset could lead to a considerable underestimation of the operational windows and maintenance replacements, compared to the case where vine copulas were used to generate time series.

2

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3

CONSTRUCTION ACTIVITIES DURATION

Time isn't the main thing. It's the only thing.

Miles Davis

Offshore wind operations face important 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 approaches do not take into account the dependence between the activities or the learning effect. This chapter proposes methods to improve the description of the stochasticity of the duration of installation activities of offshore wind turbines (WTGs). To achieve this, the use of non-parametric Bayesian Networks (NPBN) are explored using real data from realized installation projects. It was found that the proposed approach allows for a proper representation of the uncertainty on the duration of the installation activities that can lead to more accurate and reliable estimates of the installation durations. Hence, this can effectively support decision makers in optimizing the work planning of offshore activities.

Parts of this chapter have been published verbatim in PSAM proceedings [1].

3.1. INTRODUCTION AND MOTIVATION

DURING the last years, it became apparent that offshore wind energy can significantly contribute to the essential transition from conventional energy sources to renewables [2, 3]. 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 energy 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. In addition, 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 [4–11]. 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 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.

3.1.1. OUTLINE

This chapter explores different methods for improving the modeling of the duration of construction activities. Non parametric Bayesian Networks are utilized to better describe the dependence between the construction activities. Also, as possible extension autoregressive models and dynamic Non parametric Bayesian Networks are recommended to describe the learning effect during the construction project and the combination of learning effect and construction activities dependence. The theoretical background of the utilized methods can be found in Section 3.2 while Sections 3.3 and 3.4 present the application of the methods for describing the activities dependence and a possible extension to describe the learning effect and their combination respectively.

3.2. THEORETICAL BACKGROUND

3.2.1. BAYESIAN NETWORKS

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 [12]. 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 [13]. Hence, for NPBNs it is only required to specify the empirical marginal distribution for each variable and a (conditional) rank correlation for each arc [14]. A complete description of NPBNs is out of the scope of this chapter. For a complete overview, the reader is referred to [15] and [14].

There are different families of copulas. A detailed description of these can be found in [16]. 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. 3.2.1, where $F_X(x)$ is the rank of variable X.

$$r(X,Y) = \frac{E(F_X(x)F_Y(y)) - E(F_X(x))E(F_X(x))}{\sigma_{F_X(x)}\sigma_{F_Y(y)}} \tag{3.1}$$

3.3. DEPENDENCE BETWEEN ACTIVITIES

THIS section investigates 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

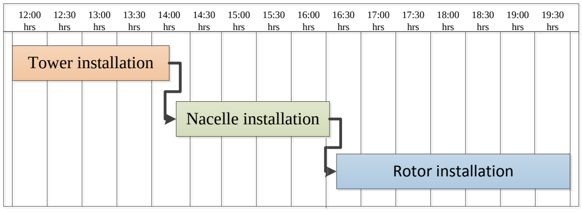


Figure 3.1: Order of installation activities of WTGs.

neglecting dependence is presented.

3.3.1. MODELING METHODOLOGY

The proposed methodology to model the dependence between construction activities can be summarized in the following steps:

1. Cluster the activities in a way that represents the construction process
2. Analyse the historical data to find for which construction activities a description of uncertainty and dependence would be sensible
3. Identify the appropriate bivariate copula that describes the dependence between pairs of installation activities
4. Build a BN model that describes the dependence between the selected installation activities

3.3.2. APPLYING METHODOLOGY

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 3.1, a hypothetical simple Gantt chart illustrates the order of consolidated installation activities for one WTG.

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

Table 3.1: Characteristics of investigated copulas.

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 3.1). In the calculation of these durations the delays due to weather conditions were not included.

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 $\boldsymbol{\Phi}$ denotes the standard normal cumulative distribution and $\boldsymbol{\Phi}_\rho$ denotes the standard bivariate normal distribution with Pearson correlation ρ.

The performed tests concern: (i) the computation of semi-correlations introduced in [16] and (ii) the Cramér-von Mises statistic presented in the "blanket test" described in [17], 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 [11, 18, 19].

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 3.2 and the results are visualized together with the normal transforms in Figure 3.2. 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 3.3 and the normal transforms are presented in Figure 3.3. 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 $C_n(u)$ given by:
$C_n(\boldsymbol{u}) = 1/n\sum_{i=1}^{n} \mathbf{1}(U_1 <= u_1, U_2 <= u_2), \boldsymbol{u} = (u_1, u_2) \in [0,1]^2$
and the parametric copula $C_{(\theta_n)}(\boldsymbol{u})$, as presented in eq. 2.10. This shows which copula family fits better the empirical copula of each pair of activities. In Table 3.2 and Table 3.3 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 [17] was also performed, with a sample size equal 1000 and grid space equal to 300, resulting in the p-values presented in Table 3.4.

	ρ	ρ_{NE}	ρ_{SE}	ρ_{SW}	ρ_{NW}	S_{gauss}	S_{gumbel}	$S_{clayton}$
Tower-Nacelle	0.4	0.226	-0.0668	-0.233	-0.576	0.453	**0.397**	0.674
Tower-Rotor	0.28	0.369	0.0186	-0.291	-0.0679	0.643	**0.586**	0.864
Nacelle-Rotor	0.53	0.693	-0.366	0.0320	0.495	**0.297**	0.337	0.357

Table 3.2: Summary of performed tests for vessel $V1$

	ρ	ρ_{NE}	ρ_{SE}	ρ_{SW}	ρ_{NW}	S_{gauss}	S_{gumbel}	$S_{clayton}$
Tower-Nacelle	0.37	0.2023	0.271	-0.0226	0.0027	0.437	**0.363**	0.755
Tower-Rotor	0.05	-0.198	0.075	0.291	-0.310	0.365	**0.359**	0.382
Nacelle-Rotor	0.01	0.222	0.426	0.219	-0.162	0.531	0.523	**0.481**

Table 3.3: Summary of performed tests for vessel $V2$

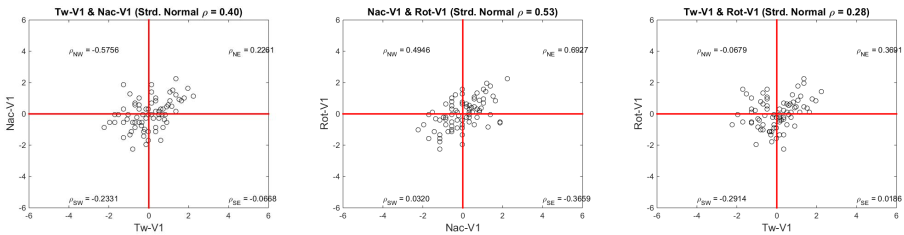
Based on the computed p-values, it is not possible to reject any of the investigated copulas. Based on the analysis described above, it was decided to use the Gaussian copula as a fair representation for all bivariate pairs of installation activities. This copula family will be used in the BN to represent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

BUILDING BN MODEL

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 [20]. 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.

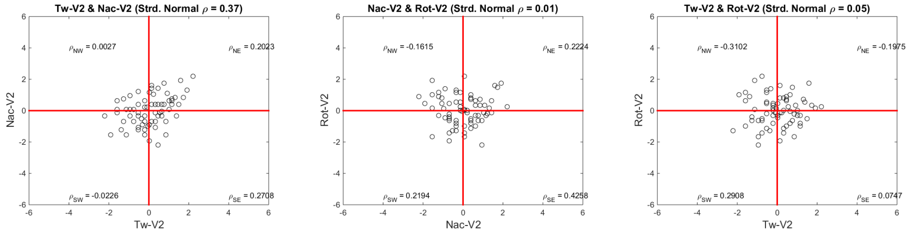
	$V1$ Gauss	$V1$ Gumbel	$V1$ Clayton	$V2$ Gauss	$V2$ Gumbel	$V2$ Clayton
Tower-Nacelle	0.758	0.841	0.484	0.768	0.859	0.417
Tower-Rotor	0.503	0.603	0.33	0.847	0.889	0.838
Nacelle-Rotor	0.949	0.889	0.869	0.639	0.653	0.709

Table 3.4: P-values from bootstrap



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

Figure 3.2: Semi-correlations and normal transforms for pairs of activities performed by vessel V1.



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

Figure 3.3: Semi-correlations and normal transforms for pairs of activities performed by vessel $V2$.

For both vessels, models with serial connection were chosen (Figure 3.4 and 3.5. for vessel V_1 and V_2 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 3.5 and 3.6. 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.

As it was mentioned before, 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 [14]. 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

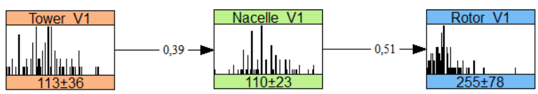


Figure 3.4: BN model for $V1$.

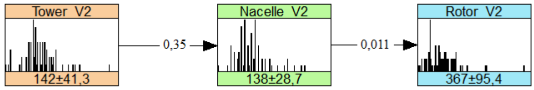


Figure 3.5: BN model for $V2$.

	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 3.5: Empirical and BN rank correlation matrices regarding vessel $V1$

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 3.7 7 while DNR is the determinant of the rank correlation matrix that is obtained by transforming the marginals to standard normals.

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.

3.3.3. TEST CASE FOR DEPENDENCE OF DURATION OF ACTIVITIES

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 3.6. First the details of a particular installation scenario (i.e. details of OWF and vessels, available environmental time series, environmental limits etc.) are loaded.

	Empirical rank correlation			BN rank correlation		
	Tower-V2	Nacelle-V2	Rotor-V2	Tower-V2	Nacelle-V2	Rotor-V2
Tower-V2	1	0.342	0.0379	1	0.353	0.0039
Nacelle-V2	0.342	1	-0.0098	0.353	1	0.0107
Rotor-V2	0.0379	-0.0098	1	0.00394	0.0107	1

Table 3.6: Empirical and BN rank correlation matrices regarding vessel $V2$

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

Table 3.7: Values of determinants for models validation.

This scenario is simulated N_ts times for every available environmental time series to introduce the weather risk and 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 N_WTG are installed. Ultimately, the cumulative distribution of the duration of the WTGs installation is computed and plotted.

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 [11, 21]. 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 [9]. 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 3.8.

Results of test case The results of the simulated scenario concerning the CDFs of the total installation duration are presented in Figure 3.7. 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.

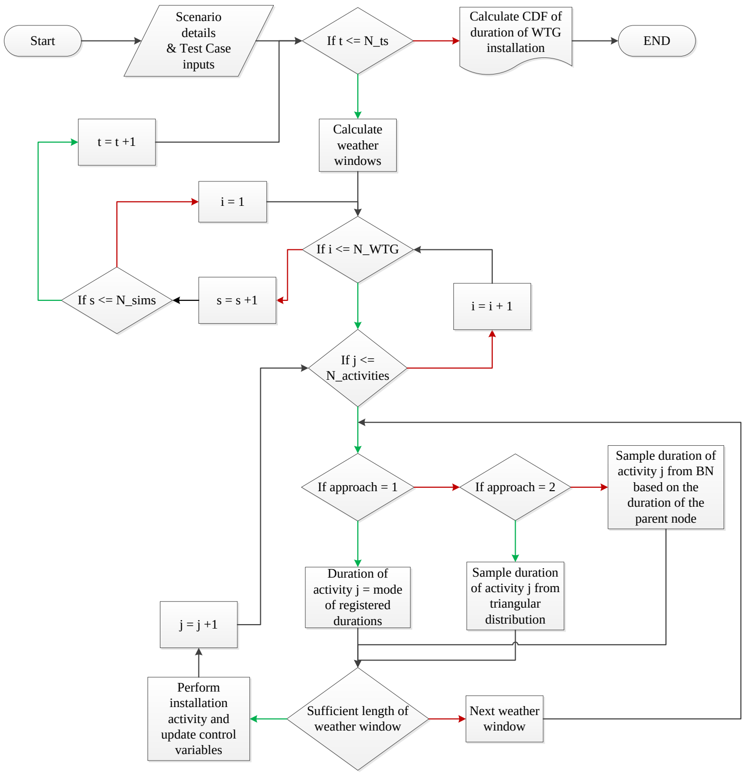


Figure 3.6: Flowchart of developed simulation algorithm (green and red arrows denote respectively positive and negative response to associated decision boxes).

Details	Values							
Number of WTGs	150							
Number of Vessels	2 (vessels V1 and V2)							
MetOcean time series	10 years of measurements for Hs and Uw							
	Tower-V1 = 115min				Tower-V2 = 125min			
Approach 1	Nacelle-V1 = 105 min				Nacelle-V2 = 125 min			
	Rotor-V1 = 230 min				Rotor-V2 = 305 min			
	V1 Triang. Distr. param.:				V2 Triang. Distr. Param.			
		a	b	c		a	b	c
Approach 2	Tower	45	115	226	Tower	65	125	310
	Nacelle	55	105	170	Nacelle	85	125	255
	Rotor	165	230	653	Rotor	245	305	795
Approach 3	Developed NPBN for V1				Developed NPBN for V2			

Table 3.8: Details of simulated scenarios

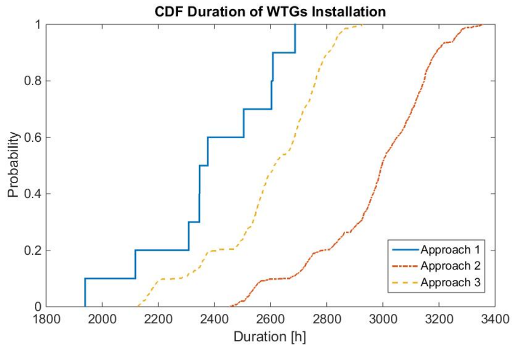


Figure 3.7: Obtained distribution of the simulated test case for different approaches.

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 50th percentile (P50) 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.

3.3.4. CONCLUSIONS CONCERNING DEPENDENCE OF CONSTRUCTION OPERATIONS

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. The presented method used the theory of Bayesian Networks 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 a difference up to 9 days less for the the estimated total duration P50 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.

3.4. POSSIBLE EXTENSION - LEARNING EFFECT

THE learning effect during construction projects with repetitive activities has been identified in the past as an important factor. Offshore construction activities such as the the installation activities of OWFs have a repetitive nature. However, this effect has not been modeled in detail in the existing models. In the following subsection a possible extension is recommended for taking into account the learning effect during the installation of OWFs.

3.4.1. PROPOSED MODELING METHODOLOGY

The methodology to describe the learning curve is described in the following steps:

- Step 1: Investigation of significance of learning effect for different activities. First of all the significance of learning effect for the different groups of activities should be explored.
- Step 2: Model the learning effect. Investigate appropriate autoregressive models for describing the learning effect for the activities that presented a significant effect from Step 1. In order to investigate different ARMA - ARIMA models the built-in econometrics toolbox in MATLAB can be used. This toolbox can support the analysis and assists in finding the model that fits better the existing data. It also enables the use of AIC and BIC criteria.
- Step 3: Lastly, the impact of the different approaches in modeling learning effect can be explored by the use of a realistic test case.

Investigate significance of learning effect A preliminary investigation was conducted. For this, real data provided by the Dutch marine contractor Van Oord were analyzed. These data were collected during the installation of offshore wind farms that were performed in the past. These data concerned the durations of the different activities performed. It was chosen to focus on the most important activities for the installation of WTGs and foundations when the vessel is at the site. For this purpose all the relevant sub-activities were clustered into the following groups:

1. preparation activities;
2. installation of tower;
3. installation of nacelle;
4. installation of rotor (3 blades);
5. finalization activities

Plots of the duration of the activities concerning the installation of WTGs of anonymized projects with the order these were performed gave an indication of the significance of the learning effect. In Table 3.9 are shown the results of fitted linear regression model along with the p-values (Note: these values were calculated using fitlm function of Matlab). The p-values concern the t-statistic for each coefficient that tests the null hypothesis that the corresponding coefficient is zero against the alternative that it is different from zero, given the other predictors in the model. In the presented case, there is only one predictor; i.e. the previous value of the duration for a particular activity. A p-value of the t-statistic below 5% means that there is no significant trend in at the 5% significance level. The analysis of the available data showed that a significant negative trend was found for installation of towers, nacelles and rotors. On the contrary, no trend was found for the preparation and finalization activities. These findings were consistent for the majority of the different available projects and vessels.

Find appropriate model for learning effect The next step is to find an appropriate model that describes the learning effect for those activities which a significant learning effect was found in Section 3.4.1. To achieve this the built-in econometrics toolbox of MATLAB can be utilized. Different tests should be performed to find the most suitable autoregressive model for the respective activities.

Combination of learning effect and dependence of activities duration Finaly, one would think what would be the impact when combining the dependence between the activities with the learning effect. In order to investigate this, it is recommended to extend the NPBN presented in Section 3.3.2. The developed NPBN can be copied as many times as the chosen relevant lags in order to create a dynamic NPBN that will capture the temporal dependence of the construction activities.

3

Activity	Estimate	P-value
'V2_Pr2_FOU_Prep'	0.233	0.667
'V2_Pr2_FOU_MPs'	-6.079	**2.657e-08**
'V2_Pr2_FOU_TPs'	-2.591	**1.469e-09**
'V2_Pr2_FOU_Fin'	-0.172	0.336
'V2_Pr2_WTG_Prep'	0.116	0.658
'V2_Pr2_WTG_Twr'	-1.243	**3.228e-09**
'V2_Pr2_WTG_Ncl'	-0.614	**8.147e-05**
'V2_Pr2_WTG_Rot'	-1.180	**0.028**
'V2_Pr2_WTG_Fin'	0.065	0.522
'V1_Pr2_FOU_Prep'	0.303	0.065
'V1_Pr2_FOU_MPs'	-4.90	**2.917e-13**
'V1_Pr2_FOU_TPs'	-2.583	**8.824e-14**
'V1_Pr2_FOU_Fin'	-0.071	0.512
'V1_Pr2_WTG_Prep'	-0.540	0.099
'V1_Pr2_WTG_Twr'	-0.646	**2.145e-04**
'V1_Pr2_WTG_Ncl'	-0.628	**1.551e-09**
'V1_Pr2_WTG_Rot'	-2.101	**2.943e-09**
'V1_Pr2_WTG_Fin'	-0.004	0.968
'V1_Pr1_WTG_Prep'	-1.059	0.079
'V1_Pr1_WTG_Twr'	-1.253	**0.0019**
'V1_Pr1_WTG_Ncl'	-0.938	**0.0037**
'V1_Pr1_WTG_Rot'	-1.851	**4.3503e-04**
'V1_Pr1_WTG_Fin'	-0.563	**0.004**
'V3_Pr3_FOU_Prep'	-1.351	0.385
'V3_Pr3_FOU_MPs'	-10.968	**2.246e-04**
'V3_Pr3_FOU_TPs'	-19.330	**2.504e-07**
'V3_Pr3_FOU_Fin'	-3.534	**0.021**

Table 3.9: Significance of learning effect for different activities and projects.

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III

Enabling Decisions with Limited Data

4

LEARNING FROM EXPERTS

An expert is a man who has made all the mistakes which can be made, in a narrow field.

Niels Bohr

Often in engineering or scientific applications relevant data for the problem under investigation are limited. In these cases, expert judgments can be used. However, in order to obtain valuable assessments the elicitation, evaluation and combination of the expert judgments should be performed in a structured manner. One of the most widely accepted and applied methods for structured expert judgments is Cooke's Classical model. The Cooke's Classical model for elicitation and combination of expert judgments has been used in science and engineering since at least the early 1990's. The most widely used program for applications of this model is EXCALIBUR. However, its code is not available for practitioners, which limits the accessibility and potential of the method. In this Chapter, a recently developed MATLAB toolbox (ANDURIL) is presented with the intention to fill in this gap. The software has been tested in a recent real-life application reproducing the results of EXCALIBUR. Various advantages for the users from having the developed source code available for practice. Recent updates of the original toolbox and applications utilizing the developed toolbox are also mentioned.

Parts of this chapter have been published verbatim in SoftwareX **7**, (2018) [1].

4.1. METHODS FOR EXPERT JUDGMENTS

IN practice, engineers, scientists and decision makers in general are often confronted with problems where sufficient relevant field data (or measurements) are not available. In these cases, modeling or expert judgments become an alternative source of valuable data.

To be able to use the judgments of different experts, these should be combined for the variables of interest. There are different approaches and methods for aggregating the assessments of the experts. The subject of treating expert judgments as an alternative source of data has been extensively discussed [2–5]. The available methods can be divided in behavioral and mathematical approaches [6]. Mathematical approaches combine by utilizing various mathematical methods the elicited individual judgments (expressed as subjective probabilities) of the experts concerning the uncertain quantity under investigation. On the other hand, behavioral methods aim at achieving consensus among the experts who are usually allowed and encouraged to discuss and share assessments. The most popular behavioral methods are the Delphi technique and the Nominal Group. For this dissertation Cooke's classical model was chosen to be applied. This method was chosen because it has been shown that such a mathematical approach has an advantage over behavioral approaches [6].

4.2. CLASSICAL MODEL FOR STRUCTURED EXPERT JUDGMENT

FOR the aforementioned reasons, Cooke in [2] has developed a method (i.e. Cooke's classical model for structured expert judgment) to aggregate expert judgments based on performance measures. Cooke's classical model (CM) is the most widely used method in practice. It has been used in many fields including the nuclear sector, chemical & gas industry, hydraulic engineering, aerospace and aviation, occupational safety, health, banking and volcanology to name some. Up to 2008 a total of 45 applications were collected in a database [7] and at least 33 more applications have been performed since then [8].

In Cooke's classical model, the experts assess their uncertainty over two types of continuous quantities. The first type corresponds to *target variables*. These are variables whose uncertainty cannot be sufficiently described using current models or field data and hence expert judgments are required. The second type of variables queried in the classical model are the so called *seed variables*. These are variables from the experts' field which are known to the (group of) analyst(s) at the moment of the elicitation (or will become known to them post hoc) but whose true values are not known to the experts at the moment of the elicitation.

Experts are thus scored according to their performance in assessing uncertainty over seed variables. Their opinions are weighted and later combined on the basis of their performance. The purpose of the classical model is to enable rational consensus. According to [2], any methodology for structured expert judgment that aims at enabling rational consensus should comply with the following requisites:

1. Scrutability: All data and *processing tools* are open to peer review and results must be reproducible by competent reviewers.

2. Empirical control: Quantitative expert assessments are subjected to quality controls.

3. Neutrality: The method for evaluating expert opinions should encourage experts to state their true opinions.

4. Fairness: Expert opinions are not judged, prior to processing the results of their assessments.

The main concepts of Cooke's classical model are summarized below. This with the purpose of making available to the reader the main elements of the method and the developed code. For details and extensive discussion the reader is referred to [2] and supplementary material for [8].

In Cooke's classical model experts are asked to provide assessments of their uncertainty concerning continuous quantities in the form of a number of percentiles of their uncertainty distribution. Most commonly the 5^{th}, 50^{th} and 95^{th} percentiles are queried.

The percentiles are assessed for uncertain quantities which are in fact the *target variables* (or *variables of interest*). These percentiles are also queried for quantities whose value is known to the analysts (or will be known to the analysts within the time frame of the research), but is not known to the experts at the moment of the elicitation. These are called *seed* or *calibration variables* and are used to ensure empirical control of experts' uncertainty assessments. Examples of a seed variable and a variable of interest concerning the example study used in this chapter for economic growth in Mexico are:

1. Seed variable: Quarterly growth rates of gross domestic product in Mexico have been below -5% in four instances between the first trimester of 1994 and the third trimester of 2013. What was the average value of the 28-day Mexican Federal Treasury Certificates (CETES) interest rate in these four trimesters? Indicate the 5^{th}, 50^{th} and 95^{th} percentiles of your uncertainty distribution.

2. Target Variable: Consider a scenario in which, at the end of 2020, the Mexican (commercial) interest rate is between 3.5 and 4.0 percent, the unemployment rate is between 5.4 and 5.6 percent, the inflation growth rate is between 3.0 and 3.3, and growth rates of gross domestic product in the USA are between 2.8 and 3.3 percent. Please provide your estimates (5^{th}, 50^{th} and 95^{th} percentiles of your uncertainty distribution) of average gross domestic product growth rate in Mexico up to 2020.

Seed variables are used to compute two measures of performance: *statistical accuracy* or *calibration* and *informativeness*. These measures are presented next.

4.2.1. STATISTICAL ACCURACY

Assume we have answers from $e = 1,\ldots,E$ experts on $i = 1,\ldots,N$ seed variables and $1,\ldots,N_1$ target variables. Assume further that we assess three quantiles: $q_{i,5}$, $q_{i,50}$ and $q_{i,95}$ for the 5^{th}, 50^{th} and 95^{th} quantiles of each uncertain quantity. That is including the target variables. There are thus $j = 1,\ldots,4$ interquantile bins. The procedures described next may be easily extended by assuming more quantiles are assessed from each expert. For each quantity, each expert divides his/her belief range into four interquantile intervals, for which the corresponding probabilities of occurrence $p = [p_1, \ldots, p_4]$ are: $p_1 = 0.05$ for a realization value $\leq 5^{th}$ percentile, $p_2 = 0.45$ for a realization value $\in (5^{th}, 50^{th}]$ percentiles, $p_3 = 0.45$ for a realization value $\in (50^{th}, 95^{th}]$ bin, and $p_4 = 0.05$ for a realization value $> 95^{th}$ percentile. The empirical version of $p = (p_1, \ldots, p_4)$ for expert e, is denoted $s(e) = (s_1, \ldots, s_4)$, where $s_j(e)$ is equal to the number of realizations of seed variables falling in the j^{th} interquantile assessed by expert e divided by the total number of seed variables.

$$
\begin{aligned}
s_1(e) &= \frac{\text{Number of realizations} \leq 5^{th} \text{ quantile}}{N} \\
s_2(e) &= \frac{\text{Number of realizations} \in (5^{th}, 50^{th}] \text{ quantile}}{N} \\
s_3(e) &= \frac{\text{Number of realizations} \in (50^{th}, 95^{th}] \text{ quantile}}{N} \\
s_4(e) &= \frac{\text{Number of realizations} > 95^{th} \text{ quantile}}{N}
\end{aligned}
$$

One way to measure the difference between p and $s(e)$ is through relative information or entropy, which is a measure of the disagreement between them.

$$
I(s(e), p) = \sum_{j=1}^{4} s_j(e) \ln \frac{s_j(e)}{p_j} \tag{4.1}
$$

Experts' assessments are treated as statistical hypotheses. Consider for each expert the null hypothesis H_0 : The inter quantile interval containing the true value for each variable is drawn independently from the probability vector p.

The quantity $2NI(s(e), p)$ where $I(s(e), p)$ is given in equation (4.1) is asymptotically χ_3^2 (the degrees of freedom are the number of interquantile intervals minus 1). This quantity can be used to test H_0 and it defines the calibration score:

$$
C(e) = P\{2NI(s(e), p) > r\} \tag{4.2}
$$

The probability in equation 4.2 can be evaluated by a χ_3^2 distribution. The calibration score $C(e)$ is the probability that a deviation at least as large as r could be observed on N realizations if H_0 were true. Where r is the percentile of interest in the χ^2 distribution of interest obtained from evaluating $2NI(s(e), p)$ for the data corresponding to a particular expert. Values of calibration close to zero mean that it is unlikely that the experts' probabilities are correct.

4.2.2. INFORMATIVENESS

The informativeness (or information score) measures the degree to which a distribution is concentrated (or spread out) with respect to a background measure. In the classical model the uniform or log-uniform background measures are used. An intrinsic range is calculated for each expert's density. The intrinsic range is obtained by adding a $k\%$ overshoot to the smallest interval containing all quantiles and realizations (when available), where k is selected by the analyst (typically $k\% = 0.1$). The lowest (l) and highest (h) values for the intrinsic range are $l_i = min\{q_{i,5}(e), v_i\}$ and $h_i = max\{q_{i,95}(e), v_i\}$ where v_i is the realization of interest. Then $q_{l_i} = l_i - k(h_i - l_i)$ and $q_{h_i} = h_i + k(h_i - l_i)$. The *information score* is then computed as:

$$I(e) = \frac{1}{N}\sum_{i=1}^{N}\left[\ln(q_{h_i} - q_{l_i}) + p_1 \ln\frac{p_1}{q_{5,i} - q_{l,i}} + \ldots + p_4 \ln\frac{p_4}{q_{h,i} - q_{95,i}}\right] \tag{4.3}$$

Notice that the information score does not depend on the realizations (other than in terms of calculating the intrinsic range when available) and hence may also be computed for the target variables. When target variables are also considered, the summation in equation 4.3 runs to N_1 which includes target variables. Also notice that in equation 4.3 a uniform Background measure is applied. For a log-uniform background measure the log of $q_{\cdot,i}$ would be used instead.

4.2.3. COMBINATION

In the classical model the combination of experts' assessments is called a *Decision Maker* (DM). This is a weighted average of individual estimates. When the weights are determined based on the performance of experts in the seed variables, we speak of *performance-based* DM. The DM probability densities $f_{DM,i}$, for every item i, are thus:

$$f_{DM,i} = \frac{\sum_{e=1}^{E} w_\alpha(e) f_{e,i}}{\sum_{e=1}^{E} w_\alpha(e)} \tag{4.4}$$

The weighs for each expert $w_\alpha(e)$ are given by the product of calibration and information scores when a certain threshold in calibration is attained. That is:

$$w_\alpha(e) = 1_{\{C(e)>\alpha\}} C(e) I(e). \tag{4.5}$$

Where $1_{\{A\}}$ denotes the indicator function for A. Values of $C(e) < \alpha$ would fail to confer the study the required level of confidence. Note that the DM can also be evaluated in terms of calibration and information. For this reason the DM is referred to as the "virtual expert". In the performance based DM the value of α is chosen such that the calibration score of the DM is maximized. The weights in Cooke's model are weakly asymptotically strictly proper. This property ensures that if an expert wishes to maximize her long run expected weight then she should do this by stating her true beliefs as answer to the seed variables [2].

There are different types of DMs obtained from different weighting (or combination) schemes. The simplest weighting schemes are equal weighting and user-defined weights which fall outside of the performance-based DMs. The *Global Weights* DM is computed as described above while the *Item Weights* DM computes the scores in equation 4.5 using the information score per item rather than the average information score (equation 4.3).

Once the different combination schemes have been investigated with Cooke's method it is common practice to perform robustness analysis. This refers to the process of excluding one seed variable or one expert at the time and re-do the analysis with the methods described in this section. However, the investigation of robustness does not necessarily has to be a "leave one out at the time" procedure. This has been discussed extensively in the context of out of sample performance of Cooke's method in recent years [8, 9].

4.3. ANDURIL DESCRIPTION

In the majority of past studies, which utilized the Cooke's method, the analysis and synthesis of expert opinions based on experts' performance in judging uncertainty were performed with the free, closed source software EXCALIBUR[1]. Hence, the value of EXCALIBUR over the past 25 years is undeniable. However, there are some limitations that stem from the fact that EXCALIBUR is a closed source software. Recently, a number of cross validation studies have been conducted using Eggstaff's MATLAB code [8, 9]. However, this code is not publicly available and it still does not implement important features of the model such as the item weighting scheme [8].

First, EXCALIBUR being a closed source software makes the understanding of the method more difficult and time consuming to researchers who are recently introduced to the method. Moreover, it is impossible to modify it with the purpose of expanding its features or investigate different approaches for combination of expert judgments. For these reasons, an open source software for Cooke's classical model [1] was developed as part of this doctoral research project. This software consists of a number of different functions which were collected in a MATLAB toolbox.

The developed toolbox was named ANDURIL[2]. Moreover, the freely available[3] ANDURIL provides the user with the required transparency of all the calculations in CM (e.g. calculations of performance measures and the aggregation of expert judgments) and it is easily modifiable by intermediate MATLAB users. This is expected to be of benefit for practitioners and researchers of CM.

A brief description of the developed MATLAB toolbox can be found in the following subsections.

[1] EXCALIBUR is freely available at: http://www.lighttwist.net/wp/excalibur.

[2] In order to avoid confusion of the minority of people, who are not familiar with the universe of Lord of the Rings by J.R.R. Tolkien, the authors would like to clarify the inspiration for the name of the developed Matlab toolbox. Andúril was the name of the sword of Aragorn, the son of Arathorn, which was reforged from the shards of Narsil (the sword that was used by Isildur to cut the One Ring from Sauron's hand). Excalibur is also the name of the legendary sword of King Arthur. Similarly to the sword, the source code of EXCALIBUR software remained accessible only to a few worthy ones. Therefore, the researchers and practitioners could only admire and use the software without being able to further investigate and explore developments of the method. To change this, the existing software had to be "broken to pieces" and then "reforged". Naturally, the name of the resulting new open source Matlab toolbox is ANDURIL. Hopefully, this will help in bringing peace to troubled researchers and practitioners of Cooke's classical model.

[3] ANDURIL is freely available at: https://github.com/ElsevierSoftwareX/SOFTX_2018_39.

4.3.1. SOFTWARE ARCHITECTURE

The first version of ANDURIL did not have a user interface, but there was a main script named `ANDURIL_Main` that can be used by the user to enter the data and run the desired analysis. The supported functionalities of Cooke's classical model by ANDURIL which can be accessed by `ANDURIL_Main` are presented below.

The main script `ANDURIL_Main` that can be used to apply Cooke's classical model to analyze and synthesize expert judgments by using ANDURIL. ANDURIL supports the following features:

1. Calculation of DM using global weights
2. Calculation of DM using item weights
3. Calculation of DM using equal or user defined weights
4. Optimization of DM
5. Robustness check itemwise
6. Robustness check expertwise
7. Plotting assessments itemwise
8. Plotting robustness results

ANDURIL consists of a number of different functions to support the aforementioned functionalities. The developed functions can be grouped according to their purpose. The different groups of functions are:

1. import values
2. analysis of judgments
3. synthesis of judgments
4. post-processing

A description of the main functions of ANDURIL is given in Table 4.1.

4.3.2. VALIDATION OF ANDURIL

ANDURIL has been validated with EXCALIBUR. For this purpose a recent structured expert judgment (SEJ) study concerning the estimation of GHG emissions in Mexico for 2020 and 2030 was used as an illustrative example [10]. The part of the study that is used to validate ANDURIL is the one concerning the estimation of Gross Domestic Product. In this study 9 experts participated and provided the 5^{th}, 50^{th} and 95^{th} percentiles of their uncertainty distribution regarding 13 seed variables and 6 target variables. The results obtained from applying ANDURIL to the test case are presented and compared with those obtained from EXCALIBUR.

Function's Name and Description
`calscore`: Calculates the statistical accuracy (or calibration score) of expert *e* over the set of *seed items* (eq. 4.2).
`calculate_information`: Calculates the relative information (or information score) of expert *e* over the set of *seed items* as well as the information score of every expert over all items (eq. 4.3).
`global_weights`: Calculates the calibration score, the information score over the seed items and subsequently the weight of every expert *e*.
`calculate_DM_global`: Calculates the distribution of the DM for every item, using the global weights or equal weights weighting schemes.
`item_weights`: Calculates the weights of every expert *e* for every item. The main difference with the global weights weighting scheme is that the weights are different for every item. In this way, the opinion of every expert has a different weight for every item. This is achieved by using the relative information of every particular item.
`calculate_DM_item`: Calculates the distribution of the DM for every item using the item weights weighting scheme.
`DM_optimization`: Calculates the distribution of the DM for every item using the significance level `alpha` (α) that optimizes the DM in terms of statistical accuracy.
`Checking_Robustness_items`: Calculates the performance measures (calibration score, information score over seed variable and over all variables with respect to the background measure) of the DM that occurs when up to `N_max_it` *seed item(s)* are excluded at most. It calculates the performance measures for every possible combination, starting from excluding one up to `N_max_it` *seed items* at a time.
`Checking_Robustness_experts`: Calculates the performance measures of the DM that occurs when up to `N_max_ex` *expert(s)* are excluded at most, similarly to `Checking_Robustness_items`.
`plotting_itemwise`: This function produces as many plots as the total number of items (i.e. seed and target items). Every plot presents the assessments (i.e. 5^{th}, 50^{th}, 95^{th} percentiles) of every expert *e* as well as every DM, for every particular item *i*.
`robustness_plots`: Produces three box plots. Each box plot corresponds to one measure of performance in judging uncertainty. Namely statistical accuracy, information score over all items and information score over seed items. Each box plot presents how the values of every measure vary with the number of excluded items (x-axis). In these plots a horizontal line is also plotted, that shows the values of the DM whose robustness is under investigation.

Table 4.1: Main functions of ANDURIL.

Five different DMs were calculated using ANDURIL:

1. The global weight decision maker(DM_1), calculated using the function `calculate_DM_global`,
2. the item weight (DM_2) using the function `calculate_DM_item`,
3. the equal weight (DM_3) calculated using the function `calculate_DM_global` with equal weights for every expert,
4. the optimized global weight decision maker (DM_4) which was calculated using the function `DM_optimization` and
5. the user weight (DM_5) which was calculated using the function `calculate_DM_global` while giving to expert 5 and 6 weights equal to 0.4 and 0.6 respectively.

It should be noted that the background measure for every item was chosen as uniform. However, the same DMs were calculated and validated when the log-uniform background measure was used for every item.

The comparison of the obtained quantiles using ANDURIL and EXCALIBUR is presented in Table 4.2. As it can be seen, there are very small differences between the output of EXCALIBUR and ANDURIL due to differences in the precision of the calculating engine. Particularly, the maximum difference is 0.0005 in absolute value across the quantiles of the DMs of interest.

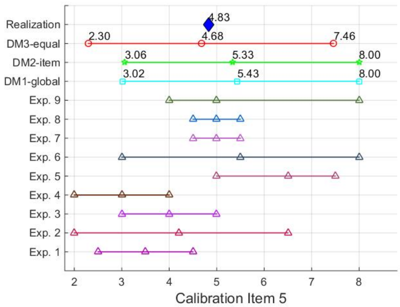
	EXCALIBUR			ANDURIL		
Name	q_5	q_{50}	q_{95}	q_5	q_{50}	q_{95}
DM_1	3.02	5.431	8.000	3.0201	5.4311	8.000
DM_2	3.063	5.327	8.000	3.0633	5.3275	8.000
DM_3	2.297	4.684	7.463	2.2971	4.6840	7.4626
DM_4	3.021	5.44	7.999	3.0209	5.4395	7.9994
DM_5	3.098	6.026	7.928	3.0978	6.0263	7.928

Table 4.2: Comparison of the four DMs' quantiles regarding seed item 5 using ANDURIL and EXCALIBUR.

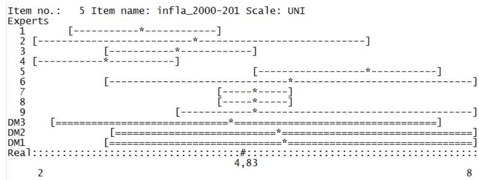
Furthermore, Figure 4.1 shows the comparison of the obtained plots for every individual expert and DMs (DM_1, DM_2 and DM_3) concerning seed item 5. The plots of ANDURIL were produced using the function `plotting_itemwise` and show that the same results are obtained with EXCALIBUR.

4.4. IMPACT OF ANDURIL

As it was mentioned before, the value of EXCALIBUR software is undeniable. However, the fact that EXCALIBUR is a closed source software causes some limitations for researchers and practitioners of Cooke's classical model. These limitations were investigated by using ANDURIL. In this section, it is illustrated how limitations regarding *intrinsic range, item weights, distributions of DMs* and *robustness* can be overcome.



(a) ANDURIL



(b) EXCALIBUR

Figure 4.1: Comparison of obtained plots for the assessments of all experts and DMs concerning seed item 5.

4.4.1. INTRINSIC RANGE

The bounds of the intrinsic range for every item i (i.e. q_{li} and q_{hi} introduced in section 4.2.2) are calculated by considering the assessments of every expert; even the ones with zero weights. Moreover, the intrinsic range for a calibration item takes into consideration the realization of the seed variable. One could argue that for the calculation of the DM's distribution only the assessments of the experts with non-zero weights could be used. This is not possible to be investigated using EXCALIBUR.

For this reason, one of the functions of ANDURIL (i.e. `calculate_DM_global`) was modified in order to investigate the effect of calculating the intrinsic ranges of every item by: i) taking into account the realization and the judgments of only those experts with non-zero weights (that produces `DM1_alt1`) and ii) taking into account only the judgments of the experts with non-zero weights (that produces `DM1_alt2`). This new function was named `alter_calc_DM_global`.

Tables 4.4, 4.5 and 4.6 present the quantiles of DM_1, `DM1_alt1` and `DM1_alt2` respectively. Some differences can be observed, especially (as expected) in quantiles q_h and q_l of every item. Particularly, the maximum absolute difference between DM_1 and `DM1_alt2` concerns the q_h quantile of seed item 8. One may investigate whether these small differences between DM_1 and `DM1_alt2` (or `DM1_alt1`) concerning q_5, q_{50} and q_{95} quantiles would result or not in differences in the measures of performance of the DMs. To investigate this, in Table 4.3 the measures of performance in judging uncertainty are presented for each DM. Some expected small differences can be observed in the information scores, because the intrinsic range of every item reduces when the quantiles of the experts with zero weights are not taken into account. However, a large absolute difference (equal to 0.189) was observed when comparing the calibration score of DM_1 with that of `DM1_alt1` or `DM1_alt2`. The reason of this 71.3% increase in calibration score, is that the changes in Q5 of `DM1_alt1` and `DM1_alt2` regarding seed item 10 caused the realization to fall into the first interquantile range. The calibration score in equation 4.2 is a fast function. Small changes in the model may lead to changes in orders of magnitude of the score. Especially when the number of seed variables is low as is usually the case in applications. It should be mentioned that such large differences in values for the intrinsic range may not be always observed in different applications. Nor the consequences of choices for intrinsic ranges in performance measures should necessarily follow the same pattern as in our presentation. This issue has not been discussed in literature for example in those related to out of sample performance of Cooke's model [8, 9]. This is a subject that could be further explored with the aid of ANDURIL.

	Calibration Score	Information Score (All it.)	Information Score (Seed it.)	Un-normalized Weights
DM_1	0.2650	0.8063	0.9548	0.2531
`DM1_alt1`	0.4540	0.8366	0.9920	0.4504
`DM1_alt2`	0.4540	0.8413	0.9988	0.4535

Table 4.3: Measures of performance of DMs.

	q_l	q_5	q_{50}	q_{95}	q_h
Seed Item 1	-4.7	3.35	27.46	59.67	87.7
Seed Item 2	-1.15	16.40	36.06	49.83	54.65
Seed Item 3	-10.1	25.89	52.10	89.44	99.1
Seed Item 4	0.2	4.33	10.84	19.86	21.8
Seed Item 5	1.4	3.02	5.43	8.00	8.6
Seed Item 6	1.00	50.00	74.46	99.69	109
Seed Item 7	1.2	4.00	5.35	6.00	10.8
Seed Item 8	-5.957	5.01	5.95	6.99	103.927
Seed Item 9	-1.92	1.80	2.44	3.50	30.72
Seed Item 10	2.1	5.17	6.03	8.60	12.9
Seed Item 11	0.03	0.95	1.35	1.50	9.27
Seed Item 12	1.49	2.51	3.74	5.19	6.41
Seed Item 13	0.344	0.48	0.88	0.95	1.016
Target Item 1	0.77	1.79	3.37	4.10	5.93
Target Item 2	0.675	1.23	2.44	3.20	4.575
Target Item 3	1.6	3.90	4.58	6.00	6.4
Target Item 4	0.86	3.00	3.88	4.50	4.94
Target Item 5	0.67	1.60	2.79	3.70	4.63
Target Item 6	1.17	3.14	4.85	5.90	6.33

Table 4.4: Quantiles of DM_1.

4

	q_l	q_5	q_{50}	q_{95}	q_h
Seed Item 1	-2.7	3.39	27.46	59.47	65.7
Seed Item 2	12.6	16.95	36.05	49.82	53.4
Seed Item 3	18.5	27.15	52.10	89.40	96.5
Seed Item 4	2.4	4.49	10.84	19.86	21.6
Seed Item 5	2.5	3.03	5.43	8.00	8.5
Seed Item 6	45	50.00	74.46	99.65	105
Seed Item 7	3.8	4.00	5.35	6.00	6.2
Seed Item 8	-3.977	5.01	5.95	6.99	103.747
Seed Item 9	1.63	1.80	2.44	3.48	3.67
Seed Item 10	4.6	5.36	6.03	8.27	9.4
Seed Item 11	0.84	1.01	1.35	1.45	1.56
Seed Item 12	2.2	2.52	3.74	5.10	5.8
Seed Item 13	0.345	0.48	0.88	0.95	1.005
Target Item 1	1.24	1.85	3.37	4.10	4.36
Target Item 2	0.78	1.25	2.44	3.20	3.42
Target Item 3	3.69	3.90	4.58	6.20	6.21
Target Item 4	2.85	3.00	3.88	4.50	4.65
Target Item 5	1.28	1.66	2.79	3.70	3.92
Target Item 6	2.71	3.27	4.85	5.90	6.19

Table 4.5: Quantiles of `DM1_alt1`.

	q_l	q_5	q_{50}	q_{95}	q_h
Seed Item 1	-2.7	3.39	27.46	59.47	65.7
Seed Item 2	12.6	16.95	36.05	49.82	53.4
Seed Item 3	18.5	27.15	52.10	89.40	96.5
Seed Item 4	2.4	4.49	10.84	19.86	21.6
Seed Item 5	2.5	3.03	5.43	8.00	8.5
Seed Item 6	45	50.00	74.46	99.65	105
Seed Item 7	3.8	4.00	5.35	6.00	6.2
Seed Item 8	4.8	5.08	5.95	6.88	7.2
Seed Item 9	1.63	1.80	2.44	3.48	3.67
Seed Item 10	4.6	5.36	6.03	8.27	9.4
Seed Item 11	0.84	1.01	1.35	1.45	1.56
Seed Item 12	2.2	2.52	3.74	5.10	5.8
Seed Item 13	0.345	0.48	0.88	0.95	1.005
Target Item 1	1.24	1.85	3.37	4.10	4.36
Target Item 2	0.78	1.25	2.44	3.20	3.42
Target Item 3	3.69	3.90	4.58	6.20	6.21
Target Item 4	2.85	3.00	3.88	4.50	4.65
Target Item 5	1.28	1.66	2.79	3.70	3.92
Target Item 6	2.71	3.27	4.85	5.90	6.19

Table 4.6: Quantiles of `DM1_alt2`.

	It. 1	It. 2	It. 3	It. 4	It. 5	It. 6	It. 7	It. 8	It. 9	It. 10	It. 11	It. 12	It. 13
Exp. 1	0	0	0	0	0	0	0	0	0	0	0	0	0
Exp. 2	0	0	0	0	0	0	0	0	0	0	0	0	0
Exp. 3	0	0	0	0	0	0	0	0	0	0	0	0	0
Exp. 4	0	0	0	0	0	0	0	0	0	0	0	0	0
Exp. 5	0	0	0	0	0	0	0	0	0	0	0	0	0
Exp. 6	0.450	0.661	0.698	0.523	0.613	0.707	0.846	0.844	0.808	0.951	0.898	0.886	0.959
Exp. 7	0	0	0	0	0	0	0	0	0	0	0	0	0
Exp. 8	0	0	0	0	0	0	0	0	0	0	0	0	0
Exp. 9	0.550	0.339	0.302	0.477	0.387	0.293	0.154	0.156	0.192	0.049	0.102	0.114	0.041

Table 4.7: Table with weights of every expert per item regarding DM_2.

4

4.4.2. ITEM WEIGHTS

When the *item weights* weighting scheme is used to combine the expert judgments, the information score of the obtained DM and the weight that is presented in the output table from EXCALIBUR are calculated using global weights [2]. For illustration, see Figure 4.2. Therefore, it is not possible for the user to know the exact weights that were used per item. On the other hand, ANDURIL provides the user with tables `W_itm` and `W_itm_tq` which contain the weights of each expert concerning the seed variables and target variables respectively.

The normalized weights `W_itm` for every expert per seed item (which were used to obtain DM_2) are presented in Table 4.7. The experts with statistical accuracy below the significance level α will have a weight equal to zero. The experts with statistical accuracy above the significance level will have an un-normalized weight equal to the product of the statistical accuracy and the information score of each variable. In the presented example, it can be seen that although only experts 6 and 9 have non-zero weights, the weights of these two experts differ significantly from item to item (e.g. item 1 and item 13). This type of information can be valuable to the analyst, in order to visualize the impact of informativeness of every expert on the weight per item.

Results of scoring experts
Bayesian Updates: no Weights: item DM Optimisation: no
Significance Level: 0,05 Calibration Power: 1

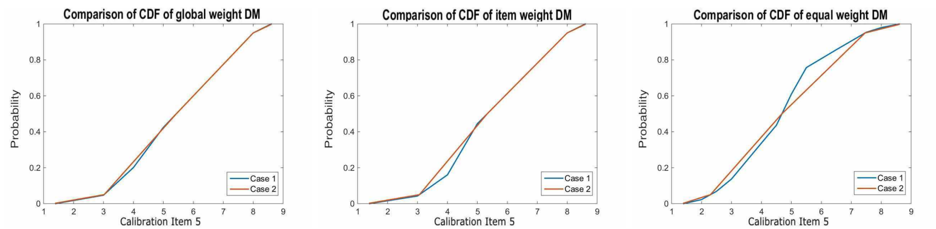
Nr.	Id	Calibr.	Mean relative total	Mean relative realization	Numb real	UnNormalized weight	Normaliz.weig without DM	Normaliz.weig with DM
1	A	5,039E-012	1,608	1,935	13	0		0
2	B	1,032E-005	1,03	1,006	13	0		0
3	C	9,215E-005	1,666	1,651	13	0		0
4	D	1,032E-005	1,302	1,484	13	0		0
5	E	0,001505	1,223	1,301	13	0		0
6	F	0,2766	1,081	1,285	13	0,3554		0,3711
7	G	0,0001545	1,825	1,944	13	0		0
8	H	1,363E-005	1,698	1,913	13	0		0
9	I	0,05304	1,078	1,285	13	0,06813		0,07114
10	DM2	0,5285	0,8461	1,011	13	0,5342		0,5578

Figure 4.2: Table from EXCALIBUR including DM_2

4.4.3. DISTRIBUTIONS OF DMS

The cumulative distribution of a DM is calculated by integrating the density of the DM (equation 4.4). To achieve this, all the values of the quantiles of the experts with non-zero weights are taken into account and the cumulative probability of every unique value is computed. Hence, the $q_{i,5}$, $q_{i,50}$ and $q_{i,95}$ quantiles of the DM are obtained. In EXCALIBUR the output distributions of the DMs are calculated by linear interpolation between these three quantiles (i.e. $q_{i,5}$, $q_{i,50}$ and $q_{i,95}$) of the DM. This may lead to differences between the distributions obtained by integration (Case 1 in figure 4.3) and the distributions that are obtained by interpolating in between quantiles (Case 2 in the same figure). Functions `calculate_DM_global` and `calculate_DM_item` of ANDURIL provide the user with the DM distributions containing the quantiles of experts with non-zero weights. After using these functions for each DM, the code presented below can be used to plot and compare the distributions of DM_1 regarding seed item 5.

Figures 4.3a, 4.3b and 4.3c present the two different distributions of DMs concerning seed item 5, combined with global, item and equal weights weighting schemes respectively. From these plots, it can be seen that interpolating linearly between $q_{i,5}$, $q_{i,50}$ and $q_{i,95}$ to obtain a distribution for the DM may cause significant variations in the resulting distributions, especially when the equal weight combination is considered. The integrated cumulative distribution contains more linear components since every percentile provided by every expert is considered in the density.



(a) Global weight DM (b) Item weight DM (c) Equal weight DM

Figure 4.3: Comparison of output cumulative distributions obtained by integration (Case 1) and interpolation (Case 2) concerning (a) global weights, (b) item weights and (c) equal weights.

4.4.4. ROBUSTNESS ITEMWISE

When investigating the robustness of the obtained DM, EXCALIBUR supports the exclusion of only one item at a time for re-calculation of the new DM. Hence, it is not possible to investigate how the performance measures (i.e. Statistical accuracy and Information scores) vary as more than one item are excluded at a time. For this reason, `Checking_Robustness_items` and `robustness_plots` functions of ANDURIL were developed. The latter produces three box-plots. Each plot corresponds to one measure of performance in judging uncertainty. Namely statistical accuracy, information score over all items and information score over seed items. Examples for our demonstration case are presented in Figures 4.4, 4.5 and 4.6 for statistical accuracy, information score (over all items) and information score (over seed items) respectively.

Each box-plot presents how the values of every measure vary with the number of excluded items (horizontal axis). In these plots a green horizontal line that shows the values of the initial DM whose robustness is under investigation. A magenta marker shows the geometric mean for every number of removed items.

It should be noted that when the number of excluded seed items increases there is the possibility that for some combinations (of excluded seed items) the calibration score of all experts reduces below the significance level alpha, resulting in zero weights for every expert. Hence, these combinations are not considered.

As it can be seen in Figures 4.4, 4.5 and 4.6 although the interval containing 95% of the recalculated scores increases as more items are removed at a time, the median remains close to the original value (shown by the green horizontal line) for every measure of performance.

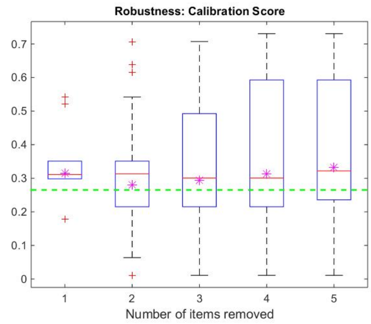


Figure 4.4: Robustness of calibration score with respect to the number of excluded seed items.

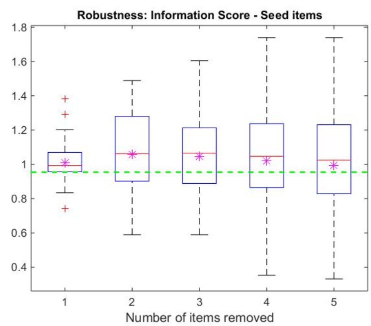


Figure 4.5: Robustness of information score over the seed items with respect to the number of excluded seed items

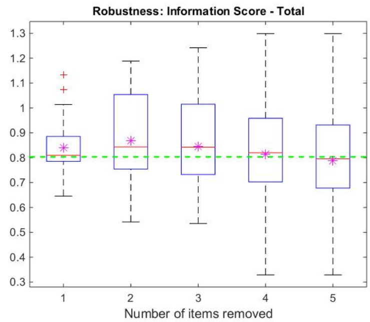


Figure 4.6: Robustness of information score over all items with respect to the number of excluded seed items

4.5. CONCLUDING REMARKS

THE developed MATLAB toolbox named ANDURIL was created to support decision making under uncertainty, when expert judgments are combined by applying Cooke's classical model for structured expert judgment. The main purpose for developing this toolbox is to create an open source software that can be used by practitioners and researcher who are interested in applying or further developing Cooke's method. The developed tool was validated with the closed source software EXCALIBUR. For this purpose a recent study concerning green house gases emissions in Mexico was used as a test case. It was shown that ANDURIL can reproduce accurately the results of EXCALIBUR.

The advantages of having a transparent open source software for applying Cooke's method were discussed. The developed toolbox can be used to investigate different ways of calculating the intrinsic range of the aggregated opinions that may result in differences in the performance measures of the obtained DMs. Moreover, it is possible to provide the analyst with the weights of each expert per item when the item weights weighting scheme is considered. Also, it gives the opportunity to the user to calculate the integrated cumulative distribution of the DM considering in the density every percentile provided by every expert with non-zero weights, rather than just interpolating in between the 5^{th}, 50^{th} and 95^{th} percentiles of the DM. Finally, the robustness of the obtained DM can be investigated while excluding more than one seed item at a time. Surely, other possibilities than the ones discussed in this chapter may be explored further by researchers interested in the method.

Concluding, the developed tool constitutes a first step towards an open source version of Cooke's classical model. Despite the limitations of the current version of ANDURIL, it is to the authors belief that the developed toolbox will be valuable to those who are interested in further investigating and applying the method. Some possible extension of the toolbox currently available in EXCALIBUR and not in ANDURIL have been discussed. It is the ambition of the developers to extend ANDURIL also with the more recent techniques of elicitation of multivariate dependence.

4.6. RECENT UPDATES

Since its creation and until the writing of this Section, ANDURIL has been continuously improved to better support the researchers and practitioners who are interested in Cooke's classical model. ANDURIL was also translated in Python [11] in order to make it accessible to those with no or limited access to MATLAB licenses. Finally, additional improvements to both versions were performed and a standalone Graphical User Interface was added to the Python version ANDURYL [12].

Until now, ANDURIL has been used to apply Cooke's classical model in [13–16]. The first application was in [13] where ANDURIL was used to analyze and synthesize the expert judgments for the application of the proposed Condition Over Time Assessment method that quantifies the uncertainty regarding the period that is required for infrastructure assets (such as bridges) to deteriorate to a given condition. Recently, ANDURIL was used in [16] to apply Cooke's Classical model with the purpose of reconstructing historical water level data based on expert assessments.

4

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5

SUPPLY DISRUPTIONS RISK

However beautiful the strategy,
you should occasionally look at the results.

Winston Churchill

Offshore asset construction is a complex and costly process that is subject to various uncertainties within the entire supply chain. Hence, both the construction management optimization and the reduction of deployment expenditures should be supported by automated decision support models which include proper representations of predominant uncertainties. One of these is the supply disruption risk that is often ignored in existing models. Therefore, this article proposes a methodology to properly take this construction risk into account. An algorithm to model this risk was developed and a study was conducted to obtain the required probability distributions of disruption delays using real data and expert judgments for an offshore wind farm construction application. The simulation of a realistic test case with an appropriately modified stochastic simulation tool showed that it is important to consider this risk in order to make optimal decisions for different offshore wind farm construction strategies.

This chapter have been published verbatim in Automation in Construction **324**, 289 (2018) [1] .

5.1. INTRODUCTION

IT is a fact that large and complex construction projects are subject to various uncertainties, which may hinder the construction processes. Therefore, models and tools, which support the management of the construction activities, must allow a proper representation of these uncertainties. Supply disruptions are an important issue that may occur in every large construction project and cause significant delays, resulting in budget and schedule overruns. Although a lot of research has been conducted in the past regarding the supply chain risk (for a thorough review the reader is referred to [2–6]), this has not been investigated for the construction of offshore assets and the fast-growing offshore wind industry in particular.

Although the previously high costs of offshore wind industry have been already partly reduced [7], the proper description of uncertainties in all different phases of the offshore wind farms' (OWFs) life cycle is needed to make offshore wind even more financially competitive. Especially, certain aspects related to construction management of OWFs should be improved to tackle the arising logistical challenges [8]. This will be particularly crucial in the coming years, in order to cope with the increasing challenges due to the necessity to move farther offshore. Furthermore, service providers have already identified "installation and logistics of OWFs as one of the main construction risks" due to capital intensive construction activities [9].

Construction activities of OWFs are not only expensive, but also complex. Their complexity stems from the fact that these are subject to various uncertainties such as environmental offshore conditions, supply disruptions and failures which may occur during the construction process. All these uncertainties should be taken into account especially during the planning phase. Otherwise, planning based on inaccurate estimates, may lead to decisions which will cause significant schedule and budget overruns during the construction phase. To avoid these undesirable outcomes, probabilistic decision support tools should be utilized in the planning phase to support optimal construction management given these uncertainties. Thus, reliable tools that take into account various uncertainties during the entire OWF supply chain, would be essential for achieving cost reduction.

For the aforementioned reasons, during the last years, various models have been developed concerning different aspects of OWFs decision support. A thorough review of the developed models until 2011 is presented in [10]. The majority of these models were focused on the maintenance strategies. Since then, more studies were conducted and various models concerning the construction (or installation) process of OWFs were developed. For example, in [11] is developed a model of the installation costs of offshore wind projects on the U.S. Outer Continental Shelf. While in [12] is proposed a method to identify the characteristics of OWFs installation processes that minimize the total time requirement for transportation and installation, without taking into account the uncertainties. Moreover, most of the developed models use a simulation-based approach and focus on developing different approaches to better describe the environmental condition uncertainty. In particular, in [13] is developed a simulation-based decision support tool to investigate different logistical approaches within the installation phase of OWFs while taking into account the external influence of weather by the use of a Markov chain with three states. In [14] is developed a software tool that relies on Monte Carlo methods to simulate multiple independent scenarios of the defined installation strategy for an offshore wind farm, while considers the risk imposed by adverse weather conditions by using a hidden Markov model (HMM). In[15] is presented the MERMAID (Marine Economic Risk Management Aid) simulation software package that was used for the analysis and optimization of marine energy installations and the investigation of a vessel designed for installation of OWFs. In[16] is proposed a methodology to produce realistic synthetic time series of wind speed and wave height in order to incorporate the environmental risk into the estimates of the duration of cable installation of OWFs. Also, in [17] is proposed a fuzzy duration forecast model for the construction of onshore wind turbines which are only subject to the impact of wind uncertainty.

Other researchers focused on investigating optimization techniques concerning the installation of OWFs. In [18] is developed an integer linear programming (ILP) model to determine the optimal installation schedule considering constraints regarding weather conditions and the availability of vessels. In [19] is proposed a Markovian model to describe the weather component and an approach that uses both general meta-heuristic optimization approaches and dedicated heuristics to optimize the project planning. In [20] is proposed a two-stage stochastic integer program that considers disruptions arising from uncertain weather conditions and the solution approach of the planning problem of wind farms is based on partial Benders decomposition strategy. In [21] is proposed a decision-support tool in a combined framework of an optimization and simulation model which improves the capabilities of both models to provide a mechanism to address current OWF installation projects while taking into account the seasonal uncertainties. In [22] is developed an optimization model for OWF installation scheduling using mixed-integer linear programming (MILP). Particularly, in [22] is recommended to develop a simulation model that takes into account possible supply disruptions and to integrate this with their model, in order to have a robust design for planning of offshore installation. Thus, none of the aforementioned models addressed the risk of supply disruptions during the installation process of OWFs. So far, only in [23] and [24] partly considered this. In [24] this is done for a limited scope regarding only the cable unavailability; whereas, in [23] is proposed a model using expert judgments which were elicited using pairwise-comparison matrices, which cannot lead to numerical estimates but only to preferences [25].

Therefore, this article proposes a methodology to model this supply disruption risk of the required components based on real data and expert judgments (Section 5.2.1). These expert judgments were elicited, evaluated and combined by using Cooke's classical model [25]. The theoretical background of the classical model and the details for applying it in this study can be found in Section 5.2.2. For the analysis and synthesis of the expert judgments, a newly developed and recently released open-source MATLAB toolbox named ANDURIL [26] (presented in Chapter 4), was used. The results of the expert judgments elicitation can be found in Section 5.3.

The current study covers the supply disruption risk of the major components which are most commonly used in OWFs. Namely, the monopiles (MPs), the transition pieces (TPs), the towers, the nacelle and the rotor that consists of 3 blades. These components of an offshore wind turbine generator (WTG) are illustrated in Figure 5.1. To quantify the supply disruptions risk an existing stochastic decision support tool (ECN Install, see

Section 5.4.1) was modified with the proposed algorithm (Section 5.2.1). This allows to simulate different scenarios and compare these in terms of the cumulative probability distributions (CDFs) of the estimated duration and cost of the installation accounting for the risk of supply disruptions (Section 5.4). Hence, the proposed method can be used to investigate the impact of supply disruptions during the construction process allowing the comparison of different scenarios and support decision makers in planning and choosing the "optimal" scenario.

Finally, it should be mentioned that the proposed methodology within this article can not only be applied to the optimization of offshore but also to inland construction management processes such as for example the road construction supply chain with its uncertainties within the entire supply chain, from the asphalt production plant until the final paving.

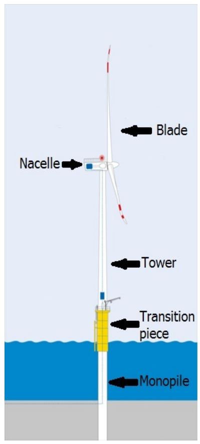


Figure 5.1: Different components of an offshore WTG.

5.2. METHODOLOGY

A methodology is proposed to include the supply disruptions risk into probabilistic models for construction of offshore assets. As it was mentioned before, the existing decision support models for scheduling of offshore constrcuction activities focus mostly on describing uncertainties regarding the environmental conditions which hinder the construction operations. Hence, the proposed methodology is particularly relevant for offshore assets. However, it could also be applied to different construction projects which are subject to various uncertainties and their planning requires probabilistic models. Assuming such a probabilistic model on hand, one who is interested in including the supply disruptions risk, should first recognize whether this is relevant for the application under investigation. If so, then the existing model should be appropriately modified in order to take into account the events that may lead to delays due to supply disruptions. Afterwards, one should investigate whether sufficient relevant data are available and perfom statistical analyses to obtain the probability distributions which are required as inputs to the modified model. If relevant data are scarce, then the application of a structured expert judgment (SEJ) method such as Cooke's classical model [25] is recommended (see Section 4.2). The proposed methodology is depicted in the form of a flowchart diagram in Figure 5.2.

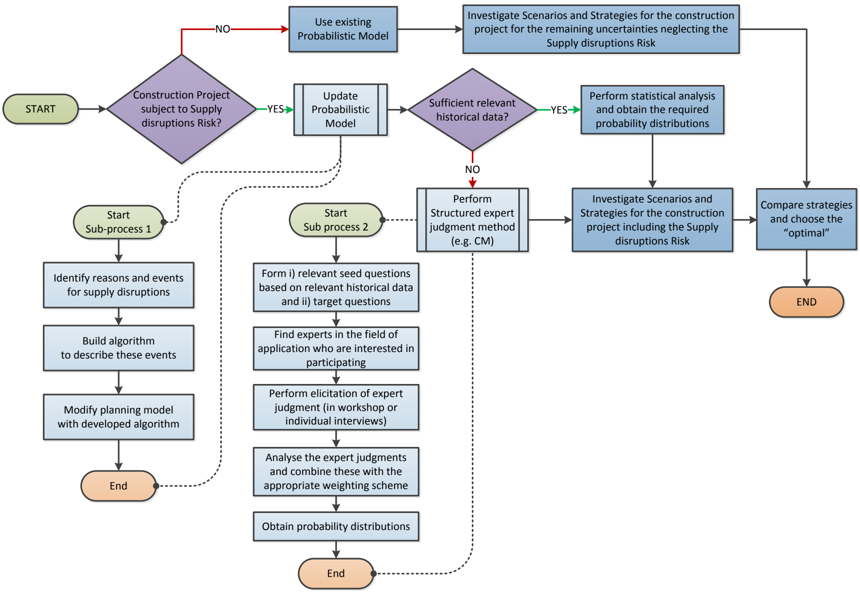


Figure 5.2: Flowchart diagram of actions one should take to include the risk of supply disruptions into a probabilistic decision support model.

In the following subsections, the proposed methodology is applied to model the supply disruptions and quantify this risk during the installation of OWFs is presented. First, in subsection 5.2.1 the reader can find a detailed description of the algorithm that was developed to model this risk. Then the application of Cooke's classical model for the quantification of the uncertainty regarding supply disruptions as well as the required theoretical background is presented in subsection 5.2.2.

5.2.1. ALGORITHM FOR MODELING SUPPLY DISRUPTIONS

Usually, different types of components of OWF such as monopiles (MPs), transition pieces (TPs), towers, blades and nacelles are transported from manufacturers to the feeder (or installation) port. Subsequently, transport vessels or installation vessels transport these components to the OWF site.

There are various reasons why the required components might not be available to be loaded to the transport vessel when the vessel is at the port. Some of these reasons can be delays, damages of components and equipment or miscommunication between the parties involved in the installation process; these may occur during transport from the manufacturers to the feeder port or even within the port. Therefore, this delay can vary significantly.

In this study, the supply risk is modeled as an event at the loading port that is caused in case the required components are not available when needed. This event is described by:

1. a *probability of occurrence* P_{U_C}, where U_C denotes the event of unavailability of the required components for every type of component $C \in (1, 2..., n)$ of the total n different types of components

2. the *delay* D_C (in units of time) which denotes the waiting time until the required components of type C are available for loading. Hence, the waiting time D_C is a random variable with a cumulative probability distribution F_{D_C}.

Figure 5.3 presents the flowchart of the developed algorithm that can be used to take into account the risk of supply disruptions. When the vessel is at the port and a new loading operation of components is about to start at time t, it should be checked if the stock level $S_{C,t}$ of the component C is sufficient to proceed. So, the first step of the algorithm is to examine the amount of components $S_{C,t-1}$ that was available in the port when the previous loading operation of this type of components C has been completed at time $t-1$. Usually, the entire installation process starts only when there is the required amount of components S'_C, concerning every type of component C, at the installation port. Thus, as far as the first loading operation ($t = 1$) is concerned, the stock $S_{C,t=0} = S'_C$. If the stock $S_{C,t-1}$ is not sufficient (i.e. there are less than the required components R_C of component type C) then a pseudo-random number $X \sim U(0,1)$ is generated. If X has a value smaller or equal than the *probability of occurrence* P_{U_C} for this particular type of component C, then the event of components' unavailability U_C occurs. Subsequently, the *delay* (or waiting time) D_C until these are ready for loading is sampled from F_{D_C}. Otherwise, if $X > P_{U_C}$, the stock S_C was replenished in the meantime with an amount equal to a user-defined replenish strategy Rp_C for the particular component C. Then, the algorithm proceeds with loading the vessel and updating the stock level S_C.

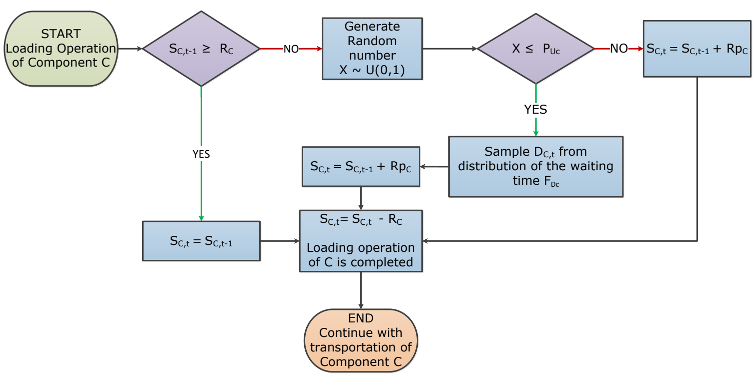


Figure 5.3: Flowchart of the algorithm that is used to include the risk of supply disruptions.

5.2.2. METHOD TO QUANTIFY RISK OF SUPPLY DISRUPTION

Detailed data concerning OWFs construction projects are scarce. Moreover, these information are commercially sensitive and it is challenging to acquire a sufficient amount of relevant data. Hence, it is not possible to do a statistical analysis to obtain representative values concerning the probability of occurrence and the distribution of the waiting time which are required to include the risk of supply disruptions (see Figure 5.3). Therefore, the best alternative is to use expert judgments to assess these uncertain variables.

In order to be able to use the judgments of different experts as inputs of the developed stochastic simulation model, these should be combined for every variable of interest. There are different approaches and methods for combining the assessments of the experts. The subject of treating expert judgments as an alternative source of data has been extensively discussed [25, 27, 28]. In this study the performance-based method named Cooke's classical model, which was presented in Chapter 4, was used to aggregate the expert judgments. This mathematical aggregation method was chosen because it has been shown that such a mathematical approach has an advantage over behavioral approaches [29]. It is also worth mentioning that Cooke's classical model was used in the past for a different application on the offshore wind field. In [30] is proposed a structured expert judgment elicitation process to quantify the required parameters associated with epistemic uncertainties and develop an availability growth model that takes into account the sources of systemic risk to provide a more accurate estimation of farm performance over early life.

For the purpose of this study three different types of DMs were obtained using different weighting schemes. The simplest one is equal weighting and hence falls outside of the performance based DMs. The *Global Weights* DM is computed as described above while the *Item Weights* DM computes the scores in equation 4.5 using the information score per item rather than the average information score (equation 4.3 in Appendix A.1). The difference between DMs will be discussed further in section 5.3.2.

SEED QUESTIONS

Relevant data from the field of offshore wind construction are needed to formulate seed questions. In this study a Dutch marine contractor (i.e. Van Oord) provided the time register database of four past projects concerning the construction of OWFs. This database contains a detailed archive with the duration of all the activities as well as the incidents that occurred during these projects. Hence, although these data, concerning four projects, were not sufficient to do a statistical analysis and draw safe conclusions, they were valuable to formulate the seed questions which were used to evaluate the performance in judging uncertainty of every participant.

For the purpose of this study, 14 seed questions were formulated. These questions concerned frequencies of occurrence as well as the registered waiting time of the delays due to unavailability of different components. The projects were anonymized but important details of these projects were provided to the experts. An example of the provided information regarding project (construction of an OWF with 32 wind turbines, located in the Irish sea) can be found in Table 5.1. To illustrate the format of the seed questions that were used, one of these is presented below:

SQ. 1*: Consider an installation project (Project 1) of an OWF consisting of 32 WTG in the Irish sea with the details presented in Table 5.1. A number of times, the monopiles*

*(MPs) were not available while the vessel was on-site ready to start the installation. What do you believe was the **maximum** registered delay, until the required MPs were available?*

5%-tile (Q_5)	50%-tile (Q_{50})	95%-tile (Q_{95})
...	...	...

Components	Monopiles	Transition Pieces
Installation port	Birkenhead, Liverpool	Birkenhead, Liverpool
Manufacturer location	Rostock	Teesport (16 TPs) Aalborg (16 TPs)
Distance of installation port from manufacturer	$\approx 1150 NM$	$\approx 750 NM$ $\approx 980 NM$
Transportation method to installation port	Shipped (vessel speed 15 kn)	Shipped (vessel speed 15 kn)
Estimated transportation duration to installation port	≈ 75 h	≈ 50 h ≈ 65 h
Number of trips from manufacturer	8	8
Buffer stock at installation port at the commencement of the installation operation	≈ 20	≈20
Transportation from installation port to OWF site	Tugs towed floating MPs to the installation vessel on-site	Barges transferred TPs to the installation vessel on-site

Table 5.1: Information provided to the experts regarding Project 1.

TARGET QUESTIONS

The purpose of this study is to obtain probability distributions regarding the delays that may occur due to unavailability of different components (such as monopiles, transition pieces, towers, blades, nacelles) during the construction of OWFs. For every different component, two types of target questions were queried, resulting in 10 target questions in total. The first type concerns the relative frequency of the event in which the required components are not available. The second type concerns the waiting time (i.e. delay) due to the occurrence of such an event. The obtained distributions can be used to support projects which will happen in the near future with certain characteristics. These characteristics are presented in Table 5.2. To illustrate the two different types of target questions (TQ. 1 and TQ. 2) that were used, an example concerning the monopiles is presented below.

***TQ. 1**: Assuming that the operation of loading monopiles (MPs) to the transportation vessel will be performed 1000 times, **how many times** would you expect that the required MPs will not be available to start the loading operation?*

5%-tile (Q_5)	50%-tile (Q_{50})	95%-tile (Q_{95})
...	...	...

TQ. 2: *If the required monopiles (MPs) are not ready for loading while the transportation vessel is in port, what would you expect to be the delay (i.e. waiting time) until the required MPs are available for loading?*

5%-tile (Q_5)	50%-tile (Q_{50})	95%-tile (Q_{95})
...	...	...

Location	North Sea
Number of Wind turbines	More than 50
Distance from manufacturers to the installation port	More than 150 NM
Distance from installation port to the OWF site	More than 20 NM

Table 5.2: Characteristics of projects which can be supported by the results of this study.

5.3. ANALYSIS OF EXPERT JUDGMENTS

In this study, 11 experts with experience in the offshore wind field have participated. The participants were affiliated to different types of companies (such as marine contractors, manufacturers, OWF owners, consultancy firms etc.) operating in 4 different European countries (i.e. the Netherlands, Germany, UK and Belgium) in order to ensure the elicitation of expert judgments from a pool of experts with diverse expertise. The criteria for the participation of an expert concerned his/her experience in the offshore wind industry and involvement in the construction of OWFs. A list with the names and affiliation of the experts can be found in Appendix A.1.

The expert judgments were elicited in the period from July 12^{th} until August 15^{th} 2017. Few experts participated in an expert judgment elicitation workshop that took place on July 12^{th} 2017 in Delft while the expert judgments of the remaining participants were elicited by individual (teleconference or in person) interviews with the analyst. The structure of all the elicitation sessions was kept the same, in order to ensure that all the experts were provided with the same information. Each elicitation session consisted of: i) a short presentation of the purpose of this study; ii) an introduction to Cooke's classical model for structure expert judgment; iii) a short example exercise and iv) the filling out of the questionnaire regarding the risk of supply disruptions during the OWF installation process. The vast majority of the SEJ studies conducted in the past made use of the closed-source software EXCALIBUR to perform the analysis and synthesis of expert judgments according to CM. In this study, the developed open-source MATLAB toolbox called ANDURIL [26] was used. This toolbox provides open access to a code that makes transparent the calculations of performance measures and the aggregation of expert judgments, allowing the current methods to be more accessible and different approaches or extensions to current methods to be further explored (for more information the reader is referred to Chapter 4). It should be noted that the obtained results were validated using EXCALIBUR software.

5.3.1. PERFORMANCE OF THE EXPERTS

As it was mentioned in Chapter 4, the performance of the experts in judging uncertainty is evaluated using two measures, the calibration score (or statistical accuracy) and the information score. Based on these measures, it is possible to compute the un-normalized weights using eq. 4.5 and subsequently the normalized weights.

Table 5.3 shows the measures of performance in judging uncertainty as well as the un-normalized and normalized weights of every participant. It should be noted that the order of these values concerning the anonymized experts does not correspond to the order of the names of the experts (provided in Appendix A.1). The presented values of the information score are computed by ANDURIL considering a log-uniform background measure and the weights are computed when considering a significance or cut-off level α equal to zero. It can be seen that experts 2 and 4 are the only experts with calibration score larger than 0.01 (a value that is usually chosen for the significance level α). This leads to larger weights which means that their judgments will mainly constitute the DM's distributions of every queried variable. It is worth mentioning that the information scores of the best calibrated experts are low compared to those of the remaining participants. Although this is not always the case, it is logical since the provided quantiles cover a larger range. In this study most of the remaining experts with low calibration scores, had high information scores. That means that these experts were confident about their assessments and provided narrower distributions for the queried seed variables, which were not statistically accurate.

Expert ID	Calibration Score	Information Score (All items)	Information Score (Seed items)	Un-normalized Weights	Normalized Weights excl. DM
Expert 1	0,0002060	0,70675	0,86518	0,00017825	0,0006529
Expert 2	0,011904	0,471358	0,516478	0,0061485	0,022523
Expert 3	6,804e-10	0,93655	1,090144	7,418e-10	2,717e-09
Expert 4	0,569084	0,452635	0,4606201	0,2621317	0,9602551
Expert 5	1,983e-07	1,214771	1,1789866	2,338e-07	8,565e-07
Expert 6	1,314e-05	0,82397	0,712980	9,366e-06	3,431e-05
Expert 7	1,192e-07	1,214716	1,195092	1,425e-07	5,219e-07
Expert 8	0,00036218	1,165429	1,137962	0,00041215	0,00150981
Expert 9	2,547e-11	0,8838053	0,802524	2,044e-11	7,489e-11
Expert 10	1,762e-05	0,8577063	0,897994	1,582e-05	5,795e-05
Expert 11	0,00441208	0,8424475	0,9259006	0,0040851	0,0149649

Table 5.3: Measures of performance in judging uncertainty and weights for every participant, obtained from the analysis with ANDURIL.

5.3.2. SYNTHESIS OF DMS

There are different weighting schemes that can be used to aggregate expert opinions for every variable and obtain the so called decision maker (DM) (i.e. the combined opinion). The simplest one is to assign equal weights to every expert, which provides the equal-weight decision maker (DM_{equal}) which of course does not take into account the performance of the experts in judging uncertainty. As it was introduced in section 4.2, CM method uses the two performance measures (i.e. *statistical accuracy/calibration score* and *informativeness*) to compute the weights based on the performance of the experts in judging uncertainty.

There are two different types of performance-based weighting schemes. The first one is called *global weights*, for which the weight of every expert is computed by taking the product of the calibration score and the average relative information over all the seed items. These global weights are multiplied with the density of every expert for every variable (see equation 4.4) to obtain the density of the combined opinion (DM_{global}). Hence, DM_{global} was synthesized using the values of the normalized weights presented in Table 5.3. The second type of performance-based weighting schemes is called *item weights* and the main difference with *global weights* is that the weights are different for every item based on the relative information for this particular item. This means that the opinion of every expert (whose calibration score is larger than the significant level α) has a different weight for every item. By multiplying the non-zero weight of every expert for every item with the expert's density of the variable, the density of the combined opinion (DM_{item}) is obtained.

The aforementioned three different weighting schemes were investigated in this study and the performance of the resulting DMs was evaluated in terms of statistical accuracy and relative information (with respect to the log-uniform background measure for every variable). To achieve this, every synthesized DM is treated as a "virtual expert" that enters the pool of experts. Table 5.4 summarizes the performance measures (statistical accuracy or calibration and mean relative information) for every decision maker obtained using different weighting schemes (DM_{global}, DM_{item} and DM_{equal}). It is interesting to note that both the statistical accuracy and the informativeness of the decision makers which were obtained using performance-based weights (i.e. DM_{global} and DM_{item}) are significantly better than those of the decision maker obtained with equal weights (DM_{equal}). Also, the statistical accuracy of the DM_{equal} is below 0.05 that is the rejection threshold usually set as significance level. Moreover, the statistical accuracy of the performance-based decision makers is higher compared to that of the expert with the higher calibration score (i.e. Expert 4). However, the relative information of the performance based decision makers is lower than that of every individual expert. This means that in general the synthesized decision makers have wider distributions than most experts for the different items. Finally, one can see that there is not a big difference between the measures of performance for the two performance-based decision makers DM_{global} and DM_{item}.

It is important to note that the asymptotic strictly scoring rule property requires a cut-off level beneath which an expert is unweighed. Usually, in practice, the value of α is either set equal to 0.01 (that is more "generous" than the traditional 0.05 for hypothesis testing) or it is chosen to optimize the combined score of the resulting DM. However, in this study, the cut-off level was chosen to be equal to zero. In this way, the judgment of every expert, no matter how small its contribution, is included in the obtained distributions. Although, all the participants in this study were experts in the field of offshore wind energy, they had different functions and were affiliated to different types of companies. Hence, the diversity of the pool of experts could be reflected to the resulting distributions, by setting $alpha = 0$. However, the analysis was also performed when considering $alpha = 0.01$. It was found that this had a minor influence to the obtained distributions and the measures of performance of the resulting performance based DMs (which can be found in Appendix A.4). This was expected as experts 2 and 4 have significantly higher statistical accuracy compared to the other experts.

Name	Calibr. Score	Inf. score (total)	Inf. score (seed items)
DM_{global}	0.96812	0.34834	0.34809
DM_{item}	0.96812	0.35677	0.35466
DM_{equal}	0.03868	0.13560	0.131805

Table 5.4: Comparison of the three DMs' performance measures.

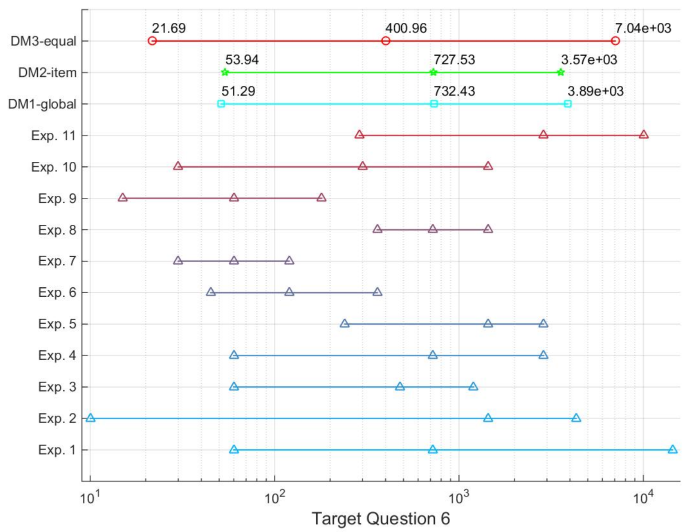


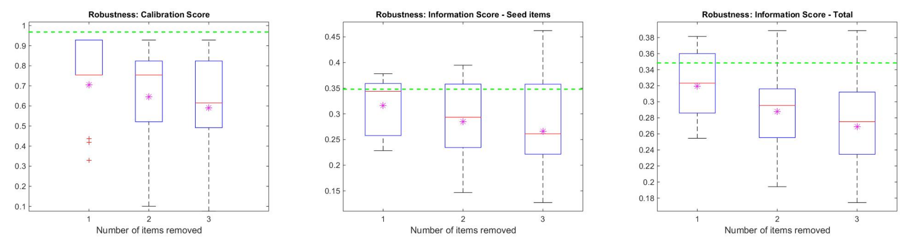
Figure 5.4: Assessments regarding waiting time (in min) due to unavailability of towers (Target Item 6).

5.3.3. Robustness of performance-based DMs using ANDURIL

It is also worth investigating the robustness of the obtained DMs with respect to the seed questions. To achieve this, one or more seed items are removed and the DMs are computed again. Then the resulting DMs are evaluated in terms of statistical accuracy and informativeness.

In this study, the robustness analysis has been performed using the newly developed ANDURIL toolbox [26]. The reason for this choice is that ANDURIL gives the opportunity to the user to decide the number of the seed items which should be excluded at a time. For the purpose of this study, it was chosen to exclude all the possible combinations up to 3 seed items at a time (i.e. a total of 469 combinations). However, it must be mentioned that excluding seed questions reduces the calibration power. Therefore, ANDURIL provides the option to the user to decide whether the calibration power is taken into account for the computation of the calibration score. In the presented results, a different calibration power was not taken into account.

The results of the robustness investigation of DM_{item} and DM_{global} are presented in Fig. 5.5 and Fig. 5.6 respectively. It can be seen that the calibration score of the DM_{item} can range from 0.7 to 0.92 approximately with a median of ≈ 0.75, when one seed item is excluded at a time. As it was expected the range of the obtained calibration scores increases as more than one seed items are excluded at a time. However, the median of the calibration score when excluding two seed items at a time remains close to the median occurring when only one seed item is excluded. On the contrary, the median of the calibration score is ≈ 0.6 when all combinations of 3 seed items are excluded at a time. Although the resulting calibration scores are not very close to the original calibration score (i.e. green dashed horizontal line), these are significantly larger than 0.05 that is usually set as the threshold at which the study would cast doubts regarding its estimates. Moreover, the resulting information scores of the DM_{item} are less spread and the medians are closer to the original value concerning both the information score over the seed items as well as the one over the target questions. As far as the robustness box-plots of the DM_{global} (Fig. 5.6) are concerned, similar conclusions can be drawn. Following the same approach, it is also possible to investigate the robustness of the obtained DM with respect to the experts. It was chosen to investigate this when excluding one expert at a time. The performance measures of the resulting performance-based DMs are presented in Table 5.5. Both measures of performance and especially informativeness decrease significantly when expert 4 is excluded, while only the statistical accuracy is reduced when expert 2 is excluded.

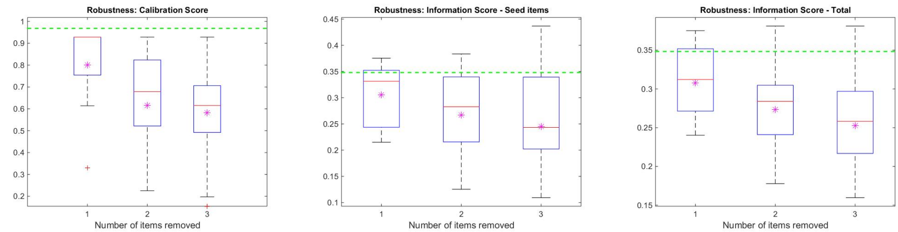


(a) Calibration score (b) Information - Seed (c) Information - Total

Figure 5.5: Robustness box-plots concerning (a) the calibration score, (b) the information score over the seed items and (c) the information score over all the queried variables of the DM_{item}, when excluding up to three seed items at a time.

5.3.4. OBTAINED DISTRIBUTIONS - INPUTS FOR SIMULATION TOOL

The obtained distributions concern the relative frequency of occurrence of a delay due to unavailability of required components and the waiting time distribution in between availability of the major components required for the installation of offshore WTGs. These components are: the monopiles (MPs) the transition pieces (TPs), the towers, the blades and the nacelles. Figure 5.1 shows the different main components of a typical offshore



(a) Calibration score (b) Information - Seed (c) Information - Total

Figure 5.6: Robustness box-plots concerning (a) the calibration score, (b) the information score over the seed items and (c) the information score over all the queried variables of the DM_{global}, when excluding up to three seed items at a time.

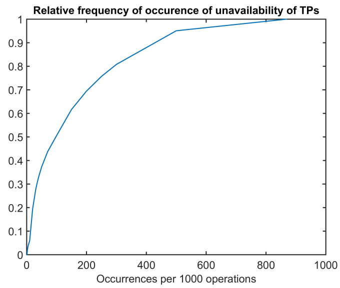
Excluded Expert	DM_{global} Calibration Score	DM_{global} Information score (total)	DM_{global} Information score (seed items)	DM_{item} Calibration Score	DM_{item} Information score (total)	DM_{item} Information score (seed items)
Expert 1	0.96812	0.33982	0.34875	0.96812	0.34771	0.35533
Expert 2	0.43118	0.37786	0.40134	0.43118	0.38028	0.39926
Expert 3	0.96812	0.34834	0.34809	0.96812	0.35677	0.35466
Expert 4	0.65873	0.15863	0.13098	0.65873	0.18163	0.17062
Expert 5	0.96812	0.34834	0.34810	0.96812	0.35677	0.35466
Expert 6	0.96812	0.34837	0.34816	0.96812	0.35680	0.35472
Expert 7	0.96812	0.34834	0.34809	0.96812	0.35677	0.35466
Expert 8	0.96812	0.35075	0.35146	0.96812	0.35927	0.35782
Expert 9	0.96812	0.33866	0.34091	0.96812	0.34699	0.34724
Expert 10	0.96812	0.34842	0.34818	0.96812	0.35686	0.35474
Expert 11	0.96812	0.35697	0.33835	0.96812	0.36722	0.35152

Table 5.5: Robustness of performance-based DMs with respect to experts.

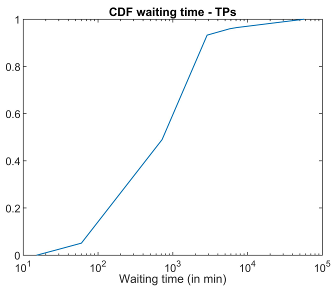
WTG that were taken into account in this study.

Among the different combinations of the experts' judgments presented in section 5.3.2, it would be a sensible decision to use as inputs for the stochastic simulation model, the distributions obtained using item weights, (i.e. DM_{item}). The main reasons for this choice are based on the evaluation of the performance of the obtained DMs (treated as "virtual experts") in assessing uncertainty. In Table 5.3 and Table 4.3, it can be seen that DM_{item} has higher statistical accuracy compared to every individual expert and higher relative information (which is a slowly varying function) compared to DM_{global}.

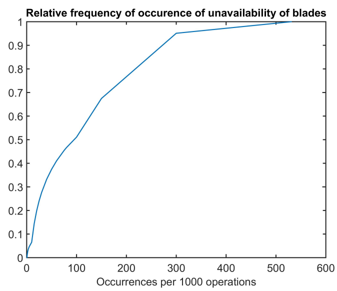
To illustrate the obtained distributions using the item weights weighting scheme, Figure 5.7 presents the distributions concerning the relative frequency of occurrence of unavailability of required TPs and required blades, as well as the waiting time due to this. The distributions, obtained with performance based weighting schemes, presented small differences across the different types of components. Moreover, these distributions can be characterized as significantly wide (e.g. the waiting time until the required TPs become available can range from minutes up to several days). This can be explained because the queried variables express large variance since these are influenced by many different aspects. Also, the obtained distributions can be used to support projects with various characteristics, rather than one project that partly express the large variance of the output distributions. In Appendix A.3 and A.3.1, one can find the figures that present the distributions of every individual expert as well as the obtained distributions of every DM concerning the seed and target variables respectively.



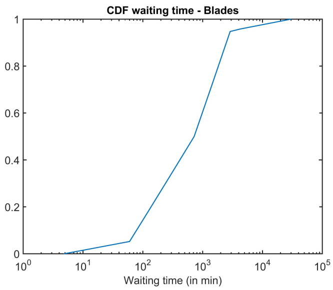
(a) Relative Frequency of occurrence - TPs



(b) Waiting time due to TPs unavailability



(c) Relative Frequency of occurrence - Blades



(d) Waiting time due to unavailability of required blades

Figure 5.7: Obtained distributions concerning the relative frequency of delays due to unavailability of the required TPs (a), blades (c) and the waiting time due to unavailability of the required TPs (b), blades (d).

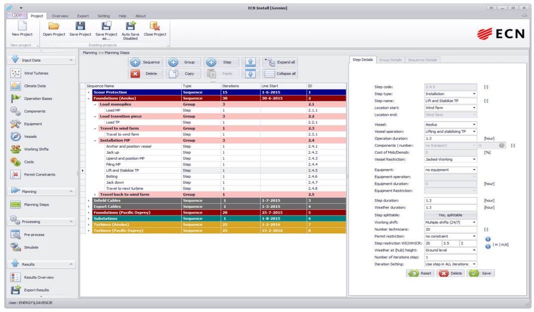
5.4. MODEL IMPLEMENTATION

THE methodology presented in Section 5.2 is applied to a realistic test case concerning the installation of offshore wind farms.

5.4.1. ECN INSTALL

In order to investigate the impact of including/neglecting the uncertainties regarding the supply disruptions during the installation process of OWFs, a realistic test case should be simulated. For this purpose, a modified version of a software developed from ECN (ECN Install v. 2.1) [31] was used to simulate different scenarios and provide the user with cumulative distributions of time and cost of each scenario. ECN Install is a time driven decision support tool that simulates an installation scenario for a different number of historical environmental time series and provides the user with the estimates regarding the duration and the cost. The tool provides excellent flexibility in the hands of the user to model the desired planning and export the cost and time outputs for any project. Due to the high reliance on the user-defined inputs, the outputs are profoundly dependent on the quality of input data. Figure 5.8 presents the start screen and the user interface of the software.

(a) Start screen



(b) Example of user interface

Figure 5.8: ECN Install software

ECN Install highlights the barriers during the installation activities and supports in eliminating project risks. ECN Install is designed to test various conceptual installation strategies for accelerating the knowledge transfer between different actors involved. It leads towards efficient resource management to minimize the possible delays and overall costs for simulated schedules. The ECN Install simulation tool is in existence from early 2014, where over the years it has seen systematic improvements. The latest commercial tool available is based on version 2.1. This version of the tool was modified with the algorithm presented in subsection 5.2.1. A realistic test case that was developed from ECN was simulated using the modified ECN Install tool.

5.4.2. TEST CASE DETAILS

The realistic test case that was developed from ECN and presented in [32], concerns an OWF consisting of 150 wind turbines and simulates scour protection activities and the installation operations of the support structures (i.e. monopiles and transition pieces), the wind turbines, the (infield and export) cables and the offshore substation. The installation plan of the simulated test case is split in the following phases:

1. Scour protection: Rock dumping is performed for each of the 150 monopiles as scour protection method. It is assumed that rock loading to the vessel takes place in the port of Eemshaven.

2. Foundations: The foundation of each wind turbine consist of a monopile and a transition piece. Two vessels were employed for the installation of foundations. Both vessels carry three complete foundations at a time. The installation of 90

foundations is performed by vessel 1 while 60 of them by vessel 2. Loading of foundations to the vessels is carried out in Orange Blue Terminal of Eemshaven port. Last, it is noted that an extra restriction concerning the piling is applied in the Netherlands from January 1st until July 1st.

3. Export cables: Two AC 220 kV export cables of over 100 km each, weighting 90 kg/m are installed. Their installation is a challenging and complex engineering process because of several restricted areas. Briefly, the installation of export cables is split in shallow waters, near shore, deep waters and connector cable installation.

4. Substations: Two 300 MW substations are installed on top of two jacket structures. A heavy lift vessel installs first the two jackets and subsequently positions the substations. The jackets are towed by tugboats from Bow Terminal of Vlissingen port whereas the substation are transported from Hoboken, Antwerp.

5. Inter-array cables: Approximately 140 km of inter-array cables are required to interconnect the wind turbines with an average weight of 30-40 kg/m. Inter-array cable laying is carried out by a cable laying vessel whereas the post-burying is performed by a multi purpose vessel and a remotely operated vehicle (ROV).

6. Wind turbines: Wind turbines installation is performed by 2 vessels (75 turbines each) while components are loaded in the port of Esbjerg. For both vessels, one loading includes three complete wind turbines and for each turbine, the tower comes at one piece while nacelle and hub are pre-assembled. Hence, five lifts are required for the installation of one turbine.

The details of the simulated test case are summarized in Table 5.6.

Number of WTG:	150
Location:	North Sea
Starting Date:	1 June
Installation operations:	Scour protection, Support structures, Wind turbines, Cables and Offshore Substations
Environmental conditions:	20 years of observations in the OWF site
Strategy 1: Initial stock at the installation port in the commencement of project	10 units of each component (MPs, TPs, Towers, Nacelles, Rotors)
Strategy 2: Initial stock at the installation port in the commencement of project	20 units of each component (MPs, TPs, Towers, Nacelles, Rotors)

Table 5.6: Details of the simulated test case.

The presented installation test case was simulated for three different approaches, which represent the risk aversion of the user regarding the supply disruptions. In *Approach 1 (or Base)*: the risk of supply disruptions is neglected, in *Approach 2 (or Neutral)*: the risk of supply disruptions is described with a “moderate" frequency of occurrence and in *Approach 3 (or Pessimistic)*: the risk of supply disruptions is included with an “high" frequency of occurrence. The terms “moderate" and “high" represent the median (50^{th} percentile) and the 95^{th} percentile of the obtained probability distributions regarding the frequency of occurrence, respectively.

5.4.3. RESULTS

The realistic test case was simulated 1000 times in total (i.e. 50 simulations for every available year of environmental time series) to properly incorporate the risk of supply disruptions. Following this approach, different strategies can be compared in order to support decisions with a certain confidence level. For illustration purposes, two different strategies concerning the initial stock in the commencement of the installation project were simulated (see also Table 5.6). The results of the test case when *Strategy 1* and *Strategy 2* are considered, are presented below. It should be mentioned that for both strategies the replenished amount of every component (as presented in Figure 5.3) was equal to 5 units and the stock in the harbor could not exceed the initial stock of every strategy.

5

INITIAL STOCK: STRATEGY 1

In Figure 5.9 and 5.10 are presented the duration of the installation (in days) and the total cost of the installation (when the cost of the components is not included) respectively. It can be seen that when the risk of supply disruption is included with a “moderate" relative frequency of occurrence (i.e. the 50^{th} percentile of the CDF of every component), the cumulative distributions of the duration and the cost of the installation present small differences compared to the case where this risk is neglected. More precisely, concerning the 80^{th} percentile (or P80 value), there is a difference of approximately equal to ≈ 4 days and ≈ 0.42 M€ for the duration and the cost of the installation respectively. However, these values differ significantly in the pessimistic case, where the risk of supply disruptions is included with a “high" relative frequency of occurrence (i.e. the 95^{th} percentile of the CDF of every component). In this case, the difference compared to the *Base* approach is ≈ 15 days for the duration and ≈ 3.9 M€, for the cost of the installation.

An important remark concerning the resulting cost CDF of the *Neutral* approach is that the total cost of the installation sometimes appears to be smaller than the *Base* approach. Although this may be counter-intuitive, it shows a more realistic modeling of the total cost calculation. The total cost of the installation is rigorously calculated based on the resources utilization. One can find a short description of the cost calculation in Appendix A.2 and a more detailed description of the cost calculation that is supported by ECN Install in [32]. The aforementioned remark can be explained by the difference in the cost of the vessels depending on their state (i.e. remaining idle, traveling or performing an activity); the weather windows that may happen to be longer and the fact that the vessels are hired for the entire day. Hence, there are a few cases where although a small delay in the loading operation results in a delay in the total duration, the total cost of the installation is lower compared to the case where this delay has not occurred.

INITIAL STOCK: STRATEGY 2

A similar trend concerning the difference between the CDFs obtained for different risk aversion approaches, can be seen when *Strategy 2* is considered for the initial stock at the

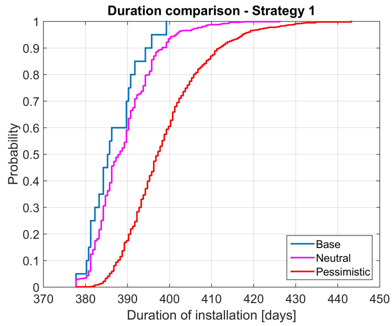


Figure 5.9: Duration of Strategy 1 for different risk aversions.

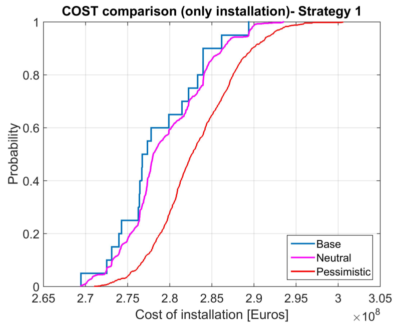


Figure 5.10: Cost of Strategy 1 for different risk aversions.

port. In this scenario, all the details of the test case were kept the same, except the cost of the harbor. Since in *Strategy 2* there are 20 (instead of 10) units of every component in the commencement of the project, it was assumed that the cost of the harbor will be twice as high as the harbor cost in *Strategy 1*. Figures 5.11 and 5.12 show the resulting CDFs of the duration and cost of the installation respectively. When *Strategy 2* is considered, the difference of the P80 value between the *Base* and *Neutral* case is ≈ 3.5 days for the duration and ≈ 0.52 M€, for the cost of the installation. Whereas the difference between the *Base* and the *Pessimistic* approach is ≈ 14.5 days for the duration and ≈ 4.23 M€, for the cost.

COMPARISON OF STRATEGIES

It was shown that there is a significant impact into the estimates of the duration and cost of the installation, when the risk of supply disruptions is included with a *Pessimistic* approach. However, it is also interesting to investigate which of the two simulated strategies, regarding the initial stock, is the most economical when this risk is taken into account. Figure 5.13 shows the CDFs of the cost of the installation for the *Strategy 1* and *Strategy 2*. It can be clearly seen that *Strategy 1* should be preferred over *Strategy 2* in terms of cost. However, it must be mentioned that this result is heavily influenced by the cost of the harbor, which was considered twice as high for *Strategy 2*. Also, as it can

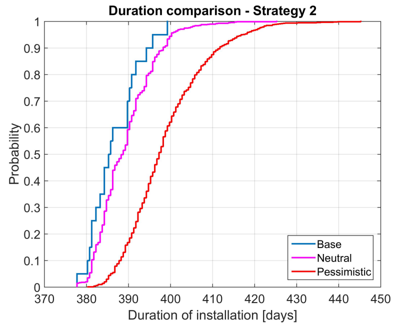


Figure 5.11: Duration of Strategy 2 for different risk aversions.

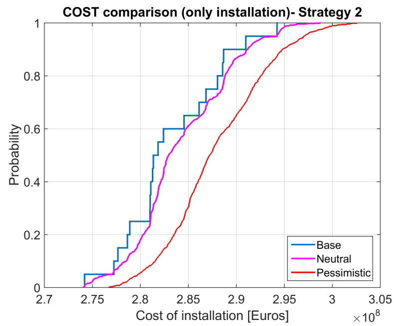


Figure 5.12: Cost of Strategy 2 for different risk aversions.

be seen from Figures 5.9 and 5.11, the estimated duration present minor differences for both strategies. This would differ depending on the amount of initial stock as well as the replenished amount of components. Numerous scenarios can be investigated. For example, an extreme scenario where it is assumed that all the required components for the installation of an OWF are available at the port in the commencement of the project, will result in a CDF of the duration identical to the *Base* approach. However, the CDF of the cost will be much different, showing a significantly higher total cost. To investigate such a scenario more realistically, the user could also add a monetary penalty above a defined threshold for the duration. These and many more different scenarios and strategies can be investigated and compared with the developed approach. In this way, it is possible for the decision makers to choose the most economical scenario with a certain confidence level.

To further explore alternative scenarios for the presented realistic test case, four different strategies regarding the initial stock of different components in the commencement of the installation process were also simulated. These strategies differ in an important characteristic of the project (i.e. initial stock of the components) that can be intuitively used as a mitigation measure for the risk of supply disruptions. The investigation of these additional strategies would show whether difference in the initial stock of particular component(s) would result in important differences in the estimated cost and time of the test case. It was found that the cumulative distribution of the total duration had insignificant differences for the simulated strategies. This can be explained by the small differences in the obtained distributions regarding the relative frequency of occurrence and the waiting time for different components. On the other hand the CDFs of the cost varied proportionally to the required area in the port. The details of all simulated strategies (including *Strategy 1* and *2*) as well as comparison of the obtained CDF of the cost for the pessimistic approach can be found in Appendix A.5.

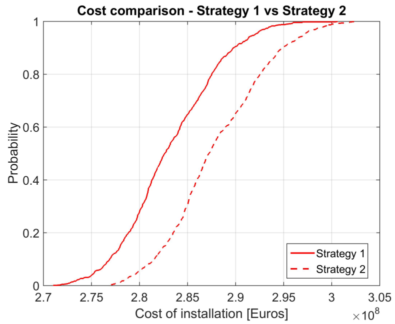


Figure 5.13: Cost comparison of different strategies for the pessimistic approach.

5.5. DISCUSSION

The proposed methodology was depicted in Figure 5.2 and it has some challenges and limitations that should be discussed. To begin with, considering the first sub-process of the proposed methodology, past construction projects from the field of application should be investigated in order to identify potential events which may cause delays due to supply disruptions. These are used for creating algorithm(s) in order to update the probabilistic model. This can be particularly challenging because in case unforeseen events are not modeled properly or are completely neglected, this might lead to underestimation of the supply disruptions risk. Furthermore, regarding the second sub-process of the proposed methodology, a number of challenges or limitations of applying a SEJ method such as the CM are listed below:

1. the data are often scarce and commercially sensitive for studies which are similar to the presented study. However, these are crucial for forming a sufficient number of seed questions based on which the performance of the experts is evaluated.

2. it can be challenging to find experts in the field of application who are interested in participating and available for several hours.

3. the analyst should have been trained in CM, to ensure the proper elicitation of the expert judgments in a structured way.

There are also limitations concerning the obtained probability distributions from applying the proposed methodology to the presented case. These probability distributions (i.e. the relative frequency of occurrence and the waiting time due to unavailability of components during the installation of OWFs) are compatible with future projects which comply with the characteristics presented in Table 5.2. These characteristics were deliberately set as such to support a wide range of future projects. However, there might be the case that in the long-term future, significant changes to the associated technology and the offshore construction practice will render the obtained distributions invalid. In this case, it should be mentioned that the proposed methodology could be applied again to update the probability distributions.

5.6. CONCLUSIONS & RECOMMENDATIONS

In order to further facilitate the transition from conventional energy sources to sustainable energy technologies, such as offshore wind, it is crucial to improve the management of the installation of OWFs. The installation of OWFs is a complex process that is influenced by various uncertainties. One important uncertainty that is usually overlooked in practice and in scientific literature, is the risk of unavailability of the required components, when needed, due to supply disruptions. To fill this gap, a methodology was proposed to model the risk of supply disruptions.

Due to the absence of sufficient relevant historical data, expert judgments were used to quantify the risk of supply disruptions for different components. For this purpose, 11 experts from different companies and countries provided their assessments. Their judgments were analyzed by using Cooke's classical model and were combined using different weighting schemes. It was found that the combined opinion using item weights (DM_{item}) performed better in terms of statistical accuracy (i.e. calibration score) and informativeness. It is worth mentioning that the DM_{item} had a much higher calibration score compared to every individual expert as well as the equal weight DM (DM_{equal}), whose score was below 0.05 that is usually the threshold below which the study would cast doubts regarding its estimates.

Afterwards, a test case was simulated when following different approaches which express the risk aversion. It was found that disregarding the supply disruptions from the estimated duration and cost may cause significant schedule and budget overrun. More precisely, in the *Pessimistic* case, neglecting this risk may lead to an underestimation of ≈ 4 M€, for the P80 value.

Furthermore, six different strategies concerning the initial stock at the installation port were investigated. It was found that despite the CDFs of the duration were similar for all strategies, a large difference, proportional to the required area in the port, was observed in the CDFs of the total cost of the installation for these strategies. Of course following the proposed methodology, it is possible to incorporate the risk of supply disruptions to various scenarios. Hence, it was shown that applying the proposed methodology allows to incorporate the risk of supply disruptions to the cost estimates of various scenarios. This can assist in comparing scenarios and making optimal decisions regarding: 1. Schedule of installation; 2. Buffer stock; and 3. Selection of vessels and installation port

Ultimately, it must be mentioned that the proposed methodology and the obtained distributions can be used in future projects (with particular characteristics) to properly incorporate the risk of supply disruptions. However, since the obtained distributions can support multiple projects which share the characteristics presented in Table 5.2, these were expected to have a wide range. To improve this in future studies, two recommendations are given. First, the expert judgments could be elicited for a particular project of which the details will be given to the experts to reduce their uncertainty. Second, a dependence model, similar to those presented in [33], can be developed, where the dependence between the obtained distributions and different project characteristics will be described. Computing conditional distributions of interest for particular projects could be an application of such a model.

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6

Offshore Wind Farms Reliability using Expert Judgments

Offshore wind farms (OWFs) are energy assets that are expected to play an essential role in the crucial transition towards a fossil-free future. Hence, their reliability and resilience must be optimized while taking into account the associated uncertainties. This chapter proposes a method to improve the representation of uncertainty of the reliability of OWFs with the purpose of enabling better decisions that will lead to more resilient energy assets. It is a fact that data concerning the operation and maintenance (O&M) of OWFs and information regarding upcoming technology improvements are limited and commercially sensitive. Therefore, the judgments of five experts in O&M were elicited and combined based on their performance in judging uncertainty. These combined probability distributions were used as input in the simulation of a realistic test case. The cumulative distribution of the energy availability was obtained while taking into account the uncertainties concerning: the number of unplanned visits, the environmental conditions and the duration of repair activities. It was shown that the proposed method allows a better representation of the uncertainty of the availability in different operational phases of OWFs. Moreover, it enables the comparison of different strategies while taking into account user's risk appetite. Thus, better informed O&M decisions can be taken for future OWFs which can lead to higher energy availability.

The study presented in this chapter was supported by Vattenfall's O&M Roadmap department. Parts of this chapter have been published verbatim in ESREL 2020 - PSAM 15 proceedings [1].

6.1. INTRODUCTION AND MOTIVATION

OFFSHORE wind energy is considered one of the main contributors towards the important and crucial transition to a fossil-free energy future. During the last years, the transition to renewable energy sources is also supported by big energy companies. This alongside with technology advancements has led to significant reduction of the levelized cost of energy (LCOE) in Europe. However, there is still room for improvement, especially in the installation and maintenance processes and the associated uncertainties, contributing 8% and 13% to the LCOE respectively.

Optimal decisions regarding the maintenance of offshore assets such as offshore wind farms are impacted by various uncertainties which may cause downtime of the assets. For that reason, a lot of research has been conducted in the past focusing on improving the operation and maintenance (O&M) of offshore wind farms (OWFs) [2]. Besides the undeniable crucial role of environmental conditions, another important factor that drives the maintenance decisions is the reliability of the offshore wind system and the way this is modelled can be improved as shown in [3]. The reliability of an offshore wind system is typically expressed using failure rates for the different components. This factor significantly increases the complexity of the optimization of such processes and poses challenges to achieve resilient offshore energy assets.

Similarly to [4] the lack of resilience of an energy infrastructure asset can be expressed as function of the supply and demand of its service. In other words, for OWFs a commonly used measure such as the production based availability (PBA) can be used to describe the resilience of the energy asset. According to the IEC Technical Specification 61400 26-2 PBA is percentage of potential energy a turbine is extracting from the wind. For a given wind resource, over a reporting period, the PBA is the actual production divided by the possible production.

Thus decisions concerning the strategies of the O&M of OWFs should aim to make these energy assets more resilient while the associated uncertainties are considered in the best possible way. Otherwise, these decisions may result in lower availability and subsequently significant revenue losses. Hence, the purpose of this study is to improve the estimates of the reliability of OWF by quantifying the uncertainty concerning events that cause standstill and require unplanned visits for manual intervention. This information can assist in making optimal decisions regarding the maintenance strategies. However, data to accurately model these unplanned visits are often scarce or insufficient. Therefore, in the absence of sufficient historical data and information concerning future WTGs designs, expert opinions can assist in order to achieve this goal.

A group of experts provide their assessments concerning the amount of unplanned visits in different life cycle stages of OWFs with certain characteristics. The combined probability distributions of these assessments will serve as inputs to a probabilistic simulation model, that simulates different maintenance scenarios. The output of this model will be the cumulative distribution of the energy availability, while taking into account the uncertainties concerning (i) the number of unplanned visits; (ii) the environmental conditions; as well as (iii) the duration of repair activities.

The results will allow the comparison of different maintenance strategies. In this way it is possible to find the optimal O&M strategy with a certain level of confidence.

6.2. PROPOSED METHOD

This chapter proposes a method that can be applied to support decisions for O&M of OWFs while improving the uncertainty representation of the estimated OWF's availability. Because of the high complexity of the O&M process, it was chosen to limit the scope of the associated uncertain variables. Hence, this study focusses on describing the uncertainty concerning the number of events (such as failures of components of the WTGs) that cause standstill of a WTG and require unplanned visits for repair. It should be mentioned that the developed methodology differentiate between the severity of these events (by classifying events due to minor-moderate or major failures) as well as the different phases of the lifecycle of the OWF.

6.2.1. DEVELOPED MODEL

An O&M logistics model has been developed in the past from Georgios Katsouris (co-author of [1]). This model includes the following functionalities:

(i) Randomly generating time of next failure;

(ii) Prioritizing scheduled and unscheduled tasks;

(iii) Allocating resources;

(iv) Weather windows / Downtime Calculation;

(v) Transit and Transfer to site;

(vi) Performing maintenance tasks.

6

The model simulates different O&M strategies and returns as output the maintenance costs and CDF of the availability.

The existing model has been modified to take into account the uncertainty regarding the afore mentioned variables. It is assumed that the inter-failure times are independent and identically distributed exponential variables. Thus, the unplanned visits can be described by a homogeneous Poisson process with the rate of occurrence of events per WTG which cause standstill and require unplanned visits. The causes of the required unplanned visit (UV) are divided in two jointly exhaustive events (i.e. minor-moderate failure and major failure). Depending on the cause of the unplanned visit different repair time distributions are utilized to compute the required time to repair. A flowchart of the algorithm of the modified model is presented in Fig. 6.1 and can also be summarized in the following steps:

1. For every WTG, a random interarrival time for the next required unplanned visit is generated, using the average number of unplanned visits corresponding to the appropriate operational phase
2. A random number $X \sim U(0,1)$ is generated
3. If $X > Pf_{minor}$ (of the corresponding appropriate operational phase), then the reason for the unplanned visit is a major failure, otherwise it is a minor-moderate failure

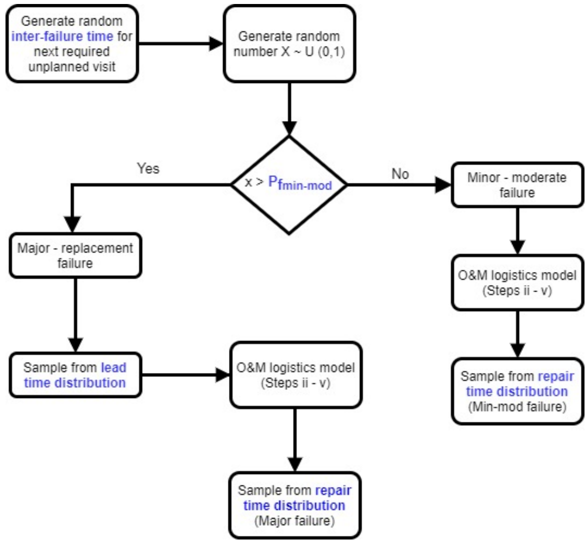

Figure 6.1: Flowchart of extended model for O&M process.

4. If the unplanned visit is caused by a major failure, then the lead time to acquire the required resources is sampled from the appropriate distribution. Then, the tasks are prioritized, the resources are allocated, the weather windows are calculated and the vessel transits to the OWF site. Finally, the required time $T_{R_{maj}}$ to repair when the technicians are on the site is sampled from the appropriate probability distribution

5. Otherwise, if the unplanned visit is caused by a minor-moderate failure, then the appropriate tasks are prioritized, the resources are allocated, the weather windows are calculated and the vessel transits to the site. Afterwards, the required time $T_{R_{min}}$ to repair when the technicians are on the site is sampled from the appropriate probability distribution

Due to lack of sufficient data to properly represent the uncertainty of the required variables for the proposed model, expert judgments can be used. The mathematical aggregation method, called Cooke's classical model, was chosen to elicit the judgments from a group of experts and optimally aggregate these to form the so called decision maker (DM). More information about this method can be found in [5, 6] and have already been presented in Chapters 4 and 5.

6.3. EXPERT JUDGMENTS ANALYSIS AND SYNTHESIS

FOR the purpose of this investigation, five experts from the energy utility Vattenfall with relevant expertise in the O&M field of OWFs provided their assessments during individual interviews. During these interviews the analysts explained the motivation of the study, described the method of expert judgments elicitation and clarified all aspects concerning the questions to remove ambiguity. The experience of the experts ranged

Characteristic	Description
Location	North Sea; Irish Sea; Baltic Sea
Number of Wind Turbines	More than 50 WTGs and less than 100 WTGs
Distance from manufacturers to the installation port (relevant for replacement)	More than 150 NM
Distance from operations port to the OWF site	More than 20 NM
Minor - moderate failure event	E.g. pitch motor, reset thermal relays etc.
Major - replacement failure event	E.g. switch gear, generator, bearings, transformer
WTG characteristics	Mature technology

Table 6.1: Characteristics of OWFs to be considered.

from 5-20 years in offshore wind field and they had different roles which are related to O&M of OWFs.

6

For the seed questions publicly available data from System Performance Availability and Reliability Trend Analysis (SPARTA) initiative were used along with data from Vattenfall's data centre. The data from SPARTA concern 22 anonymized OWFs in the UK in the period 2017-2019 [7, 8], while the data from Vattenfall's data centre concerned the company's operational offshore wind portfolio. The available data from SPARTA concern only OWFs in the UK and do not provide information about different lifecycle phases and reasons for transfers. Hence, it is not possible to use these directly as input for the model. Also, the available data are not sufficient to properly describe the associated uncertainty. However, both of the available datasets can be used for the purpose of measuring the performance of the experts in judging uncertainty. Thus, based on these data, ten seed questions were formulated regarding different measures of the recorded availability, the amount of non-access days to the OWFs, the number of transfers and the OWFs' capacity factor.

The target questions were formulated in such a way to elicit uncertainty estimates concerning the number of unplanned visits (UVs) for each wind turbine in a year, the relative frequency of failures and the repair time. These were elicited for offshore wind farms with the characteristics presented in Table 6.1. The uncertainty estimates regarding the number of UVs as well as the relative frequency of minor-moderate failures were gathered for 3 different operational phases of the lifecycle of an OWF. These were: (i) Operational Phase 1, during 1st and 2nd year of operation; (ii) Operational Phase 2, ranging from 3rd year of operation until 10 years before decommissioning of the OWF; (iii) Operational Phase 3, during the final years of OWF's lifecycle.

In [9], it was shown that only for certain components (such as the converter and electrical components), significant differences were observed in the failure rates during the lifetime of an offshore wind turbine, that resemble the failure trend suggested by bathtub curve. In this study minor-moderate failure events are caused mainly by similar compo-

Expert ID	Statistical accuracy $C(e)$	Information (all items)	Information (seed)	Weight $w(e)$
Exp. 1	0.00131	1.3004	0.8007	0.00105
Exp. 2	0.00281	0.7427	0.6320	0.00177
Exp. 3	0.06085	0.6994	0.8083	0.04918
Exp. 4	0.00138	0.6598	0.6507	0.00089
Exp. 5	0.01397	0.7227	0.8822	0.01232

Table 6.2: Performance measures of experts.

nents, thus it was decided to differentiate over the 3 aforementioned distinct operational phases in the life cycle of an OWF to reflect the experts' uncertainty concerning failures during these phases. The duration of the periods were chosen in consultation with an expert.

Every expert provided his assessments individually and the analysis and synthesis of these was performed using the recently developed ANDURIL Matlab toolbox [10]. Plots showing the assessments of the experts and the DMs regarding the seed questions which were based on publicly available data and the target questions can be found in Figure 6.2 and 6.3 respectively. The performance of the experts in judging uncertainty is summarized by the performance measures in Table 6.2. In general it can be seen that the statistical accuracy is low while the information score can be considered high. This means that most of the experts were overconfident in their uncertainty assessments. However, Expert 3 and Expert 5 have a statistical accuracy larger than 0.01 which is often used in practice as cut-off level beneath which an expert is unweighted.

According to Cooke's classical model, there are different ways of combining the experts' assessments in order to form a DM [11]. Therefore, 4 different weighting schemes were investigated. The simplest weighting scheme (DMequal) assigns equal weights to every expert irrespective of the expert performance in judging uncertainty. The remaining three weighting schemes calculate the DMs using the computed performance measures. DM_{global} is obtained when every expert receives one weight while DM_{item} is obtained when every expert receives a different weight based on its information score per item. $DM_{global-opt}$ is obtained when the weights of every expert are computed using a cut-off level that maximizes the statistical accuracy of the DM. The obtained DMs can also be treated as "virtual experts". These are added to the pool of experts and the same measures of performance in judging uncertainty are computed. Table 6.3 summarises the performance measures of the obtained DMs.

DM	Statistical accuracy $C(e)$	Information (all items) $I(e)$	Information (seed)
DM_{equal}	0.1135	0.1705	0.1824
DM_{global}	0.2441	0.4637	0.5226
DM_{item}	0.2441	0.5176	0.5965
$DM_{global-opt}$	0.4925	0.3352	0.3648

Table 6.3: Performance measures of obtained DMs.

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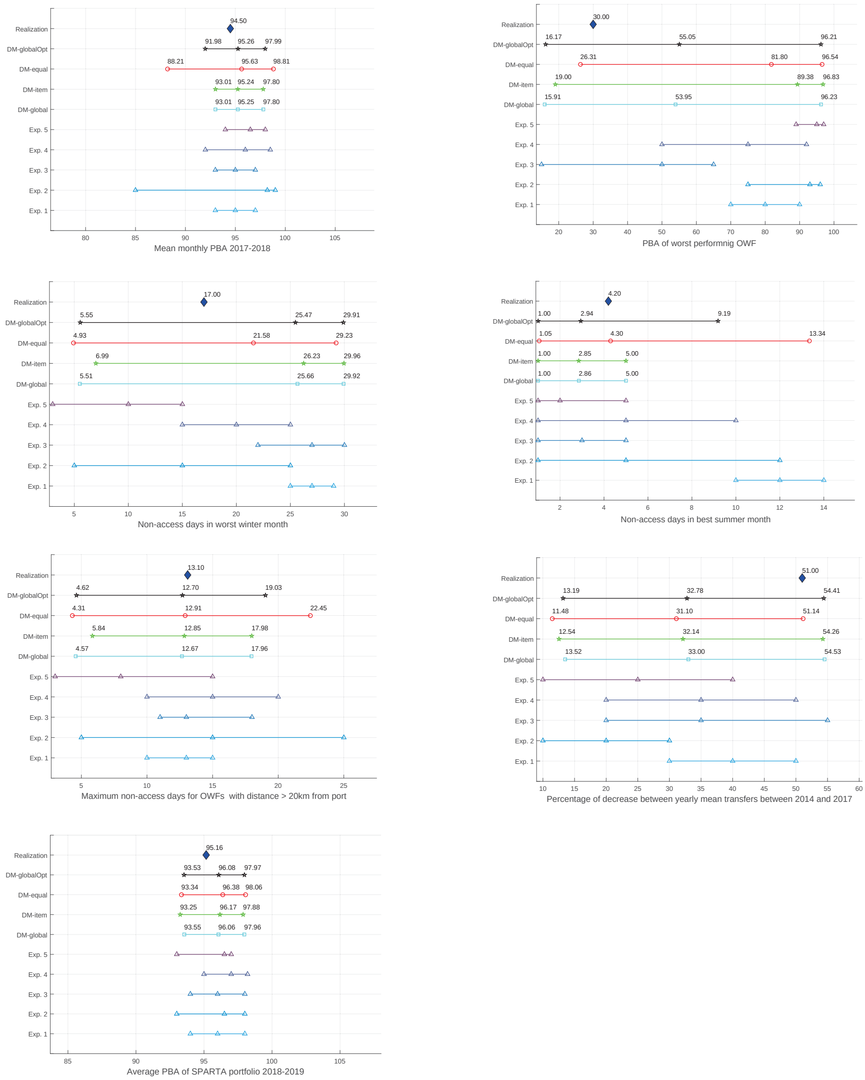

Figure 6.2: Plots of calibration questions based on publicly available data form SPARTA.

From Table 6.3, one can make a number of observations. First of all, it is interesting to mention that all DMs have a larger statistical accuracy compared to the more statistically accurate expert (i.e. Expert 3). However, the informativeness of the DMs is lower compared to all experts. Also, the DM with the lowest overall performance (i.e. statistical accuracy and informativeness) is DM_{equal}. The DM with the highest statistical accuracy and overall performance is $DM_{global-opt}$. Hence, it was chosen to use the obtained distribution from $DM_{global-opt}$ weighting scheme as input to the modified model. In Table

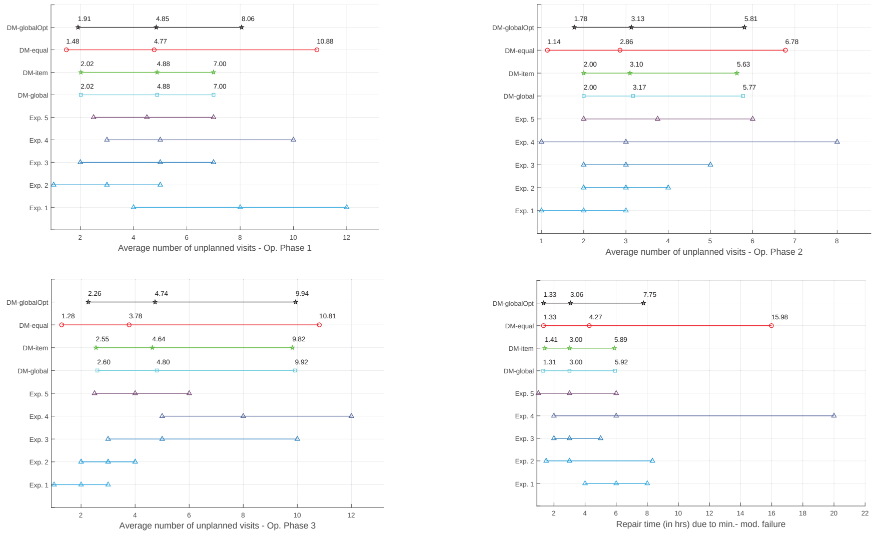

Figure 6.3: Plots concerning the obtained assessments for the target questions.

Target Variable	Operational Phase 1	Operational Phase 2	Operational Phase 3
Average Number of UVs	P5: 1.9 P50: 4.9 P95: 8.1	P5: 1.8 P50: 3.1 P95: 5.8	P5: 2.3 P50: 4.7 P95: 9.9
		All Operational Phases	
Repair time minor-moderate		P5: 1.33 hrs P50: 3.06 hrs P95: 7.75 hrs	

Table 6.4: Obtained values of $DM_{global-opt}$ for TQs relevant for the simulated test case.

6.4, one can find the values of obtained distributions when combining experts' assessment using the $DM_{global-opt}$ weighting scheme. These values were used as input in the hypothetical test case presented in Section 6.4.

6.4. O&M APPLICATION

A realistic hypothetical test case was simulated to investigate the effect of the uncertainty of the variables concerning the unplanned visits. Two different O&M strategies were assessed with respect to the access method to the offshore wind turbines, specifically Crew Transfer Vessel (CTV) based access and a variant including Helicopter. In essence, for cases where a Helicopter complements CTV operations, availability is increased due to higher accessibility to offshore locations. This study focuses on the impact of uncertainty on availability under different O&M strategies but it is mentioned that maintenance costs should also be considered for optimal O&M planning. More details of the

Characteristic	Description
Location	North Sea
Number of Wind Turbines	50 WTGs
Distance from operations port to the OWF site	27 NM
Access methods	CTV; CTV + Heli
Technicians	3 teams of 2 technicians
Maintenance Scope	Minor - Moderate failure events
WTG characteristics	> 8 MW

Table 6.5: Specifics of the test case.

test case can be found in Table 6.5.

Each strategy is simulated using the Monte-Carlo framework of the O&M logistics model for 500 simulations of yearly operations representing the 3 different operational phases. The uncertainty variables for each simulation include the MetOcean conditions, different distribution of UVs based on the elicited estimates regarding their average yearly number and a random repair time for each task based on the distribution given in Table 6.4.

The choice of the values concerning the number of UVs represents the risk aversion of the analyst. Thus, a risk averse analyst would choose to use an average number of UVs based on P95 confidence level where in most cases P50 values are used in practice. For the purpose of this study, the impact of UVs in availability is investigated during Operational Phase 2 using CTV based access in Figure 6.5. Moreover, a comparison between strategies utilizing CTV and CTV+Heli access during Operational Phase 1 under various confidence levels is presented in Figure 6.4.

Various conclusions can be drawn based on Figures 6.4 and 6.5. First, yearly availability increases by approximately 1% when moving from operational phase 1 to 2 due to the reduction in the failure rates. For CTV based access during phase 2, a risk averse option (P95) for the UVs reduces the expected availability by 1.5% compared to the P50 option while in the worst case scenario by 3.5% demonstrating also the higher range associated to P95 confidence. Last, comparing CTV versus CTV+Heli access, we see an availability upside of 1% and 2% for P50 and P95 UVs respectively. This means that the helicopter option is more attractive when risk appetite is relatively low which is also something that we see in practice.

6.5. CONCLUSIONS

This chapter proposed a method to improve the uncertainty representation of the reliability of OWFs. To achieve this a previously developed O&M logistics model was modified and experienced experts from the offshore wind field provided their uncertainty estimates for a number of questions. Cooke's classical model was used to optimally aggregate their judgments regarding the target variables. The obtained distributions were used for a realistic hypothetical test case. For this test case, two different O&M strategies were assessed. It was found that the proposed approach allows a better representation

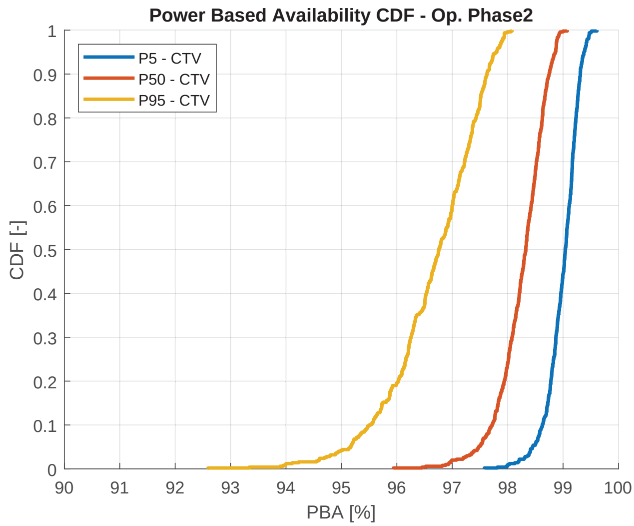

Figure 6.4: PBA CDF during Operational Phase 2 – CTV.

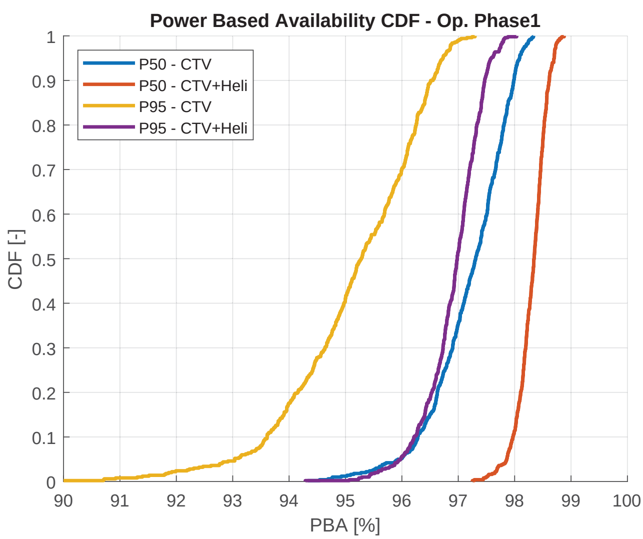

Figure 6.5: PBA CDF during Operational Phase 1 – CTV vs CTV+Helicopter.

of the uncertainty of the availability in different operational phases.

Moreover, it enables the comparison of different strategies while taking into account user's risk appetite. In this way, the "best" O&M strategy that results in higher availability of the OWF can be chosen according to the user's confidence level of choice

Finally, it should be mentioned that the proposed method together with the obtained expert assessments can be used in future projects to support the decisions concerning O&M strategies with a higher confidence level. This along with further development of the model to incorporate the cost of alternative strategies would allow an holistic evaluation of O&M strategies under uncertainty and assist in having more resilient energy assets in the future.

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IV

Conclusions and Recommendations

7
CONCLUSION

In this chapter, the most important findings of this research are summarized. Furthermore, their scientific and technical implications for society are discussed. Finally, recommendations are given for further research with the purpose to further advance the conducted research and overcome its current limitations.

7.1. MAIN FINDINGS & VALORIZATION

The purpose of this research was to investigate and propose methods that can be used to support decisions concerning the construction management of offshore wind energy assets. These decisions are subject to various uncertainties and therefore these should properly be taken into account. Hence, probabilistic risk analysis methods were explored. More specifically, Monte Carlo simulations proved to be an efficient method to allow for investigating the aggregated effect of different uncertainties.

A distinction was made between cases where sufficient relevant data exist and where these are limited. When sufficient data were available, these were analyzed using statistical methods to describe the dependence of these random variables. In this work, methods such as copulas and non-parametric Bayesian networks were utilized to describe the dependence of environmental conditions and the uncertainty of the subsequent offshore construction operations.

On the other hand, when sufficient relevant data are not available, expert judgments were used to quantify the uncertainty. A mathematical aggregation method that is Cooke's classical model was chosen to take into account the performance of the experts in judging uncertainty. This method was applied in different applications related to offshore wind assets such as the risk of supply disruption during the installation phase and the unplanned events that initiate corrective maintenance activities during the operational phase. This approach was proven particularly useful to quantify the uncertainty of events and take decisions for mitigating these risks. In the context of this research, an open-source Matlab toolbox named ANDURIL was developed which can be used for applying Cooke's classical model. This toolbox enables researchers and practitioners in understanding and applying and further developing this method. As a showcase of possible developments, the investigation of the robustness of the obtained combination of expert judgments was presented. It is worth mentioning that the creation of this open-source toolbox allowed for further improvement and development of a modern software to apply Cooke's classical model while including the most important functionalities of its ancestor EXCALIBUR. ANDURIL became scriptable and was also developed in Python (i.e. ANDURYL) to make it accessible to those with limited or no access to Matlab licenses. Moreover, the updated versions allow for user-defined quantiles and missing items. Finally, a stand-alone graphical user interface was developed for ANDURYL that makes the software more accessible to researchers and practitioners of Cooke's classical model with limited Matlab or Python experience.

The investigations concerning the predominant uncertainties of the construction management of offshore assets and their main findings are listed below:

- *Environmental uncertainties.* Typically, a large amount of hindcast weather data is used to incorporate the environmental uncertainty into the estimated duration of the installation of OWFs. When a sufficiently large amount of historical/hindcast data is not available, synthetic time series can be used. These synthetic time series enable the evaluation of different scenarios while taking into account more possible MetOcean conditions than the existing historical observations. For the purpose of a test case synthetic time series were constructed and validated by comparing important characteristics such as workability and persistence with those of the observed time series. It was found that dependently constructed synthetic time series provide a better insight into the duration of installation scenarios. Especially, when more uncertainties such as the duration of certain activities are taken into account. More specifically, for the investigated test case, when only limited hindcast data were used, the estimated 70^{th} percentile of the total time to completion from different runs differed $2\%-7\%$ compared to the more robust P70 value which was estimated with the synthetic time series.

- *Supply disruptions.* Supply disruptions can occur during the execution of large construction projects such as the installation of an OWF. These disruptions can be modeled as an event with a probability of occurrence and an impact (i.e. delay, waiting time until the required components become available). Due to lack of sufficient relevant data which are typically commercially sensitive, expert judgments were collected and combined using Cooke's model to quantify the supply disruption risk. A realistic test case was simulated to investigate the impact of neglecting this risk. It was found that neglecting the supply disruption risk can lead to an underestimation of 2% (i.e. approximately 4 million Euros) of the installation cost. The obtained distributions can be used in future OWF installation projects to support decision for mitigating this risk or estimating the required amount of the allocated contingency budget.

- *Uncertainty and dependence description of offshore construction operations.* Stochasticity of the duration of construction activities is often neglected in the models which are used to support decisions for construction management of offshore wind assets. Moreover, the dependence of the durations of construction activities is not taken into account in practice. A non-parametric Bayesian network (NPBN) with serial connection can represent the dependence between consecutive construction activities of offshore WTGs. Sampling from this NPBN allows to evaluate installation scenarios of WTGs while taking into account the uncertainty and the dependence of construction activities. For the simulated test case, it was found that neglecting the dependence and assuming constant duration of construction activities can lead to approximately 7% decrease concerning the 50^{th} percentile of the estimated total duration.

- *Reliability estimates for O&M strategies.* To improve the representation of the uncertainty concerning the reliability of an OWF during it's lifetime, expert judgments can be used. In a study supported by Vattenfall, Cooke's classical model was applied to obtain uncertainty estimates of unplanned events which can cause standstill and revenue loss. For this study, distinction was made for different operational phases and different types of failures (i.e. minor-moderate and major). This approach can be combined with a simulation model for O&M logistics. In this way, it is possible for the decision makers to compare different maintenance strategies according to their risk appetite and choose the "optimal" strategy according to the confidence level of their choice. In the simulated test case, it was found that a risk averse (or pessimistic) modelling approach leads to 1.5% reduction in the expected production based availability compared to a moderate risk appetite modelling approach for the same maintenance strategy (CTV based access).

The investigated methods can be combined in a simulation framework that allows for the quantification of the aggregated effect of the predominant uncertainties. Moreover, this simulation framework enables the comparison of different realistic scenarios as well as possible mitigation measures. In this way, the decision makers can base their decisions on results which include the associated quantified uncertainties and choose a quasi-optimal scenario.

The proposed methods were applied mainly to studies concerning offshore wind assets. It was shown that these can improve the representation of uncertainty and subsequently support decisions that will further reduce the associated costs. This reduction will be crucial for the urgent energy transition towards renewable energy sources as it will enable further expansion of the offshore wind energy field which is considered one of the most promising renewable sources. Thus the proposed methods can be used by professionals in contractors, manufacturers and developers of the offshore wind industry, to achieve a fossil-free energy future.

In addition, it should be noted that the proposed methods in this research context could also be used to quantify uncertainty and support decisions in different fields. More specifically, for example, the developed Matlab toolbox ANDURIL was also used in recent studies such as one concerning the decision support of maintenance strategies including the uncertainty of the condition of assets with long service-life.

7.2. DISCUSSION AND RECOMMENDATIONS

Among the investigated topics of this research, there is a number of topics that are worth further research. Therefore, specific limitations concerning the different parts of this research are discussed and recommendations are given below:

- The synthetic time series method, which was proposed to incorporate more possible metocean conditions into the estimated duration of an offshore wind installation project, did not allow to produce synthetic samples that exceeded the recorded values. Thus, it is also not possible to take into account climate change. Climate change can lead to more frequent extreme events and more extreme metocean conditions in general, which are not described in the historical data and therefore will not be described in the synthetic as well. Hence, investigation of a method that combines extreme value theory with the proposed copulas method for synthetic environmental time series might assist in order to take into account climate change. Moreover, it would be valuable to investigate how it would be possible to decide which of the available historical years are relevant for representing the altered climate for the scenarios under investigation.

- Since its creation, ANDURIL Matlab toolbox is continuously updated by researchers in Technical University of Delft. The toolbox was also developed in Python (named ANURYL) and a user interface was added. The value of this toolbox can be improved by extending the current functionalities by adding the measures of experts' performance in judging the dependence of random variables.

- Another recommended investigation that can use ANDURIL as showcase is the addition of a proximity performance measure which can maybe be combined with the performance measures of Cooke's classical model. This might be useful in studies where experts are providing estimates that are very far from the realization of the seed items.

- The proposed method for modeling supply disruptions can be extended in order to take separately into account manufacturing delays that may occur in an offshore wind installation project. This can be particularly interesting in the future due to the increasing demand for offshore wind turbines and the limited number of suppliers who would be capable of supplying these.

- When considering the uncertainty of the duration of offshore construction activities the learning effect was not included in the proposed method. It was shown that the learning effect during an offshore wind construction project can be important. Based on few past projects and particular repetitive activities there was a significant learning effect. Hence, it is recommended to investigate the application of autoregressive models and dynamic Bayesian networks.

- Ultimately, while all the investigated and proposed methods of this research can be used in a simulation framework to support decisions for offshore wind assets, the identification of the "optimal" scenario is limited by the investigated scenarios that will be chosen by the user. Therefore, the investigation of stochastic optimization methods will be worthwhile in order to take into account the aggregated effect of all predominant uncertainties and find the truly optimal scenario.

A

APPENDIX

A

A.1. PARTICIPANTS OF THE STUDY

Name	Affiliation	Country
Andersen K. J.	Veja Mate	Germany
Claus M.	Siemens	the Netherlands
De Ridder E.	Jan de Nul	Belgium
Engelmann L.	Maritime Technik	Germany
Garrett C.	DNV-GL	United Kingdom
Holy A. L.	Vattenfall	Germany
Knipping D.	Van Oord	the Netherlands
Rabaut D.	DEME	Belgium
Rainey P.	EON	United Kingdom
Robert P.	DAMEN	the Netherlands
Warnaar P.	ECN	the Netherlands

A.2. COST CALCULATION - ECN INSTALL

ECN Isntall calculates the cost of the installation process by keeping track of the installation activities in the time domain and hourly save the utilization of resources. For every performed simulation, information is gathered regarding the working time and waiting time (due to weather, supply disruptions, harbour and shift delays) for every vessels and equipment. Then, these are used accordingly to the user-defined costs. More precisely, the total cost of the installation process is computed using equation A.1.

$$Cost_{installation} = c_{vessels} + c_{equipment} + c_{ports} + c_{labour} \tag{A.1}$$

where:

$$\begin{aligned} c_{vesssels} = \sum_{v \in V} c_{fixed,v} + N_{dr,v} * d_{r,v} + N_{drw,v} * d_{rw,v} + \\ N_{mob/demob,v} * c_{mob/demob,v} + N_{trips,v} * c_{add,v} \end{aligned} \tag{A.2}$$

where v and V a vessel and the set of vessels respectively; $c_{fixed,v}$ the fixed cost of vessel v; $N_{dr,v}$ and $N_{drw,v}$ the number of working and waiting days of vessel v respectively; $d_{r,v}$ and $d_{rw,v}$ the day rates for working and waiting respectively; $N_{mob/demob,v}$ and $c_{mob/demob,v}$ number and cost of (de-)mobilizations respectively; $N_{trips,v}$ and $c_{add,v}$ number of trips and additional cost respectively.

$$c_{equipment} = \sum_{e \in E} c_{fixed,e} + N_{dr,e} * d_{r,e} + N_{drw,e} * d_{rw,e} \tag{A.3}$$

where e the equipment and E the set of used equipment; $c_{fixed,e}$ the fixed cost of the equipment; $N_{dr,e}$ and $N_{drw,e}$ the number of working and waiting days of equipment e respectively; $d_{r,e}$ and $d_{rw,e}$ are the day rates while working and waiting respectively.

$$c_{ports} = \sum_{p \in P} c_p * D_p \tag{A.4}$$

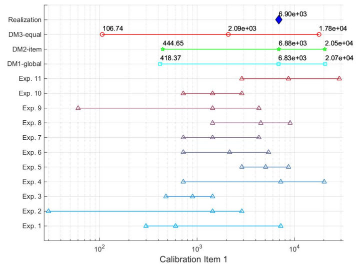
where p and P denote one port and the set of ports respectively; c_p and D_p are the cost of port p per day and the number of days port p was used.

$$c_{labour} = \sum_{d_l \in D_l} c_l \tag{A.5}$$

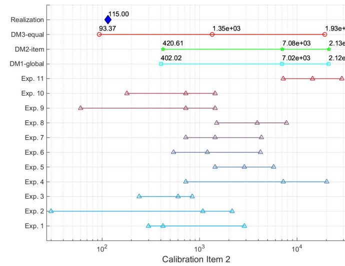
where d_l and D_l denote one day and the set of days for which labour is performed; c_l is the labour cost per day.

A

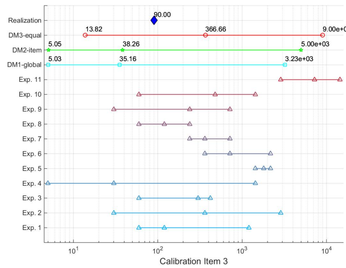
A.3. CALIBRATION VARIABLES



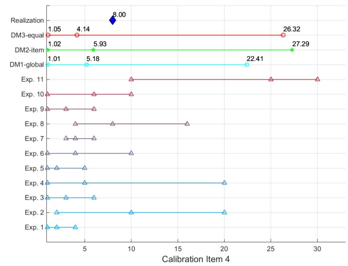
(a) Maximum registered delay because required MPs not available (Prj. 1).



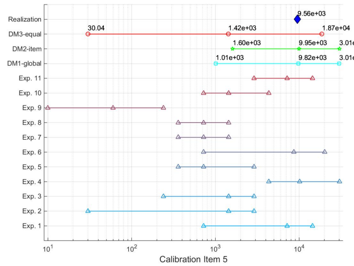
(b) Maximum registered delay because required TPs not available (Prj. 1).



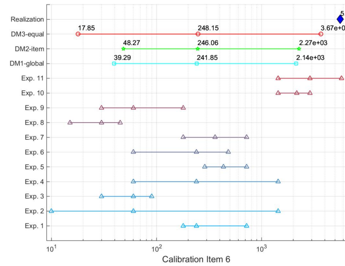
(c) Average of registered delays because required TPs not available (Prj. 1).



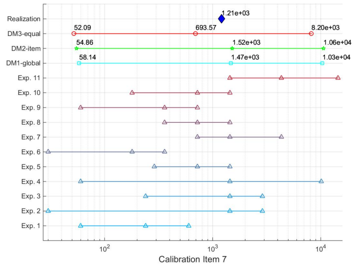
(d) Number of times there was a delay larger or equal to one hour because the required MPs were not available (Prj. 1).



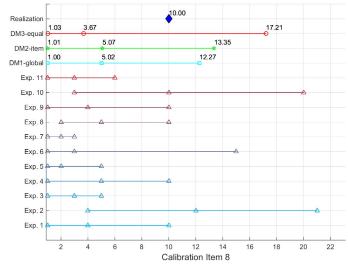
(e) Maximum registered delay because required TOWERS not available (Prj. 2).



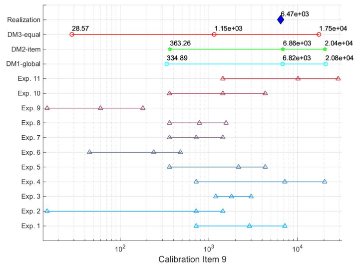
(f) Average of registered delays because required TOWERS not available (Prj. 2).



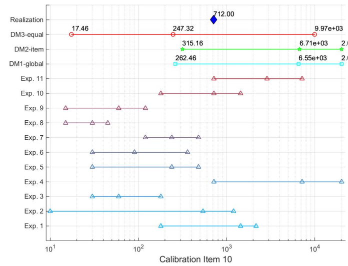
(g) Maximum registered delay because required BLADES not available (Prj. 2).



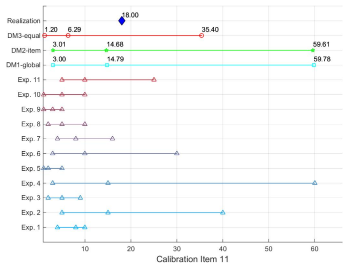
(h) Number of times there was a delay ($\geq 1h$) because the required TOWERS were not available (Prj. 2).



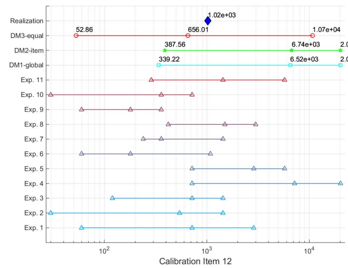
(i) Maximum registered delay because required MPs not available (Prj. 3).



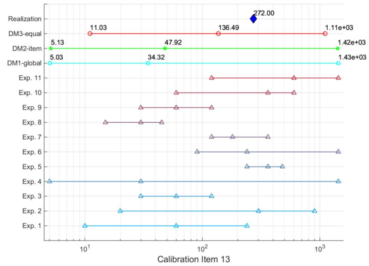
(j) Average of registered delays because required MPs not available (Prj. 3).



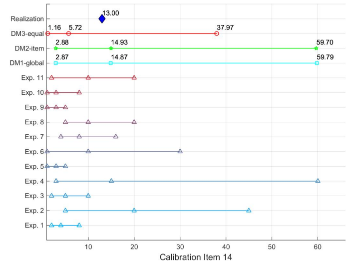
(k) Number of times there was a delay larger or equal to one hour because the required MPs were not available (Prj. 3).



(l) Maximum registered delay because required MPs not available (Prj. 4).

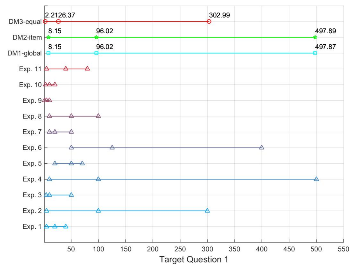


(m) Average of registered delays because required MPs not available (Prj. 4).

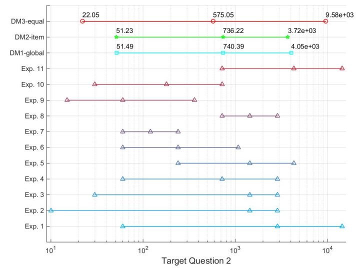


(n) Number of times a delay (>= $1h$) occurred because the required MPs were not available (Prj. 4).

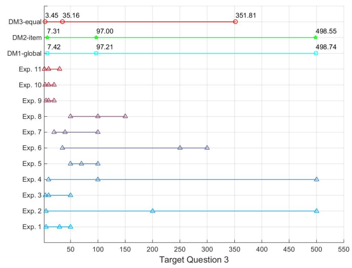
A.3.1. TARGET VARIABLES



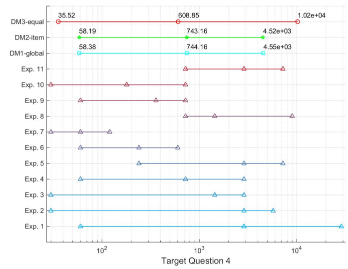
(a) Relative frequency of occurrence (per 1000) of unavailability of required MPs.



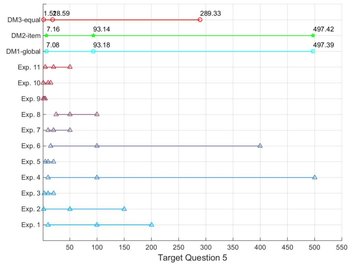
(b) Waiting time (in minutes) because required MPs not available for loading.



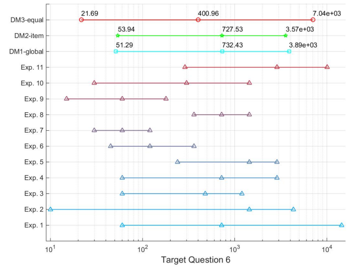
(c) Relative frequency of occurrence (per 1000) of unavailability of required TPs.



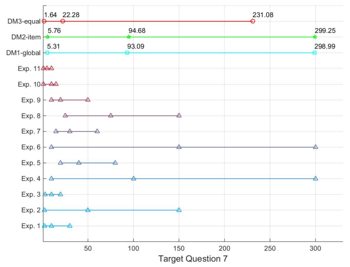
(d) Waiting time (in minutes) because required TPs not available for loading.



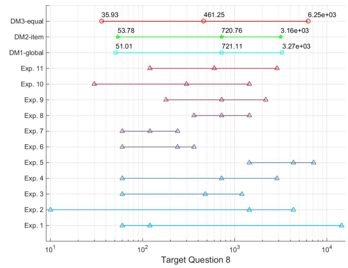
(e) Relative frequency of occurrence (per 1000) of unavailability of required Towers.



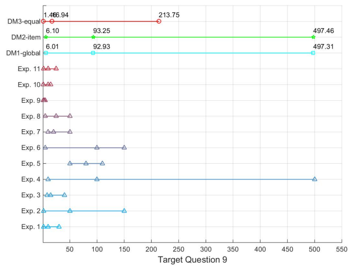
(f) Waiting time (in minutes) because required Towers not available for loading.



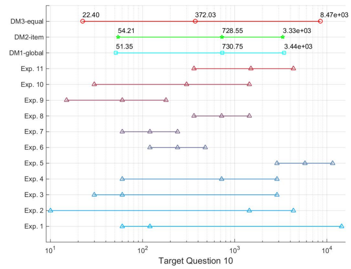
(g) Relative frequency of occurrence (per 1000) of unavailability of required Blades.



(h) Waiting time (in minutes) because required Blades not available for loading.



(i) Relative frequency of occurrence (per 1000) of unavailability of required Nacelles.



(j) Waiting time (in minutes) because required Nacelles not available for loading.

A

A.4. EXPERT JUDGMENTS ANALYSIS WITH $alpha = 0.01$

Expert ID	Calibration Score	Information Score (All items)	Information Score (Seed items)	Un-normalized Weights	Normalized Weights excl. DM
Expert 1	0,0002060	0,70675	0,86518	0,00	0,00
Expert 2	0,011904	0,471358	0,516478	0,0061485	0.0229
Expert 3	6,804e-10	0,93655	1,090144	0,00	0,00
Expert 4	0,569084	0,452635	0,4606201	0,2621317	0.9771
Expert 5	1,983e-07	1,214771	1,1789866	0,00	0,00
Expert 6	1,314e-05	0,82397	0,712980	0,00	0,00
Expert 7	1,192e-07	1,214716	1,195092	0,00	0,00
Expert 8	0,00036218	1,165429	1,137962	0,00	0,00
Expert 9	2,547e-11	0,8838053	0,802524	0,00	0,00
Expert 10	1,762e-05	0,8577063	0,897994	0,00	0,00
Expert 11	0,00441208	0,8424475	0,9259006	0,00	0,00

Table A.1: Measures of performance in judging uncertainty and weights for every participant, obtained from the analysis with ANDURIL using a cut-off level equal to 0.01.

Name	Calibration Score	Information score (total)	Information score (seed)
DM_{global}	0.96812	0.38179	0.36811
DM_{item}	0.96812	0.39156	0.38038

Table A.2: Comparison of the performance measures of two performance-based DMs for $alpha = 0.01$.

A.5. ALTERNATIVE STRATEGIES

Strategy 1: Initial stock at the installation port in the commencement of installation	10 units of each component (MPs, TPs, Towers, Nacelles, Rotors)
Strategy 2: Initial stock at the installation port in the commencement of installation	20 units of each component (MPs, TPs, Towers, Nacelles, Rotors)
Strategy 3: Initial stock at the installation port in the commencement of installation	20 units of foundation components (MPs, TPs) and 10 units of WTGs components (Towers, Nacelles, Rotors)
Strategy 4: Initial stock at the installation port in the commencement of installation	10 units of foundation components (MPs, TPs) and 20 units of WTGs components (Towers, Nacelles, Rotors)
Strategy 5: Initial stock at the installation port in the commencement of installation	20 units of MPs, TPs, Towers and 10 units of Nacelles, Rotors
Strategy 6: Initial stock at the installation port in the commencement of installation	20 units of MPs, TPs, Nacelles, Rotors and 10 units of Towers

Table A.3: Details of the different simulated strategies.

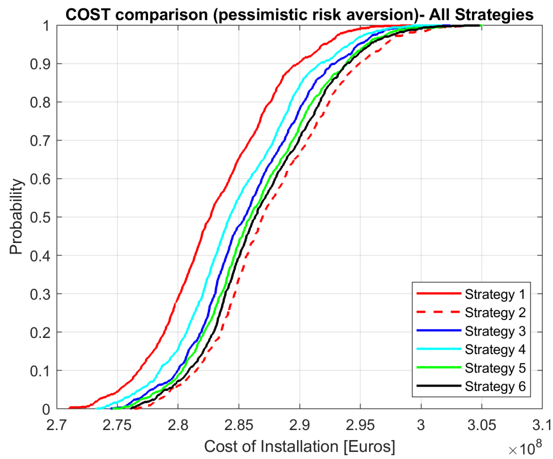


Figure A.3: Cost comparison of all different simulated strategies for the pessimistic approach.

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Writing this part of the dissertation signifies the end of a long and challenging journey. Although I am not big supporter of the notion that the journey is more important than reaching the destination, I have to admit that during this process I learned a lot and in general I matured. Hence, I would like to reflect on some moments of this journey and express my gratitude to the persons who played a role in making this possible.

This journey started with a casual question about the idea of doing a PhD, in the staircase of CiTG building in spring of 2015. I decided to take the challenging opportunity and pursue a PhD in a field that I found fascinating and meaningful. Almost five years and a pandemic later, I am happy that I am able to add the final words to this work.

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Curriculum Vitæ

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List of Publications

12. **G. Leontaris** and G. Katsouris, *Improving uncertainty representation of offshore wind farms reliability using expert judgments*, in Proceedings of the 30th European Safety and Reliability Conference and the 15th Probabilistic Safety Assessment and Management Conference, edited by F. D. M. Piero Baraldi and E. Zio Research Publishing, (2020).

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