Improving workability estimates for the offshore wind industry

Estimating the workability of marine operations more accurately using the dynamic response motions of vessels and turbine structures

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Van Oord

Marine ingenuity

TU Delft

Estimating the workability of marine operations more accurately using the dynamic response motions of vessels and turbine structures

Improving Workability Estimates for the Offshore Wind Industry

by

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Preface

Before you lies my Master of Science thesis on 'Improving workability estimates for the offshore wind industry'. This thesis describes the research work that was conducted to obtain my Masters degree in Civil engineering at the Delft University of Technology (TU Delft). Over the period from October 2020 to September 2021, I was engaged in researching and writing this thesis as a graduate intern at Van Oord Marine Contractors B.V. Therefore, I would like to thank Van Oord for facilitating this amazing opportunity and providing this research with the necessary data.

I would like to express my gratitude to my daily supervisors Gerben de Boer and Pieter van Halem for helping me through the research process, their feedback and knowledge. Without your support I would not have been able to conduct this research. Apart from my daily supervisors, I would like to thank my committee members, Mark van Koningsveld, Julie Pietrzak, Arne van der Hout and Floor Bakker for their excellent guidance, support and contribution to this research. My sincere appreciation to engineering specialist Kevin van de Leur who helped me with so many engineering questions and my fellow Van Oord graduate Marius Smorenberg for his time.

Finally, I would also like to thank my friends, my girlfriend and my parents for their continuous support throughout my education and research work.

I hope you enjoy your reading.

Thijs Reedijk

Abstract

In recent years, several logistic optimisation models have emerged as powerful tools to assess and optimise the planning, costs, and workability of marine operations. Nevertheless, these models often rely on two underlying assumptions: (1) the significant wave height and peak wave period adequately describe (directional) wave fields, and (2) these two parameters sufficiently describe the conditions causing weather downtime. However, little is known about how these underlying assumptions affect the reliability of logistic optimisation tools. This study, therefore, presents an alternative model that integrates response motions of vessels and turbine structures into a logistic optimisation tool to address and expose the implications that follow from using these assumptions. A case-study approach, on two recently realised offshore wind farm projects, showed that integrating response motions results in, up to 10%, less favourable workability conditions. Further analysis on the data showed that it is crucial to include the two-dimensional wave energy distribution to expose more complex sea states that induce weather downtime. Moreover, a failure analysis approach found that the conditions inducing downtime events are more accurately described by response motions instead of sea state parameters. Therefore, the findings of this study suggest that integrating response motions into logistic optimisation models improves the reliability of the model estimates. Besides, this study suggest that the industry's approach potentially overestimates the true workability and, therefore, imposes unnecessary operational risks. Hence, the results of this study demonstrate the importance of integrating hydrodynamic engineering knowledge into the assessment and optimisation of project planning, costs, and workability.

Summary

Introduction

In recent years, several logistic optimisation models have emerged as powerful tools to assess and optimise the planning, expenditure, and workability of marine operations. Nevertheless, these models commonly rely on two underlying assumptions:

1. The significant wave height and peak wave period adequately describe the two-dimensional wave energy distribution of a (directional) wave field.
2. The wave conditions associated with weather downtime are sufficiently described by these two parameters following a workable limit analysis.

However, what is not yet understood is the extent to which these assumptions affect the reliability of the planning and engineering of marine operations. This study, therefore, presents an alternative model that integrates response motions of vessels and turbine structures into a discrete-event simulation based logistic optimisation tool to address and expose the implications that follow from using these assumptions.

Model description

The model presented in this thesis computes time-series of the response motions during the weather window analysis based on historical data of the governing directional wave spectra and response amplitude operators (RAOs). To compute time windows of workable and not workable periods, the model compares these time-series to their respective critical limits and subsequently uses these alleged weather windows to schedule the installation activities.

This approach provides at least two advantages: (1) the two-dimensional wave energy distribution is maintained; and (2) the operational limits depend on the structural dynamics only and apply to all sea states.

Model implementation

A case-study approach was adopted to generate sample data for both methods. This thesis describes the application of the model to two recently realised offshore wind farm projects, the Hollandse Kust Zuid (HKZ) and Borssele III&IV offshore wind farms. The two projects were specifically chosen because the weather restricted activities that were modelled correspond to operations that involve the motions of floating equipment as well as the motions of a wind turbine generator (WTG) structure. Besides, during the realisation of both projects, the operations encountered numerous times unexpected weather-related downtime.

For each project, the installation sequences that are described by their respective work methods, were simulated. During the initial simulations, the floating equipment was aligned with the mean wave direction. Subsequently, the simulations were repeatedly (10,000 times) run with varying start dates over a period from 1990 to 2020.

Case-study results

The data obtained from the simulations show that the response motion-based model estimated, for both projects, substantially (up to 10%) less favourable workability conditions. Further analysis on the data from the Hollandse Kust Zuid (HKZ) case-study showed that, despite the vessel's alignment with the mean wave direction, excessive roll (60% of the cases) and pitch (92% of the cases) motions were the predominant cause of weather downtime events. However, the study also found that using an optimising algorithm to acquire the least response motions helped to improve workability conditions. Moreover, a failure analysis approach demonstrated that the response motion-based method approximated the limiting conditions experienced at site more closely than the allowable sea state approach. Therefore, the case-study findings show that utilising response motions during the weather window analysis results in less favourable, but more accurate workability estimates.

Discussion and conclusion

Perhaps the most important finding of this study is that the current approach used by the industry potentially overestimates the true workability and therefore imposes unnecessary operational risks. In particular, this study found that it is crucial to include the 2D wave energy distribution to expose those (more complex) sea states that induce weather downtime. Moreover, the results of this study imply that allowable sea state based operational limits do not appropriately describe the critical conditions that are associated with operational downtime.

Furthermore, this study showed that the implications of the two underlying assumptions can be resolved by integrating response motions instead of allowable sea states into logistic optimisation models. This study also illustrated that integrating response motions increases the reliability of workability estimates which is an import aspect for optimising the logistics of marine operations. By combining engineering knowledge from hydrodynamics and logistics, this study presented a quantitative logistic optimisation model that can predict the workability more accurately and enables to optimise the project planning and expenditures of future offshore wind farm projects.

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Chapter 1

Introduction

1.1 Background

The construction of an offshore wind farm is often associated with substantial installation costs. In recent studies, it was shown that marine contractors spent 15 to 20% of their capital expenditures (CapEx) on constructing an offshore wind farm (Taylor et al., 2016). Therefore, several researchers tried to reduce the installation expenses by optimising the logistic operation. However, only few addressed the operational risks associated with weather downtime that is often accountable for a significant amount of the project expenses. In a report by BVG Associates (2019), it was stated that the most effective approach in affecting the financing costs is by reducing the project risks.

Conventionally, the weather-related operational risks are expressed using the workability. In marine engineering, assessment of the workability is considered fundamental in approximating the costs of marine operations. A comprehensive workability analysis provides the tools to estimate the weather downtime, size equipment and select the appropriate installation strategy. Project engineers can subsequently use such information for planning and engineering purposes and to determine the overall project expenses.

In literature, the **workability** parameter is often understood as a measure to express the probability of weather downtime. For instance, according to Rip (2015):

> “the workability is the amount of time that a time series is in the operable state, i.e. a certain operation can be executed in a safe manner”

Traditionally, engineers estimated the workability from metocean statistics. Often using scatter diagrams, (joint) probability distributions of one or multiple metocean parameters, and through persistence statistics. Persistence statistics describes the availability of sufficient weather windows by means of probability exceedance curves and is in literature frequently identified as a crucial parameter for indicating the occurrence of weather downtime. In that context, Graham (1982) stated:

> "Although one vessel may have a lower charter rate than another, a study of the planned operations in the context of the weather persistence characteristics might well show that overall, a more expensive charter, with less potential weather downtime, is more economic."

Weather windows are explained as periods of time during which the offshore conditions allow for safe execution of the marine activities. (Tomaselli et al., 2021).

However, such methods do not account for the sequential nature of marine operations (Kikuchi & Ishihara, 2016).

Moreover, the construction of an offshore wind farm often involves multiple vessels each executing particular tasks of the logistic operation. A major interest is to understand how the weather constraints of one vessel impacts the fleet performance. Therefore, instead, researchers developed scenario simulation models to simulate the installation process and to assess and optimise the planning, costs and workability of constructing an offshore wind farm.

Common frameworks to model and analyse the characteristics of logistic operations are discrete-event simulation (DES), linear programming (LP), and Markov Chain (MC). However, the capacity to model complex logistic flows and to examine alternative configurations is an important advantage of using discrete-event simulation over linear programming and Markov Chain analysis (Jacobson et al., 2013).

In 2018, den Uijl (2018) carried out a research to develop a concept evaluation tool to enable fast and accurate assessment of various work methods of dredging projects. His thesis, resulted in the development of a DES-based logistic optimisation tool, OpenCLSim. The tool became the foundation of further optimisation studies, such as van der Bilt (2019), who assessed the emission performance of dredging projects, and van Halem (2019), who introduced a new algorithm for optimising shipping routes that are highly affected by dynamic flow fields.

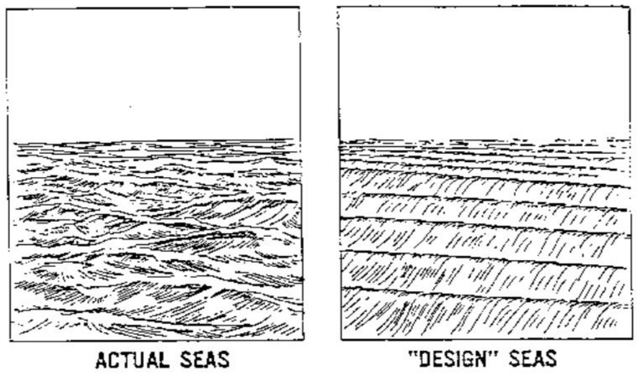


Fig. 1.1 – Illustration of how describing the sea states by only two characteristic parameters affects the input of state-of-the-art models.

1.2 Research problem

1.2.1 Problem description

Nevertheless, today's state-of-the-art models describe the sea state in at most two spectral parameters, the significant wave height (H_s) and peak wave period (T_p). Such models rely on two underlying model assumptions:

1. The significant wave height and peak wave period adequately describe the two-dimensional wave energy distribution of a (directional) wave field.
2. The wave conditions associated with weather downtime are sufficiently described by the two characteristic parameters following a workable limit analysis

However, it is well-known that floating equipment responds to the combination of the wave height, wave period and wave direction. Besides, mixed-seas of wind-sea and swell are frequently encountered at sea. The effects of such seas are hardly captured when considering a small number of input parameters.

Moreover, during the dynamic analysis of the installation activities, it is common to describe the wave conditions by a unimodal, JONSWAP, wave spectrum. Consequently, details of the various wave components and their respective propagation directions are omitted.

Therefore, in operations scheduling studies, the operational constraints imposed by the offshore environment are poorly described. The potential modelling and data errors may, subsequently, contribute to unexpected costs and poor performance of the selected installation strategy.

1.2.2 Previous studies

Studies to describe the occurrence of weather downtime events have been conducted by several researchers. Most notably, in a paper by Acero et al. (2016), the authors developed a systematic methodology to derive the wave conditions associated with operational downtime more accurately. The methodology aims at identifying critical installation activities to establish response-based operational limits in terms of the allowable sea states, characterised by the significant wave height and peak wave period. However, the authors acknowledged that various sources of uncertainty still needed to be addressed. To include the uncertainties in wave spectral energy distribution, Acero & Li (2018) extended the methodology in a succeeding study. The authors commented on the previous with:

> "Because wave spectra at an offshore site may be multi-modal and not necessarily resemble the typical JONSWAP or PM models, the operational limits will vary for every offshore site."

The extended methodology uses 2D directional hindcast wave spectra to compute response motions of an auxiliary parameter (i.e. the crane tip velocity) describing the limiting conditions. For critical values of the auxiliary parameter, the significant wave height and peak wave period are collected from the corresponding wave spectrum. Because the critical value of the auxiliary parameter can be violated for a range of (H_{m_0}, T_p) combinations, limiting combinations that correspond to a characteristic value (i.e. the 5-percentile) are selected.

In a more recent study, Tomaselli et al. (2021) developed a numerical tool for safe and cost-efficient short-term planning of operation & maintenance (O&M) activities based on more direct measures of the workability, such as seasickness and vessel (bow) motions. Based on a five-day metocean forecast, the authors showed that traditional methods would frequently suggest to allow for commencement, though more direct measures would not.

1.2.3 Knowledge gap

However, little is known about how the underlying model assumptions affect the weather window analysis and what the consequences are for the reliability of logistic optimisation tools.

Moreover, existing literature on the development of workability assessment models lacks clarity about the accuracy of the applied model approach.

1.2.4 Purpose of new research

Over the past decades, the ever increasing interest in generating offshore renewable wind energy caused the industry to develop fast (Seyr & Muskulus, 2019). Because of this development, the levelised costs of energy (LCOE) per kilowatt hour (kWh) fell significantly, leading government to end subsidising the development of offshore wind energy. Inevitably, the shrinking subsidies cut down profit margins and demanded the industry to adjust, optimise and innovate new installation strategies to cost-effectively construct offshore wind farms (Graré et al., 2018).

However, despite recent developments, the construction of an offshore wind farm involves substantial operational costs. Besides, new developments indicate a trend in which designated sites are assigned to more remote regions (Díaz & Guedes Soares, 2020) offering significantly more persistence and less turbulent winds. Nevertheless these regions are usually less accessible and impose high weather-related operational risks. Therefore, in the interest of marine contractors, it is necessary to obtain accurate estimates of the workability for the planning and engineering purposes of marine operations.

1.3 Research questions and objectives

The central problem raised in previous sections is that the installation costs are substantial due to high operational risks. However, a reduction of these risks benefits the industry and the development of offshore renewable energy. Moreover, it was established that uncertain estimates of the workability are the principal cause of these operational risks. Therefore, in this thesis, the research aims to improve the reliability of workability estimates to reduce operational costs and allow for optimising the performance of marine operations. Hence, the main research question addressed in this report is described by:

> “How can the reliability of workability estimates involved in the planning and engineering stage of an offshore wind farm installation be improved?”

Therefore, the literature study of this research work aims to answer the following research questions:

1. What methods exist in literature for estimating the workability of marine operations?
2. What are the weaknesses of today’s state-of-the-art workability models?

Furthermore, following the literature study, this study identified two commonly applied model assumptions. Nevertheless, research regarding the appropriateness of these model assumptions and its consequences for the engineering process is limited. Given the lack of research regarding the current modelling approach, this study aims to understand how the underlying model assumptions affect the reliability of the weather window analysis and what the corresponding consequences are for the analysis and optimisation of the logistic operation. Therefore, this study aims to identify, evaluate the significance of, and address the consequences of implementing the underlying model assumptions in logistic optimisation models. Hence, this study sets out to answer the following research question:

3. What are potential implications of utilising the underlying model assumptions during the weather window analysis?

Moreover, the literature study found that the marine industry describes the operational limits often in terms of the significant wave height and peak wave period only. However, research regarding the accuracy of this approach is limited. Therefore, this study aims to validate the accuracy of the operational limits to what is experienced on site. The corresponding research question is given by:

4. How accurate describe allowable sea state limits the conditions experienced at site that result in weather downtime?

1.4 Report outline

This remainder of this thesis report is structured as follows: In Chapter 2, the relevant theory that form the basis of this study is provided. It reviews the governing wave theory, the current methods used (by the industry) to determine the operational limits of marine operations and existing workability models. In Chapter 3, the overall research approach is discussed as well as the development of the workability assessment model. The chapter also specifies the model choices and introduces the methods that were used for validating the model. In Chapter 4, the model is applied to two case studies. These case studies are used to assess the performance of the model and to explore the different workability assessment methods. In addition, the section also presents the results of the model validation in order to verify its performance with on site workability measurements. In Chapter 5, an interpretation of the model results is provided as well as a discussion on the limitations of the model and recommendations for future studies. Finally, Chapter 6 summarises the research work by answering the research questions and a general conclusion is provided.

Chapter 2

Literature study

2.1 Ocean surface waves

It is not surprising that, besides winds and currents, ocean surface waves account for a significant part of the workability of marine operations. Therefore, to understand how operational limits of certain installation activities affect the performance of the logistic operation, one must have a general understanding of how ocean surface waves behave. In the following sections, the governing wave theory that describes the development, behaviour and mathematical representation is provided.

The focus of this study is in particular on the fluid structure interaction (FSI) caused by wind generated waves. It is common to categorise wind generated waves into two categories: (1) wind-sea and (2) swell. Where wind-sea is known as the surface waves generated by the locally prevailing wind field. In contrast, swell is considered as the surface waves propagating independently from the wind. It is important to note that swell waves are also formed by wind. However, they have propagated out of the source (storm) area and are, therefore, only affected by resistance and land boundaries.

An important distinction is that a wind-sea wave field is characterised by its irregularity, whilst swell waves have become more regular over time as a consequence of *dispersion*. That is, a wind-sea dominated wave field has often various sized waves with a large range of wave frequencies (and wave lengths). A swell dominated wave field is typically characterised by relatively similar waves with a narrow band of wave frequencies.

Moreover, the simultaneous presence of both wind-sea and swell wave fields highlights an critical sea state often found at sea. In a great number of — especially oceanic — regions across the globe, the local wave field can be affected by multiple wave trains (comprised out of wind-sea and one or multiple swell wave trains). This is also referred to as a mixed-sea state or multimodal sea state and is one of the important drivers for this study.

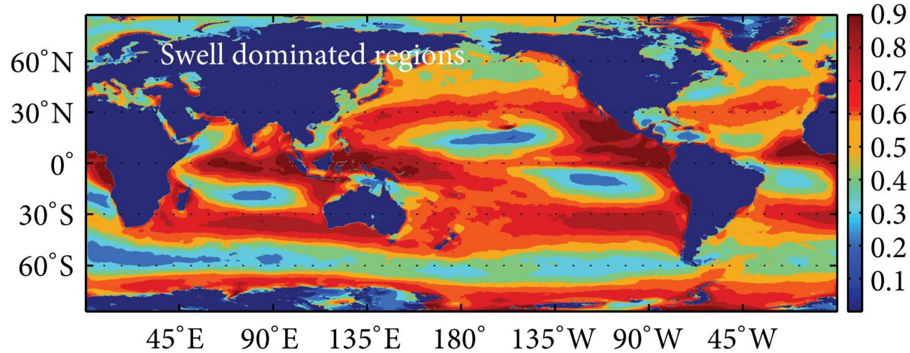


Fig. 2.1 – Oceanic regions where swell wave fields dominate (Zheng et al., 2015).

It is common to describe the governing surface elevation, $\eta(x, y, t)$, of an *irregular* wave field as the sum of many *regular* sinusoidal waves, also known as the superposition principle that was first introduced by St Denis & Pierson Jr (1953) (Fig. 2.2). Such that,

$$\eta(x, y, t) = \sum_{i=1}^{N} \sum_{j=1}^{M} [a_{i,j} \cos(\omega_i t - k_i x \cos\theta_j - k_i y \cos\theta_j - \alpha_{i,j})] \tag{2.1}$$

where a is the amplitude of the partial wave (regular wave component), ω is the wave frequency (with $\omega = 2\pi/T$), k is the wave number (with $k = 2\pi/L$), θ is the propagation direction and α is the random phase angle. The same principle is seen in the Fourier Transform (FT), a mathematical transformation that decomposes a time dependent function into the sum of infinite sinusoidal functions. The result following the transformation operation is often represented in the frequency domain, in which the amplitude of all the harmonic components are expressed against its frequencies.

In ocean engineering, the Fast Fourier Transform (FFT) algorithm is applied to buoy observations to transform the data from the (temporal) time domain into the frequency domain (US Department of Commerce & Administration, 1996), also referred to as the response spectrum. By means of response amplitude operators the response spectrum is then transformed into a so-called **wave spectrum**.

However, as mentioned by Holthuijsen (2010):

> "The aim of describing ocean waves with a spectrum is not so much to describe one observation of the sea surface (i.e., one time record)

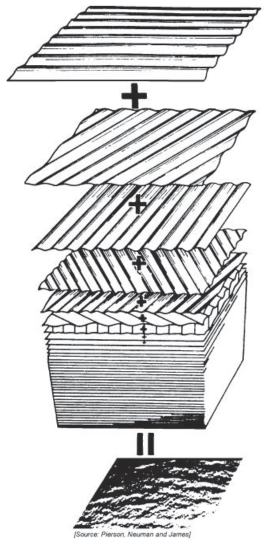


Fig. 2.2 – The superposition principle where the sum of many regular sine waves makes an irregular wave field (St Denis & Pierson Jr, 1953).

> in detail but rather to describe the sea surface as a stochastic process, i.e., to characterise all possible observations (time records) that could have been made, in the conditions of the actual observation."

Which gives rise to the *random-phase/amplitude* model. In this formulation, the amplitudes and phase angles of the (regular) harmonic components, defined by their respective frequencies, are treated stochastically. Thus, the transformation of a single observation (into a wave spectrum) is formally treated as one realisation of the stochastic process. In fact, to obtain a reliable wave spectrum, it is common to compute the *expected value* of the wave spectrum (i.e. by considering $E\{a_{i,j}\}$). This, however, requires multiple wave records (measured at the same site) which are often not available. Instead, to address this rather practical issue, the time record is often divided into a number of non-overlapping segments. To each section of the record, the Fast Fourier Transform is then applied. From which the expected value of the wave spectrum is derived.

Nevertheless, because, in linear wave theory, the wave energy is proportional to the variance, it is more relevant to compute the variance of each of the harmonic components. Also, since the measurements present the information based on discrete frequencies, whereas all frequencies are present at sea, the spectrum is often modified by distributing the variance over the frequency bands. Hence, often one finds the wave spectrum in terms of energy density that is given by

Eq. (2.2).

$$E(f,\theta) = \lim_{f_i \to 0} \lim_{\theta_j \to 0} \frac{1}{\Delta f_i \Delta \theta_j} E\left\{\frac{1}{2}\, a_{i,j}^2\right\} \tag{2.2}$$

From the resulting wave spectrum, a number of characteristic sea state parameters can be obtained, such as the significant wave height (H_{m_0}), the peak wave period (T_p), and mean wave direction (θ), but also the maximum wave height (H_{max}) and the probability that a certain wave height exceeds a particular threshold level ($P(\underline{H} > H)$).

The *significant wave height* is given by,

$$H_{m_0} = 4\sqrt{m_0} \quad \text{where:} \quad m_0 = \int_0^\infty \int_0^{2\pi} E(f,\theta)\, d\theta\, df \tag{2.3}$$

The *probability of exceedance* is given by,

$$P(\underline{H} > H) = \exp\left(-\frac{H^2}{8m_0}\right) \tag{2.4}$$

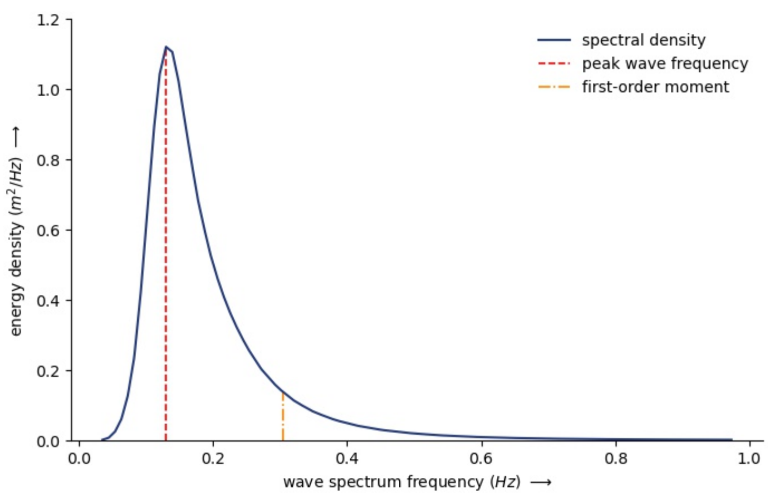


Fig. 2.3 – One-dimensional wave spectrum with the definitions of the spectral parameters. Note, the first-order moment (m_0) highlights the position of the significant wave height within the spectrum.

It is common for many research and governmental institutes to store and distribute the corresponding historical wave data by the significant wave height, peak wave period and mean wave direction instead of the spectral data. However, characterising the detailed (two dimensional) distribution of the energy density into three spectral parameters (H_{m_0}, T_p and θ) is only favourable if the current sea state can be considered *unimodal*. That is, if the spectral density distribution is only characterised by a single peak (Fig. 2.3).

Nevertheless, many ocean regions are affected by not only the local prevailing wind field, but also by swell waves developed at a distant site. As a result, the wave spectrum has multiple peaks and is therefore *multimodal* (or *bi-modal* if it consists of two peaks), this is illustrated in Fig. 2.4. In order to preserve these sea state characteristics, a spectral partitioning algorithm is applied to the spectral data to distinguish the different features. After the various (wind-sea and swell) components are discriminated, the significant wave height, peak wave period and mean wave direction can be determined for each of the corresponding components. In order to reconstruct the energy density distribution,

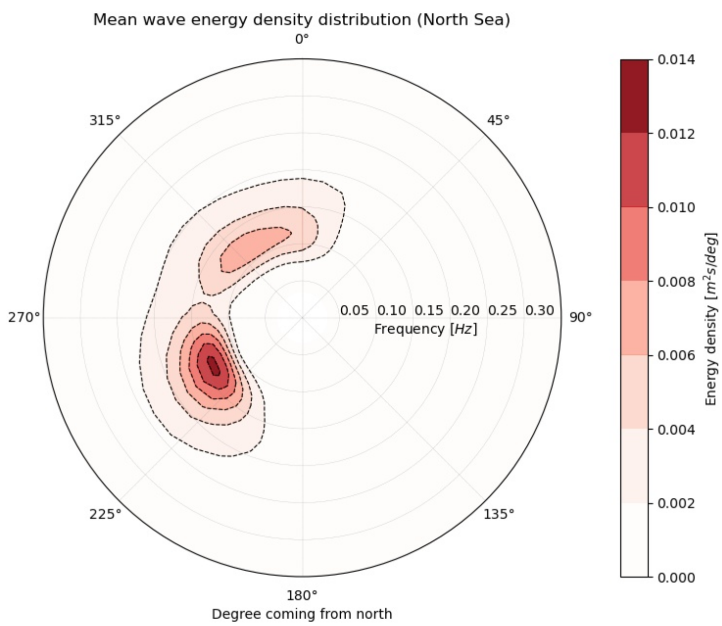


Fig. 2.4 – The time averaged (1990-2020) two-dimensional energy density distribution of the North Sea wave field (Dutch coast). In this area, most wind-sea waves originate from the west-southwest (WSW) and swell waves solely emerge from the northwest (NW).

theoretical distributions are commonly used. These are often the well-known JONSWAP and Pierson–Moskowitz spectra. The JONSWAP spectra is given by Eq. (2.5).

$$S(\omega) = A\omega^{-5} \exp -B\omega^{-4}\gamma^{\alpha} \tag{2.5}$$

In which, according to Hasselmann et al. (1973),

$$A = \frac{4\pi^3 H_{m0}^2}{T_p^4},\ B = \frac{23\pi^3}{T_p^4}, \gamma = 3.3,\ \alpha = \exp -\Big(\frac{0.2049 T_p \omega - 1}{\sqrt{2}\sigma}\Big)^2 \tag{2.6}$$

However these spectra are, by definition, one-dimensional and are only applicable to unimodal sea-states. Nevertheless, it was found by Garcia-Gabin (2015) that fitting theoretical distributions, such as the JONSWAP spectrum, to the discriminated spectral components (wind-sea and swell) allows to estimate bi-modal spectra — derived from buoy measurements — more accurately compared to using a single spectra based on dominant values.

By utilising a directional spread function, the resulting spectra can be used to reconstruct a 2D representation of the directional and multimodal wave field. Such directional wave spectra can be obtained by Eq. (2.7) (Ananth et al., 1993).

$$S(\omega,\theta) = S(\omega) \cdot D(\omega,\theta) \tag{2.7}$$

Where $S(\omega)$ is the non-directional wave spectrum and $D(\omega,\theta)$ is a directional spreading function. A well-known analytical model used to describe the angular distribution function was proposed by Longuet-Higgins & Smith (1965). The authors developed a so-called cosine spreading ($\cos^{2s}$) model that takes the mean wave direction (θ_0) and width of the directional distribution (σ) (Eq. (2.8)).

$$D(\omega,\theta) = A \cos^{2s}\left(\frac{\theta - \theta_0}{2}\right) \tag{2.8}$$

2.2 Workable limit analysis

2.2.1 Background

A workable limit analysis is often conducted during the engineering phase of marine activities. It allows marine engineers to assess the operational limits at which certain activities can be performed in a safe manner and to adjust the work method if needed. The results of a workable limit analysis are often reported in terms of feasibility and risk assessments prior to the operation, but also help for active control and anticipation during the operation.

As mentioned in the introduction, in previous studies, a number of researchers aimed at deriving appropriate methodologies for assessment of the operational limits. Most notably, in studies published by Acero & Li (2018); Acero et al. (2016), the authors aimed at obtaining operational limits in terms of the significant wave height (H_s) and peak wave period (T_p), that account for the effects on the operational limits caused by the wave energy distribution. In this section, the method proposed by Acero & Li (2018) is reviewed as well as the current approaches used in today's industry.

2.2.2 Research methodology

In the paper by Acero & Li (2018), the authors aimed to establish response-based operational limits in terms of the significant wave height as a function of the peak wave period ($H_s(T_p)$) that account for the uncertainties from a two-dimensional wave energy distribution. Therefore, the authors proposed the following procedure:

1. Simulate the critical installation processes using hydrodynamics and multi-body system dynamics.

The first step in establishing operational limits is to simulate the dynamic system corresponding to a critical installation activity. Therefore, it is essential to have identified critical events and corresponding limiting parameter, such as the lowering velocity of a load, the load displacement, or impact force. After defining hazardous events and limiting parameters, the non-stationary installation activity can be modelled and simulated using dynamic analysis software (for example, using OrcaFlex).

In order to perform a dynamic analysis, a number of input parameters need to be specified. For instance, the dynamic response of a rigid body to wave motion needs to be prescribed using so-called *response amplitude operators* (RAOs). Response amplitude operators define the first-order motions of a rigid body in response to wave-induced pressure fluctuations. The resulting motions are, subsequently, described by six independent parameters, three translatory and three rotatory, that define the degrees of freedom (DOF) a rigid body can move in, i.e. surge, sway, heave, roll, pitch and yaw (Fig. 2.5).

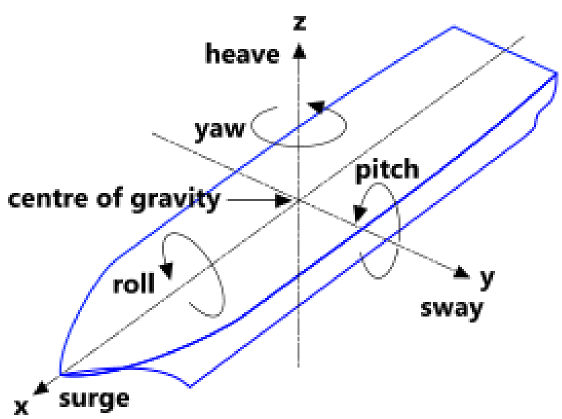


Fig. 2.5 – Illustration of the independent degrees of freedom of ships

Computing the dynamic response is than a matter of multiplication using Eq. (2.9).

$$\underbrace{S_r(\omega_e)}_{\text{response spectrum}} = \int_0^{2\pi} \underbrace{\left|\frac{r_a}{\zeta_a}(\omega_e,\theta_e)\right|^2}_{RAO} \cdot \underbrace{S_\zeta(\omega_e,\theta_e)}_{\text{wave spectrum}}\, d\theta \tag{2.9}$$

in which the subscript, e, indicates the encounter (wave) frequency and direction. The resulting response spectrum describes the displacement amplitudes per frequency per degree of freedom. Hence, integration over the frequency bands, subsequently, allows to derive the motion response amplitude, r, for each of the six degrees of freedom.

The accelerations for each of the frequencies can be obtained by considering the corresponding harmonics (Eq. (2.10)).

$$d(t,\omega_e) = S_r(\omega_e) \cdot \cos\left(\omega_e \cdot t + \phi\right) \tag{2.10}$$

Where $d(t,\omega_e)$ represents the displacement over time caused by a certain frequency. The second time derivative allows to obtain the corresponding acceleration.

$$a(t,\omega_e) = \frac{d}{dt^2}\Big(S_r(\omega_e)\cdot\cos\left(\omega_e \cdot t + \phi\right)\Big) = -\omega_e^2 S_r(\omega_e)\cdot\cos\left(\omega_e \cdot t + \phi\right) \tag{2.11}$$

Simulating the critical installation activities also includes modelling the multibody system. Often, the dynamic system can be simplified to the vessel's structure, the crane's hoist sling and the crane load, each of which may experience translational and rotational displacements. Based on the response motions of the floating structure to wave motion, the governing equations of motion allow to derive the displacement and accelerations of the remaining bodies. Therefore, it is possible to derive internal forces and stresses that define the safety of the operation.

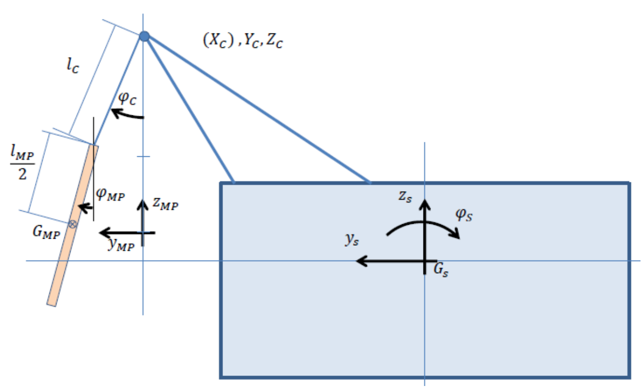


Fig. 2.6 – Illustrative diagram of the bodies involved in lifting a monopile from a floating body.

It is worth mentioning that the simulations are based on the rigid body assumption. That is, the vessel's structure is considered as a solid body in which deformations are assumed to be zero. Therefore, the vessel's dynamic behaviour is governed by the motions of a solid body exerted by waves. Consequently, the dynamic system is significantly reduced in complexity as the large number of degrees of freedom's (DOFs) has been lowered to only 6 DOFs per body. Therefore, the dynamics are governed by the combined actions of different external forces and moments, as well as by the inertia (resistance against motion) of the bodies themselves (Journée et al., 2015).

Moreover, it is important to note that the objective of this step is to obtain time-series of the limiting parameter for a given set of wave conditions.

2. Evaluate time-series of the limiting parameter against allowable limits.

After conducting multiple simulations, time-series of the limiting parameters are evaluated against predefined threshold levels that define the failure limits. Based on the predefined allowable limits, points of intersection (where failure occurs) are identified, from which subsequently the corresponding significant wave height and peak wave period measurements are collected.

3. Acquire a probability distribution using a statistical analysis of the collected values of H_s and T_p.

In order to find probability distributions, measurements of the significant wave height are stored in grouped intervals of the peak wave period. For each group, a histogram or probability distribution of H_s can accordingly be obtained. Note that multiple samples of the limiting significant wave height exist for a particular peak wave period as a consequence of uncertainties following from a 2D wave field, i.e. varying wave direction and multimodal sea states.

4. Based on required safety levels, the characteristic values can be found.

Finally, for each interval group, the characteristic $H_s(T_p)$ value is obtained from a certain percentile that is related to the required safety level. Notice that the characteristic value expresses the resistance against operational failure. Therefore, by definition, the percentile defines the number of significant wave height measurements that lead to failure for a particular characteristic value. In other words, based on the given sample set, failure occurs only to X-percent of the time for a given significant wave height related to the X-percentile.

2.2.3 The industry's state of the art

Often, assessments of the workable limits differs from the previously described methodology. In a tech report by DNV-GL (2017), the common and recommended practices of the marine (in particular the oil and gas) industry are formulated. In order to estimate the hydrodynamic forces, a number of methods are proposed. In this section, the time domain analysis is discussed.

In the time domain analysis, the aim is to obtain safe operational limits in terms of the significant wave height as a function of the peak wave period and wave direction. For each defined wave direction, independent simulations are realised.

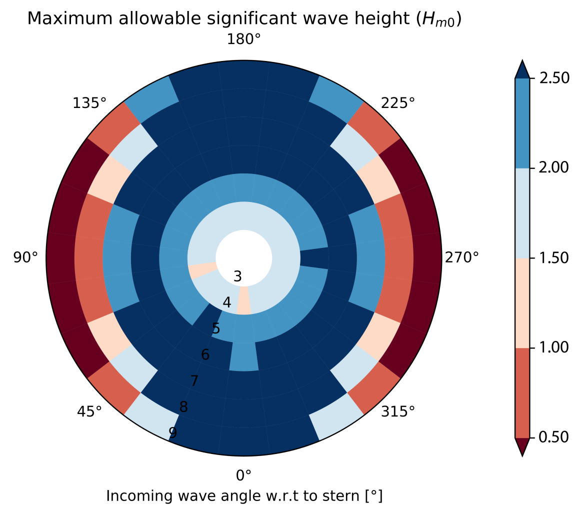


Fig. 2.7 – Example of allowable sea state limits derived using a time-domain analysis.

The allowable limits are based on wave "train" realisations from a JONSWAP wave spectrum. Hence, for every wave direction and peak wave period, a JONSWAP wave spectrum is generated using incremental steps of the significant wave height. Subsequently, the marine operation is simulated under each of these conditions until critical response parameters exceed (safe) threshold levels.

It is worth mentioning that the time-series of response parameters under certain conditions can be re-written in terms of a spectrum (using a Fourier Transform). Therefore, the "exceedance" probability that a certain response parameter exceeds a predefined threshold can be estimated accordingly.

2.2.4 Drawbacks

The above mentioned methods have both advantages and disadvantages. For instance, although the "scientific" methodology provides the quantitative tools to decide effortlessly if an operator or marine warranty surveyor should allow to initiate operations, it produces probabilistic operational limits that are dependent on the accuracy and specifics of the given wave information and response amplitude operators. Consequently, the operational limits depend on the location of the construction site instead of only on the details of the marine activity itself.

In addition, the safety standard of an operation is determined by the probabilistic analysis that governs the characteristic values of the significant wave height as a function of the peak wave period. Nevertheless, the variance of a sea state parameter is undoubtedly affected by its global location. As a result, the variance of the operational limit depends on the location of the construction site as well. Thus, the operational limits on certain locations may be highly uncertain and require conservative threshold levels.

Moreover, the proposed methodology implicitly implies that the dynamic responses of critical response parameters are of a stochastic nature. However, it should be stressed that it is the stochastic nature of the offshore environment (variations in wave loading conditions, in particular, wave energy distribution) that allows the operation to fail at particular combinations of the significant wave height and peak wave period.

Nevertheless, the industry's standard approach neglects the possibility of having multiple simultaneous wave components such as wind-sea and swell. The operational limits are solely dependent on a so-called *total sea*, in which multimodal sea states are simplified to or represented as an unimodal sea state. As a result, multiple multimodal wave spectra may be described as the same unimodal wave spectra that, subsequently, produces a single response spectrum. However, these multimodal wave spectra may each produce different response spectra due to differences in the components wave directions. Thus, it might be possible that response parameters (not) exceed their threshold levels, whereas the workable limit analysis indicates otherwise.

2.3 Workability assessment models

2.3.1 Background

It is common practice for offshore engineers to assess the workability of a marine operation in the early stages of a project using a so-called *workability analysis*. A workability analysis usually involves (1) gathering the relevant environmental data (e.g. wave, wind and current data), (2) defining the operational limits in terms of the significant wave height as a function of the peak wave period (corresponding to the specific installation activities e.g., lifting, transport, etc.) and (3) deriving the (monthly) workability as a fraction of the project duration or as the availability (probability of occurrence) of a sufficient weather window.

In literature, three types of workability models exist (den Uijl, 2018) that enable to compute the workability of marine operations: (1) strictly statistical models, (2) time-domain models and (3) scenario simulation models. Below these three types of models are discussed in more detail.

2.3.2 Statistical models (wave scatter method)

The first category of workability models is characterised by strictly statistical models. A well-known example of this type of model is the *wave scatter* approach, in which (joint) probability distributions of one or more metocean parameters, usually the significant wave height (H_s) and peak wave period (T_p) are used to estimate the workability for a given period of time (e.g. month).

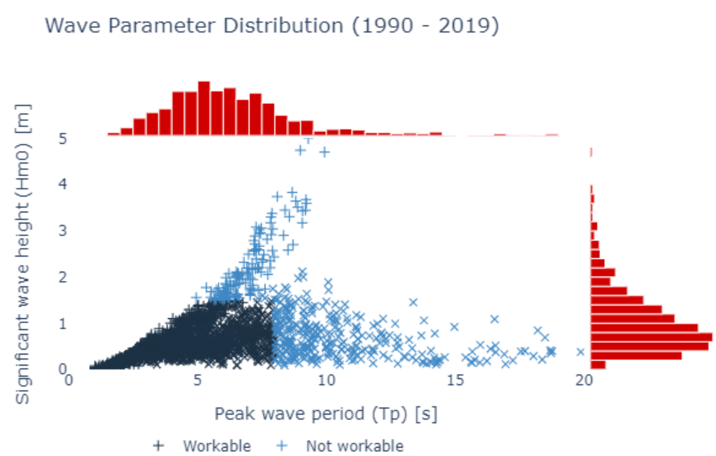


Fig. 2.8 – Observations of the significant wave height and peak wave period. The method obtained its name because of its graphic visualisation using scatter diagrams

Based on a set of operational limits, one can derive the number of occurrences and corresponding return period of a certain sea state. It is common practice to collect multiple years of measurements and bin those per month and year. For each month in the dataset, the workability is derived using Eq. (2.12) (given that the sample interval is constant throughout time).

$$W = \frac{\text{number of observations } X_i \leq x_{\text{lim}}}{\text{total number of observations}} \tag{2.12}$$

A sufficiently long data record, subsequently, allows to compute the probability distributions, histograms and box plots of the workability per month (Fig. 2.9).

It should be stressed that the estimated downtime is a fraction of the planned operational period. Therefore, if one expects to complete the operation in the first week of January with a 50% workability, the adjusted operation length becomes 1.5 weeks. Nevertheless, the additional 3.5 days may experience downtime as well. As such, the method does not provide a clear insight in the actual workability with respect to the duration of the marine operation.

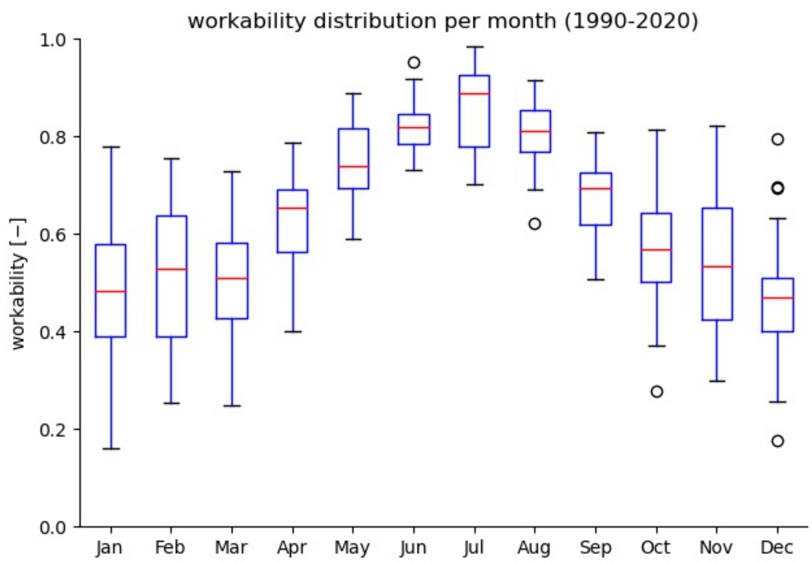


Fig. 2.9 – The estimated workability distributions per month according to the scatter diagram approach ($H_s < 1.5$ [m] & $T_p < 8$ [s]).

Besides, the method takes only the total sea spectrum into account. Therefore, the simultaneous presence of both swell and wind-sea is not accurately described, since it only considers two parameters.

2.3.3 Time-domain models (persistence statistics)

The second type of workability models are time-domain models. A well-known example of a time-domain model is the *persistence statistics* method. In literature, many authors identified the persistence of a certain weather state as a crucial parameter for indicating the occurrence of weather downtime. That is because the method describes the availability of workable weather windows, which in turn, is directly related to the occurrence of waiting on weather events. Hence, the availability of weather windows and presence of waiting on weather events can be studies by means of *persistence statistics* (Rip, 2015).

One of the first to describe persistence statistics was Graham (1982). In his paper, the author developed a persistence model that was based on two basic principles: (a) the persistence average duration may be directly related to the threshold exceedance probability; and (b) the probability of occurrence of persistence durations may be defined in terms of a Weibull distribution.

In 2013, Walker et al. (2013) developed an equivalent *Weibull persistence model*. The presented model was able to calculate not only the likelihood of a certain weather window based on a limiting parameter, but also allowed to assess the expected waiting time for such window to occur. The authors used a *Weibull* approach to produce probability of exceedance data. That is, collecting measurements of the significant wave height (or any other wave characteristic parameter) when the acceptable/workable threshold levels are exceeded.

The persistence of a certain weather state is defined by its annual weather window *occurrences* and *durations*. In which a single occurrence relates to a time period of a number of hours duration when conditions remained either above or below a pre-defined threshold (Graham, 1982).

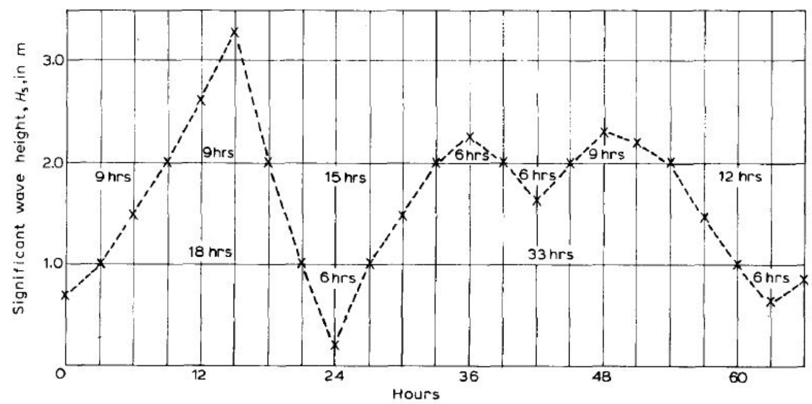


Fig. 2.10 – Illustrative representation of the persistence according to Graham (1982)

It is common to represent the persistency by exceedance curves in which the frequency of exceedance of weather window durations are shown (see Fig. 2.11). It is worth noticing that these curves indicate how sensitive downtime estimates are to operational lead and lag times (Graham, 1982).

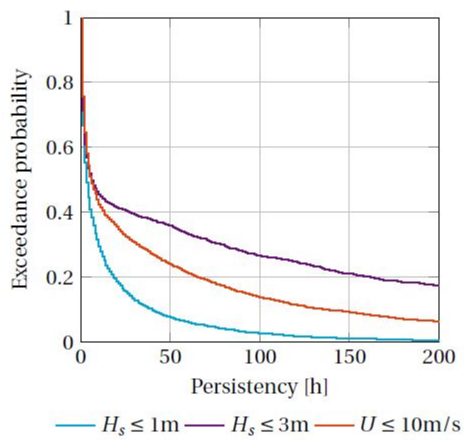


Fig. 2.11 – Example exceedance curves (courtesy Rip (2015)).

A measure of persistence was given by Graham (1982), who used the average duration to parameterise the persistence (see Eq. (2.13)).

$$\bar{\tau} = \frac{T_g}{N_g} \tag{2.13}$$

in which:

$\bar{\tau}$	Average duration that offshore conditions exceed threshold levels.
T_g	Total hours in which the threshold levels are exceeded.
N_g	The number of occurrences in which the threshold levels are exceeded.

In preceding studies, it was found that there exists to some degree a linear log-log relationship between the "greater than" average duration ($\bar{\tau}$) and the significant wave height (H_s). After some further examination, it followed that the relationship was most adequately fitted using a Weibull distribution (Graham, 1982). It is this principle that led to the development of a persistence model that would take (1) the threshold significant wave height, (2) the exceedance probability of the significant wave height and (3) the total time period for which the persistence is calculated and returns a statistical estimate of the downtime in terms of a Weibull-model.

A major disadvantage, however, is the models dependence on a single metocean parameter. That is, although it was proven that there exists similar linear relationships with the wind velocity, the time dependence of the threshold level due to its dependence on other parameters such as, the peak wave period and incoming wave angle, is not taken into account.

2.3.4 Scenario simulation models

The third type of workability models are so-called *scenario simulation* models. Scenario simulation models aim to simulate the logistic system of the installation process to assess the project duration, corresponding costs, and weather downtime. Besides the advantages of being able to assess produce the project duration and costs, the method was highlighted in previous studies as potentially being the most accurate approach to estimate weather downtime (den Uijl, 2018).

Below, a probabilistic and a discrete event (scenario) simulation model are discussed in further detail.

Two-state Markov Chain models

In 2019, a paper was released by Bruijn et al. (2019) proposing a new probabilistic model to assess the weather downtime of marine operations. The proposed model was based on the concept of *Markov chain* theory. A stochastic system describing a sequence of possible events in which the probability of each event depends only on the state attained in the previous event.

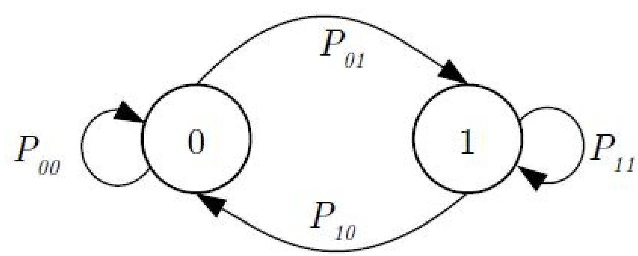


Fig. 2.12 – Illustration of the Markov Chain concept (courtesy of Rip (2015)).

The proposed model transforms the actual metocean conditions into workable states '1' and non-workable states '0' depending on the operational limit. Based on hindcasting and pre-defined operational limits, a so-called binary 'workability-array' is created. This array is subsequently used to estimate the Markov transition probabilities between the workable and non-workable states from which a sequence of workability events can be generated.

In other words, to build a model which predicts the workability, two states can be assumed, workable and non-workable. Based on hindcasting or historical records, the corresponding probabilities of occurrence can be estimated. Therefore, using a random generator a daily sequence of workability states can be simulated. This would generate a sequence in which the workability states would randomly jump from one to another, wherein real data the probability of a workable state often depends on the previous state. I.e. the probability of having a workable state tomorrow might be greater if the operations are allowed to be run today (Vicapow, 2014). Hence, transitional probabilities are introduced.

The acquired sequence of workability states can then be used to schedule the marine operation and assess the expected weather downtime. If multiple activities, each having their own operational limits, are involved in the marine operation, multiple sequences may be generated. These sequences can, subsequently, be used to schedule the successive activities.

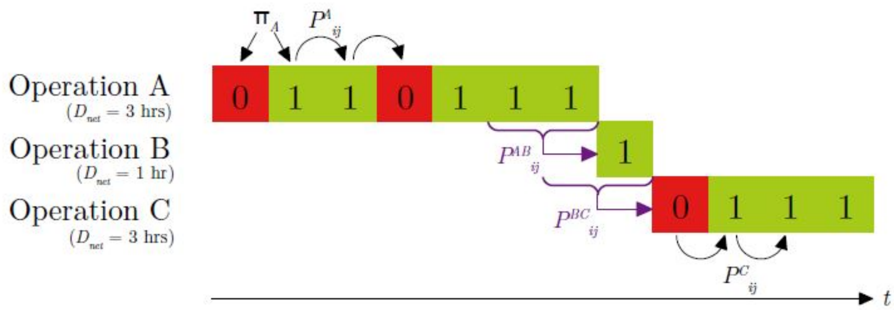


Fig. 2.13 – Multiple operations scheduled using multiple binary sequences generated using the two-state Markov chain model (courtesy of Rip (2015)).

The researchers noticed that the proposed model showed promising results for analysing the downtime risk. Especially for large cyclic projects, for which the variation in predicted project duration is greater. However, it was highlighted that hindcasting could also introduce errors. Specifically when a data record contains a once in 1000-year storm. It will treat such events with a return period equal to the length of the data record, whilst its actual return period might be around 1000 years.

To develop the model a number of assumptions were used. For instance, (1) the operational limits imposed are strict. Therefore, a time instant is either workable or not. Nevertheless, a workable limits analysis shows that the workable limits in terms of wave height, period and direction may vary depending on the current velocity. Also, it is well possible that when a certain operational limit is violated, the work is still continued. Though, at a much slower rate. Moreover, (2) the net duration of an operation was modelled as a deterministic process. Therefore, any length variations in repeated cyclic operations are simplified. As a consequence, whilst the persistency is known to be a vital parameter, the risks imposed due to these variations are neglected.

Discrete event simulation models

Discrete event simulation (DES) models are frequently found in literature as an approach to generate project estimates, such as costs, project duration and lately also the expected weather downtime. In discrete-event simulation, it is tried to model the installation process of an offshore wind farm by means of *entities*, *events* and *processes*. DES represents individual entities, like vessels, that move through a series of queues and activities (processes) at discrete points in time (Tekle Muhabie et al., 2018). An event is defined as the occurrence of a system state change at a particular time instant, e.g., the arrival or departure event of vessels at a certain port. Hence, by its definition, there are no state changes between consecutive events. Consequently, the model is allowed to "jump" to the next event without having to iterate over fixed-incremental time-steps, which is known as *next-event time progression*.

The main aim, and probably the most valuable property, of discrete event simulations models is to gain insight in the performance of a logistic operating system at large. Discrete event simulation models assist in identifying (1) bottlenecks to improve throughput and resource utilisation, and (2) to assess the required capacity needed for an efficient and effective installation process. Moreover, the capacity to model complex logistic flows and to examine alternative configurations of logistic operations is an important advantage of using discrete-event simulation over linear programming and Markov Chain analysis (Jacobson et al., 2013).

In DES-models, resources are modelled by means of servers, queues and clients, in which servers process requests received from clients, and requests are stored in a queue until the server becomes available. For example, a vessel (the client) aims to dock at a certain port (the resource). Therefore, the vessel's captain sends a request to the port authorities (the server) requesting for an available berth. The port authorities, subsequently, store the request in a queue and appoint the vessel to a so-called *anchorage area*. Once a particular berth has become available for the vessel to dock, the request is granted and the vessel is permitted to dock. Finally, after departure, the berth is released and available to other vessels.

Now, assuming that a port has multiple berths available and the arrival rate of vessels at that port is described by a stochastic process, the discrete event simulation model will highlight the utilisation of the available berths as well as the delay that is related to queuing. Hence, the port authorities have been provided with a decision-tool that allows them to assess the efficiency of any number of berths available.

The core principle of resources can also be used in order to model the offshore environment. Identical to the two-state Markov chain model, for each operation, the offshore environment may be described in workable and not-workable states. Prior to a weather restricted operation, a request, including details on the operation, is submitted by the operator (the client) and received by the marine warranty surveyor (the server). The marine warranty surveyor stores the request in a queue until an appropriate workable weather window prevails. As soon as the offshore conditions allow for a safe and efficient operation, the request is granted and the operation is initiated.

The time between request and approval is known as weather downtime related delay. It is interesting to note that, because of modelling the offshore environment as a resource, the effects of weather downtime that affects the logistics of marine operations are exposed. Also, notice that the availability of the resource is described by persistence statistics. Since the persistence is known as a crucial parameter for the accessibility of a certain site, the utilisation of a resource can be considered equally important.

Chapter 3

Methodology

3.1 Research method

3.1.1 Problem description

In the literature section, this study identified two underlying model assumptions often used in existing workability assessment models:

1. The significant wave height and peak wave period adequately describe the two-dimensional wave energy distribution of a (directional) wave field.
2. The wave conditions associated with weather downtime are sufficiently described by the two characteristic parameters following a workable limit analysis.

However, little is known about how these underlying assumptions affect the reliability of logistic optimisation tools. The potential modelling and data errors may, subsequently, contribute to unexpected costs and poor performance of the selected installation strategy.

Therefore, this study sets out to acquire a general understanding in how these assumptions affect the performance of DES-based logistic optimisation models. More specifically, this study aims to understand how the underlying assumptions affect the weather window analysis and what the consequences are for (the optimisation of) scheduling, resource allocation and capacity planning of marine operations in logistic optimisation tools. Besides, the study aims to assess how accurate the significant wave height and peak wave period describe the wave conditions experienced at site that result in weather downtime.

3.1.2 Approach

To expose the effects of applying the underlying model assumptions, this study adopted a case study approach in which a DES-based logistic optimisation model coupled with a response motions based hydrodynamic model is implemented on recently realised offshore wind farm projects.

The presented model (discussed in Section 3.2) integrates response motions of vessels and turbine structures into the weather window analysis of the hydrodynamic model. Integrating response motions, instead of allowable sea states, into the weather window analysis provides at least two advantages:

1. The encountered sea states are described in full detail, and therefore, the approach does not generalise complex sea states that consists of multiple wave components. Hence, the wave energy distribution is maintained.
2. The operational limits are established from the multibody system dynamics and are therefore independent of wave motion. Consequently, the approach excludes uncertainties involved in characterising the wave conditions.

In the remainder of this study, this is referred to as the response motion approach. In order to evaluate the response motions based approach, the hydrodynamic model was adapted to allow for the use of allowable sea state limits. In following sections, this study refers to this industry standard approach as the allowable sea state approach.

In a recent study by Tomaselli et al. (2021), a similar approach was adopted to develop a decision-support tool for the short-term planning of operations and maintenance activities of offshore wind farms. In addition, several researchers used discrete-event simulation models in their studies to improve the installation strategy of marine operations. In this study, we adapt the existing open source OpenCLSim model to enable a response-motion based weather window analysis.

Moreover, a case study approach on (recently) realised offshore wind farm projects provides the possibility to validate and assess the accuracy of the presented modelling approach with field data. The validation methods are discussed in Section 3.3.

3.2 Model description

3.2.1 Overview

The alternative model discussed in this thesis relies on the discrete-event simulation framework to model and simulate the logistic installation process of an offshore wind farm. Therefore, the models main objective is the scheduling of the corresponding installation activities. During the model simulations, the scheduling of installation activities is based on (1) the required sequential order of the installation activities and (2) the availability of resources such as berths and cranes, but also the presence of sufficient weather windows.

Because the computation of weather windows (by means of a weather window analysis) can independently be conducted from the logistics simulation, the model can be distinguished by two main components: the logistics simulator and the weather resource module. The logistics simulator is used to define, model and simulate the installation process. The weather resource module stores and processes information regarding the offshore environment. However, the logistics simulator uses the output of the weather window analysis. Therefore, both elements communicate throughout the simulations. The conceptual design of the model is illustrated in Fig. 3.1.

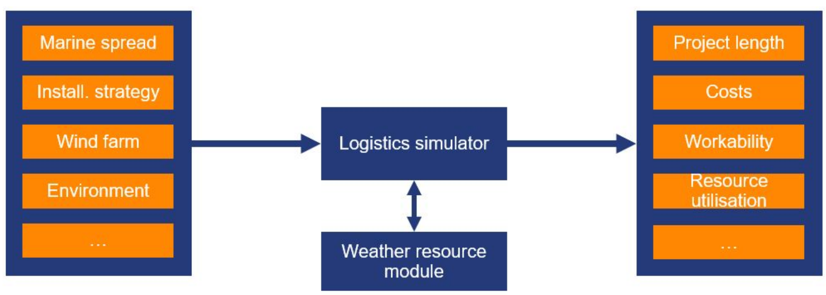


Fig. 3.1 – Conceptual illustration of the workability assessment model.

The workability assessment model takes as input parameters: (1) project details; such as wind farm size, etc. (2) marine spread details; number and type of vessels, vessel characteristics, response amplitude operators, etc. (3) the installation strategy and its corresponding activities, (4) hindcast or historical data of the offshore environment, and (5) the start date of the simulation.

After a *single* realisation of the model, the model returns the project duration, costs, estimated waiting on weather events, resource utilisation, an overview of start and stop dates of the activities, etc. Moreover, to obtain probability distributions of the workability for a certain month, multiple model realisation should be acquired. That is, simulating the installation process for multiple start dates for a certain range of start dates.

To optimise the logistics, multiple models can be developed using the same framework in which one can adjust the marine spread, the installation strategy, etc. to establish a more economic and suitable logistic operation. In fact, further development of the presented model could allow to numerically derive the most suitable solution.

3.2.2 Logistics simulator

For the development of the case study specific logistic simulation models, this study uses the OpenCLSim Python package. OpenCLSim is based on the SimPy framework which is a Python module for process-oriented discrete-event simulation. That is to say, the model uses processes (in this case Python generator functions) to generate events, e.g. the arrival event of vessels in a port is generated by one process and the port handling operations by another. A general simulation process manages the event set.

Thus, DES describes the construction of an offshore wind farm by means processes. Therefore, despite the construction of an offshore wind farm involves a large number of installation activities, it can be generalised by the following processes:

1. Arrival of vessel(s) at base port.
2. Transfer of structural components and equipment from port to deck.
3. Transit from port to construction site.
4. Positioning on site (using AHVs[1] or DP[2]).
5. Installation of turbine structure components.
6. Return transit from site to port or transit to next site.

This generalised installation cycle is illustrated in Fig. 3.2.

Between these processes, events take place. For instance: (1) arrival in port, (2) departure from port, (3) lift off, (4) completion, etc. During these events, system state changes occur, e.g. the number of monopiles in stock, turbines installed, etc.

In order to model weather delays in the logistics simulator, the model uses the DES notion of *resources*. This approach was also used by Tekle Muhabie et al. (2018). The weather resource is responsible for processing requests and puts the installation activity in a queue till a suitable weather window is 'forecasted'.

[1] AHVs: anchor handling vessels
[2] DP: dynamic positioning

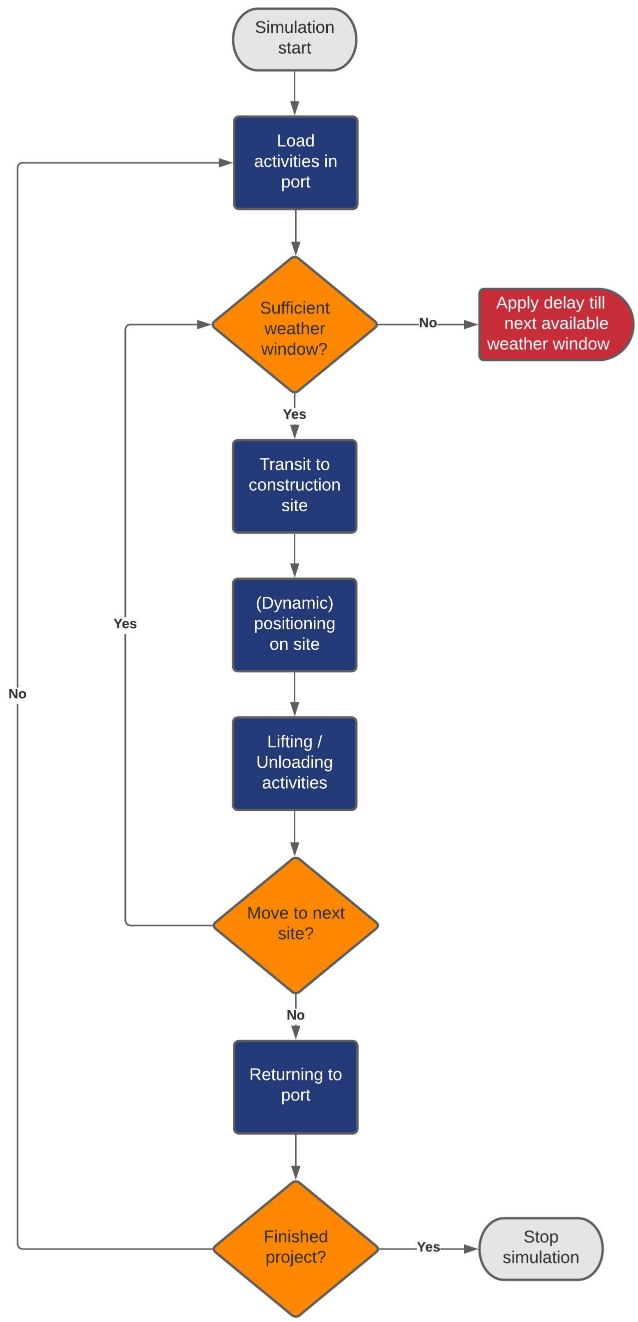


Fig. 3.2 – Generalised OWF installation process in DES.

Because each independent installation process demands specific weather windows to be available, the resource operates similar to a warehouse. In SimPy, this may be achieved by using the *FilterStore* class.

Moreover, as demonstrated by the yellow boxes, in-between processes, decisions take place. The decision made at those simulation steps are known as *start events* and are responsible for initiating the processes right after.

However, it is important to note that the "*sufficient weather window*" decision-box in DES-models is frequently located in the wrong position considering the actual process. That is, generally the decision to initiate an activity takes place hours prior to the actual start based on forecasted conditions. For instance, if only operational limits are imposed on lifting activities, the decision to departure from port and transit to the construction site depends on the presence of a sufficient weather window in the forecasted data. Therefore, the delay is occurring prior to the transit activity instead of the lifting activity. Consequently, uncertainties included in weather forecast are inevitably causing delay. In addition, prior to the start of the lifting operation, a marine warranty surveyor[3] has to approve commencement. Subsequently, if forecasts allowed for a safe execution, it is still possible to encounter downtime due to severe conditions on site.

This also means that when using hindcasting, accurate observations of the environmental conditions are available for the entire installation process. Therefore, it is irrelevant to model unforeseen weather downtime related delays that occur on site. As a result, the decision to initiate an activity or add delay to the simulation, may be considered as a process that is part of the activity on which the operational limits are imposed. Hence, it is sufficient to apply the weather downtime related delay whilst the vessel is on site.

3.2.3 Weather resource module

The weather resource module is responsible for describing and the offshore conditions and communicates with the logistics simulator during the simulations. As indicated by Fig. 3.1, the module is independent of the logistics simulator and only processes request made during the simulations. This approach enables for a much faster computation time as the database operations involved demand a serious amount of computational power. Prior to the "actual" simulation start, the module performs a number of initialisation steps as illustrated in Fig. 3.3.

During the initialisation process, the marine operations defined for the logistics simulator are gathered. For each of the activities, the corresponding response amplitude operators, planned operational period (duration) and operational lim-

[3]A marine warranty surveyor (MWS) is someone who will oversee various phases of a project and issue their approval of documents, specific operations and the suitability of vessels and equipment by review (documents), certificates of approval (project operations) and suitability inspections (vessels and equipment). (English, 2019)

its are determined. In combination with (historical) records of the metocean conditions, the response motions are computed using Eq. (2.9). Subsequently, the time-series of the response motions are used to derive workable weather windows — using a weather window analysis — over the given period of the metocean database. The resulting weather windows are cached in memory for fast and efficient use during the logistics simulation.

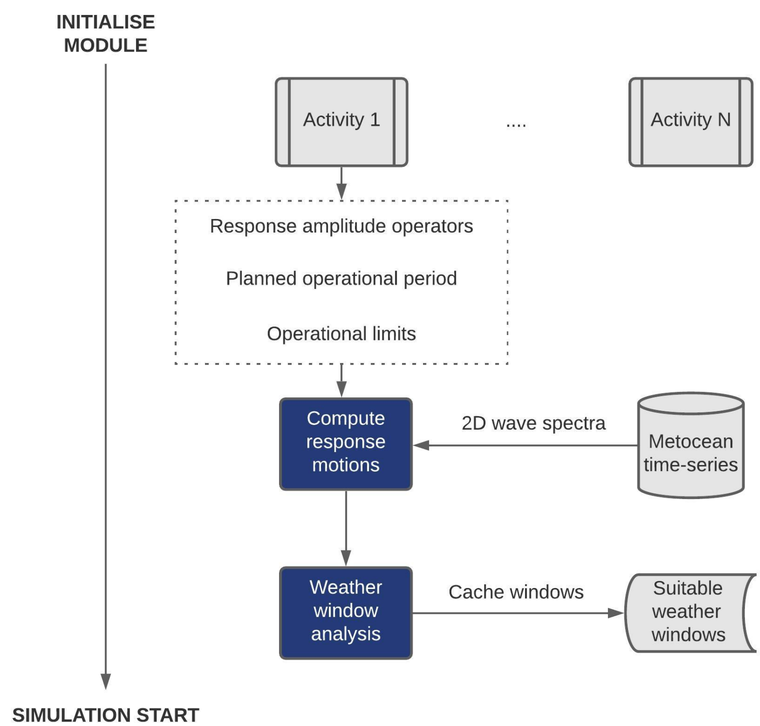


Fig. 3.3 – Initialisation steps of the weather resource module.

To compute time-series of the motion response spectrum, the spectral wave data and response amplitude operators are structured in a 3D fashion using Python's xarray module. Both the spectral wave data and response amplitude operators are dependent on the same coordinate reference system, which is described by the wave frequency, wave direction and time (Fig. 3.4).

However, it is worth mentioning that response amplitude operators are dependent on time because the physical properties of floating equipment, in particular mass and inertia, are time dependent as a consequence of the marine operations. However, since the response amplitude operators are considered to be activity bound and the interest is often in the most unfavourable conditions, one may impose time independent response amplitude operators for each separate activity.

Moreover, it should be stressed that the response amplitude operators are also dependent on which degree freedom they describe. Therefore, the data structure is four dimensional (4D) instead of three dimensional (3D).

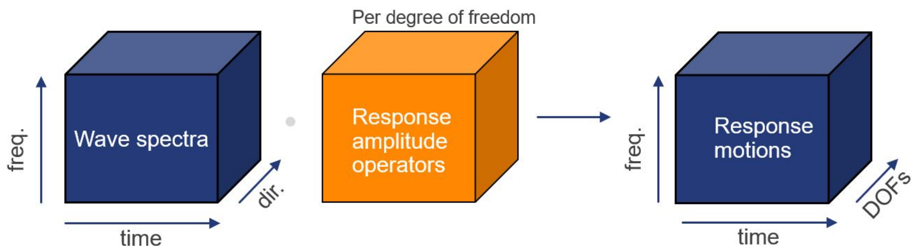


Fig. 3.4 – Data structures applied in the weather resource module to compute response motions.

Most favourably, the metocean records consist of a 3D wave spectrum as described above. However, if these do not exist over the given period of time, each observation record should at least contain a partitioned swell and wind-sea component. For each component, the significant wave height, peak wave period and mean wave direction and directional standard deviation should be known. Subsequently, a 3D directional wave spectrum can be reconstructed using theoretical wave spectra, such as the JONSWAP (Eq. (2.5)) and Pierson-Moskowitz wave spectrum. This was discussed in further detail in Section 2.1.

Furthermore, in a previous section it was stressed that the wave direction affects the response motions of floating equipment. However, it should be highlighted that it is the encounter wave angle with respect to the vessel's stern that determines the magnitude of the response motions. Hence, the vessel's heading determines the encounter wave angle and must be included in the computations of the response motions. In fact, often the best orientation is chosen by the operator to acquire the least response motions and therefore enables the vessel to operate in more turbulent sea states.

To simulate this process, the model applies an algorithm to obtain the vessel's heading corresponding to the most favourable response motions conditions. This optimisation algorithm is included in the initiation of the weather resource module. Alternatively, one could select the mean wave direction of the total sea or select the vessel's heading based on wind and current direction. Note that the former approach is implicitly incorporated in today's state-of-the-art workability assessment models because they omit the wave direction and often establish the limits on 1D spectra.

To find the most suitable heading, the algorithm translates and interpolates the response amplitude operators (for each degree of freedom) on a set of vessel orientation angles, such that they correspond to the wave propagation directions (coming from North). For each time instant and orientation angle, the magnitude of the response motion vector (Eq. (3.1)) is calculated. Then, for each time instant, the response motions and heading that correspond to the smallest magnitude are selected and used for further computation of the workable weather windows.

$$\vec{r} = [r_{\text{heave}}, r_{\text{surge}}, r_{\text{sway}}, r_{\text{roll}}, r_{\text{pitch}}, r_{\text{yaw}}]^{\mathsf{T}} \tag{3.1}$$

The translation of the encounter wave angle coordinates to propagation angle coordinates is accomplished by using .

$$\theta = \left(\text{heading} + 180 - \theta_e\right) \mod 360 \tag{3.2}$$

From Fig. 3.4, it is observed that the resulting response motions are expressed as a function of the harmonic frequency, i.e. a response spectrum. However, the operational limits apply to the irregular responses. In many cases, ship motions can be assumed linear (Journée et al., 2015). Therefore, the behaviour of a vessel or floating structure to an irregular wave field, of which the energy distribution over the frequencies is known, can be derived by superposition of the resulting response to the regular harmonic components. The transformation of an irregular wave field to an irregular response motion is illustrated by Fig. 3.5.

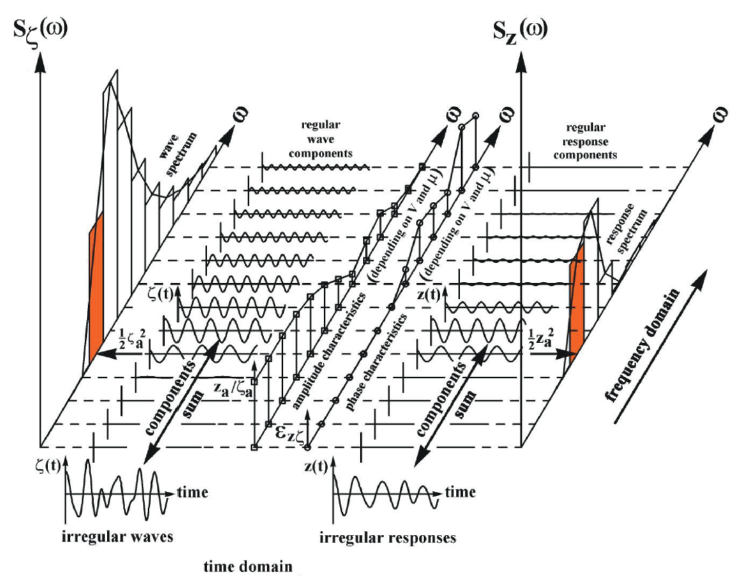


Fig. 3.5 – Transformation of the wave energy spectrum to the response energy spectrum by means response amplitude operators (courtesy of (Journée et al., 2015)).

However, because spectra describe all possible observations that could have been made (Section 2.1), one is often interested in the significant response motion amplitude or the probability that a certain threshold value is violated. Therefore, one can use Eq. (2.3) and Eq. (2.4) on the response spectra instead to compute time-series of these parameters. After consulting project engineers, it was decided to use the significant response motion amplitudes. However, future studies are recommended to consider the exceedance probabilities because it is a practical measure to express the operational risks.

The next process in the initialisation of the module is to determine the workable weather windows for each of the activities. Calculating weather windows and waiting for weather events accounts for a significant part of estimating the workability. The expected outcomes of a weather window analysis are the consecutive time periods (windows) in which each of the characteristic parameters describing the environmental state are below or above a certain threshold level. In particular, the start and stop dates as well as the length of these windows are of interest. The (workable) weather window analysis is commonly found in *time-domain* and *scenario simulation* workability models (Section 2.3). For the sake of completeness, the analysis is explained below in more detail.

Usually, in order to derive weather windows based on historical records, time series of characteristic metocean parameters are analysed and subsequently transformed to *binary sequences* (sequences of zeros and ones) of workable and non-workable time steps (Rip, 2015). The transformation requires a so-called *limit expression* (also known as the *limit state function*) in which the operational limits are defined. These are essentially Boolean expressions and return a True (1) or False (0) value depending on the state of the sea and critical values (see Eq. (3.3)).

$$\text{LSF} = H_{s,crit}\big(t, T_p(t), \theta(t)\big) - H_s(t) > 0 \tag{3.3}$$

It is worth mentioning that the limit state function is commonly expressed in terms of the significant wave height (H_s) whose critical value depends on the incoming wave angle (θ) and peak wave period (T_p). This is particularly convenient as the threshold level is only expressed in a single parameter. However, as a consequence, the corresponding threshold level varies with time (Fig. 3.6).

The same approach could be used to limit the motion response (r) instead. Hence, we may rewrite the limit state function, such that:

$$\text{LSF} = \vec{r}_{crit}(t) - \vec{r}(t) > 0 \tag{3.4}$$

Unlike the allowable sea state limit expression, the response motion's limit state function is, in this study, defined by critical displacements (and corresponding accelerations) in each of the six degrees of freedom. Therefore, the critical values of the displacements and accelerations are independent of each other. It should be noted that, imposing threshold levels on equipment's accelerations results in time-dependent limits. That is because the conversion from displacements to accelerations is based on the wave frequency (Eq. (2.11)), which is a time-dependent parameter. After finding the suitable weather windows for

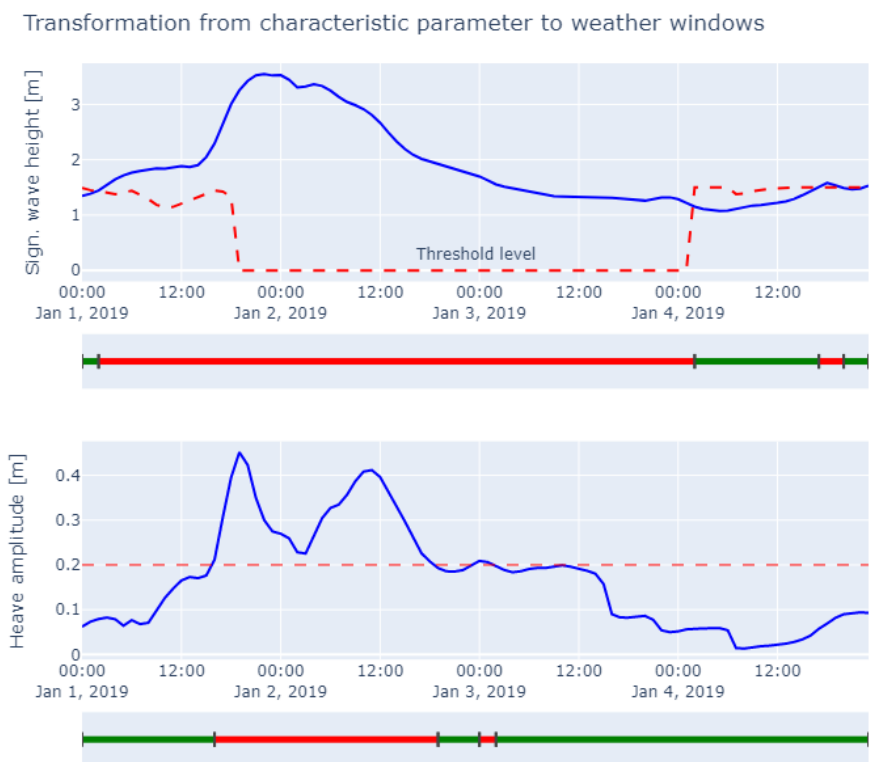


Fig. 3.6 – Illustration of the weather window analysis. For a given characteristic parameter (blue lines) and corresponding operational limits (dashed red lines) the corresponding weather windows can be found.

each of the activities, the simulation is executed. Throughout the simulation, the weather resource module functions as a "resource" and processes requests as discussed above and in Section 2.3.4.

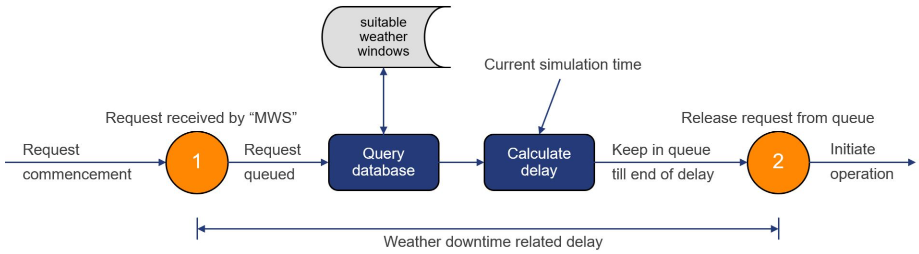


Fig. 3.7 – Illustration of the request processing by the weather resource module.

3.2.4 Model assumptions

1. The current model imposes weather downtime related delay only prior to the consecutive marine activity based on accurate measurements of the offshore conditions. In practice, however, the decision to commence the activity is also made hours prior to the activity, in which forecast accuracy plays a significant role. Therefore, the current model does not apply the uncertainties that are involved in that decision-making process.

2. In the current model, the workability is determined by two workability states, workable or not-workable. However, often marine operations can still proceed, yet at a slower progression rate. Therefore, the workability produced by the current model is expected to be more strict than observed in field.

3. The current model generates workable weather windows based on the most optimal wave heading and least response motions. Therefore, the workability is expected to be underestimated for operations in which the orientation is determined by the activity.

3.3 Model validation

The most common and probably most appropriate approach to validate (numeric) models is by comparing estimates (model results) with observations. Often, this is achieved by performing multiple tests and comparing the observations to model results. Usually, the various tests are nearly identical and allow for a thorough assessment. However, due to the sheer size and complexity of offshore wind farm projects, it is to a great extent impossible to run multiple identical tests.

Nevertheless, the construction of an offshore wind farm is usually well recorded and much data is available. For instance, it is common to log start and stop dates of the marine activities in a so-called activity log administration. In addition, vessel motions are usually recorded using onboard sensors. Therefore, facilitating the possibility to validate the accuracy of the estimated response motions. However, validating the estimated response motions with observed values suggests that the response amplitude operators are validated, a process that has already been conducted by software developers of hydrodynamic simulation models.

3.3.1 Single installation cycle

Alternatively, a single offshore wind farm project can be considered as multiple cyclic activities. For example, the construction of X monopiles, requires (almost) the same approach for each of the monopiles. Therefore, one can consider the installation of many monopiles (that share the same construction method) as a series of tests.

However, this implies that the construction of each monopile is an independent process. But, unfortunately that is not the case. Because the operations are executed in a sequential manner, i.e. one operation directly follows after another has been completed, the operations become time dependent. In other words, the completion duration of one operations affects the start of another. As a result, the prevailing weather conditions of the Nth operation, depends on the completion duration of the (N-1)th operation. Therefore, the workability of one installation cycle depends on the workability of the previous installation cycle. Hence, despite the repetitive nature, decomposing the installation process (and removing parts of the logistic cycle) to obtain independent tests may be considered as an insufficient validation of the DES-based model.

3.3.2 Failure analysis

A second approach to validate the model is to consider the *point of failure*. In this case, the point of failure is referred to as the conditions (expressed by the significant wave height) for which certain installation activities experience delay due to workability concerns. This approach helps to understand how accurate current modelling approaches are in describing the actual limiting conditions experienced at site.

In order to evaluate the models, observations of the significant wave height are drawn from the wave database during waiting on weather events. Subsequently, probability exceedance diagrams are developed from the collected set. Simultaneously, waiting on weather events can be extracted from the onboard activity logs. During each of the waiting on weather events, the prevailing significant wave height is collected from the wave database and probability exceedance curves can be drawn. The resulting diagrams expose specifically the statistical threshold levels in terms of the significant wave height at which a waiting on weather event is generally declared and how much the estimates deviate from the actual observations.

Chapter 4

Case studies

4.1 Introduction

In the following chapter, the workability assessment model, described in the previous chapter (Section 3.2), is applied to two recently realised offshore wind farm projects; the Hollandse Kust Zuid (HKZ) and Borssele III&IV offshore wind farms. For each project, the model's input values are discussed, such as the site specific details (environmental loading conditions), the installation method, and operational limits. Furthermore, this chapter presents the case study results. In addition, the results are analysed, evaluated and validated using the methods described in Chapter 3.

Moreover, the two project were specifically chosen because the weather restricted activities that were modelled correspond to operations that involve the motions of Van Oord's floating equipment as well as the motions of a wind turbine generator (WTG) structure. Besides, the projects provided sufficient data for the validation and modelling steps.

4.2 Hollandse Kust Zuid (HKZ)

One of the study areas considered is the Hollandse Kust Zuid (HKZ) offshore wind farm. An offshore wind farm that is located in the North Sea, approximately 18 kilometres of the Dutch coast, and operated by Vattenfall. As part of the construction, Van Oord was awarded with a contract from TenneT (who was responsible for the realisation and operation of the offshore and onshore wind area connections to its onshore high voltage grid) for the delivery and installation of export cables from the wind farm's AC substation platforms to the onshore station (located at the Maasvlakte II).

The installation comprised of the burying of the export cable up to 5 meters below the sea bed over a total distance of (approximately) 50 kilometres. In order to accomplish the task, Van Oord developed together with sub-sea experts from Soil Machine Dynamics Ltd (SMD) the Deep Dig-It trenching tractor, a tracked remotely operated vehicle (TROV) that is deployed and operated from Van Oord's heavy-lift vessel the MPI Adventure.

4.2.1 Installation campaign

The corresponding installation campaign of the MPI Adventure and Deep Dig-It trenching tractor was derived from the (onboard) activity log[1] of the MPI Adventure. It was found that the installation campaign can be represented by the following processes: (1) transit (from port to site and vise versa), (2) transit in field, (3) dynamic positioning (onto the launch location), (4) launch, (5) jet trenching, and (6) recovery (see Fig. 4.1).

It is worth mentioning that during the jet trenching operations, the MPI Adventure sails alongside the Deep Dig-It trenching tractor towards the exit point. Moreover, the Deep Dig-It trenching tractor is repeatedly recovered to deck for maintenance activities. It is estimated, from the activity log, that the Deep Dig-It trenching tractor is recovered after approximately 2,000 meters. Therefore, it is considered that a minimum of 25 launch and recovery operations took place during the cable burying operations. It should be stressed that this is the estimated number of installation cycles, and is therefore, expected to differ from the observations.

Table 4.1 – Example durations of the installation activities.

Activity	Duration
Transit to field	4 hrs
Transit in field	1 hr
Dynamic positioning (DP) on site	0.50 hrs
Launch / Recovery	1 hr
Jet trenching	200 m per hr

The duration of the installation activities was determined from the average values stated in the activity log. In addition, common estimates of the activity durations made during the tender stage were accessed. Based on the experience of Van Oord's engineers and the values derived from the activity log, appropriate values were selected. Therefore, enabling to develop a representative model of the installation sequence.

[1] An activity log is a dataset that holds information of the installation activities such as the start- and stop-dates and the activity details and remarks.

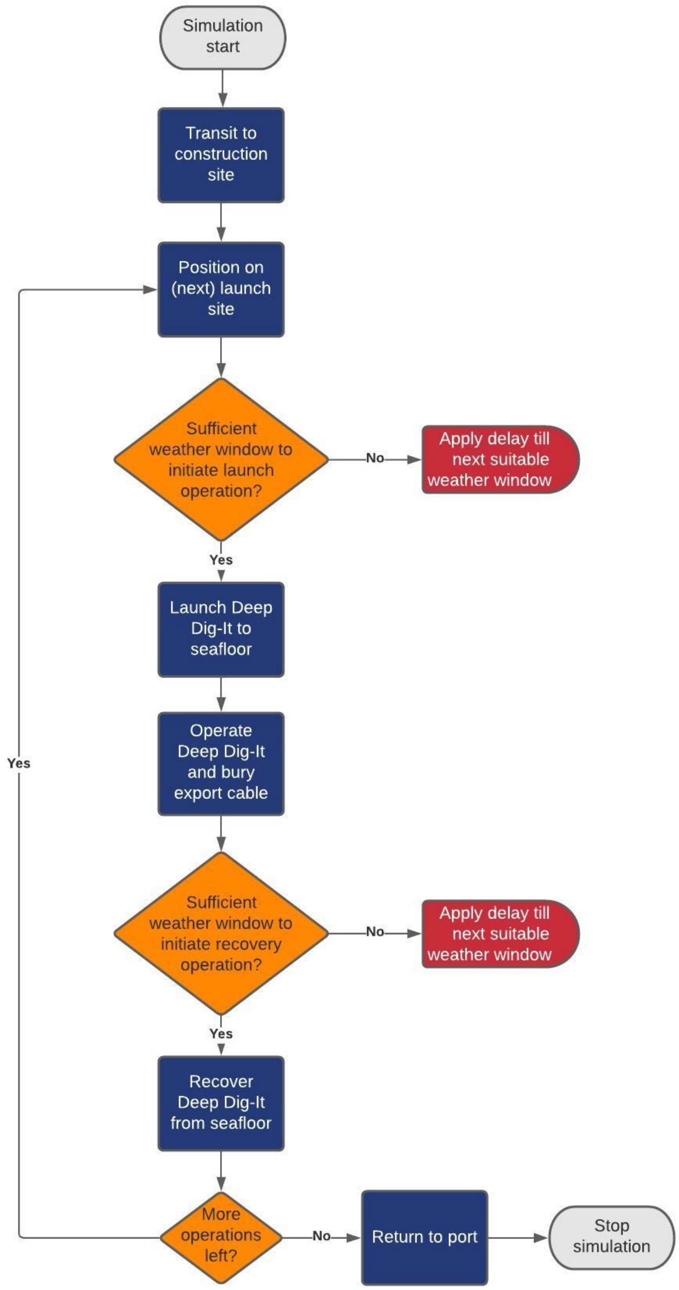


Fig. 4.1 – The installation process of the MPI Adventure and Deep Dig-It trenching tractor as modelled using the workability assessment model.

4.2.2 Operational limits

Because the Deep Dig-It trenching tractor operates on the seafloor and is operated remotely (from the MPI Adventure), it is to a great extent not subject to environmental loading conditions. Therefore, commencement of the installation activities is only dependent on the weather restrictions of the launch and recovery operations. The operational limits of these lifting activities were established by Van Oord's engineers following a workable limit analysis (Section 2.2).

As part of the analysis, the engineers modelled the lifting operations of the Deep Dig-It trenching tractor through the splash zone using OrcaFlex. Based on a range of values of the significant wave height and the peak wave period, a number of JONSWAP spectra were constructed. Using the cosine directional spreading model (Section 3.2), the 1D wave energy density spectrum was subsequently transformed to a 2D spectrum. Then, for each spectrum the response motions were computed utilising the corresponding response amplitude operators (RAOs) of the MPI Adventure. Finally, based on the physics of the multibody dynamics (equations of motion, etc.), OrcaFlex simulated the installation activity. The hydrodynamic properties of the MPI Adventure, such as the response amplitude operators, were established using Ansys Aqwa.

By defining the limiting criteria, such as the vessels accelerations at the slewing center, the dynamic load and stroke length of the onboard crane, winch velocity, trencher motions, etc., the significant wave height, peak wave period and encounter wave angle corresponding to failure were established.

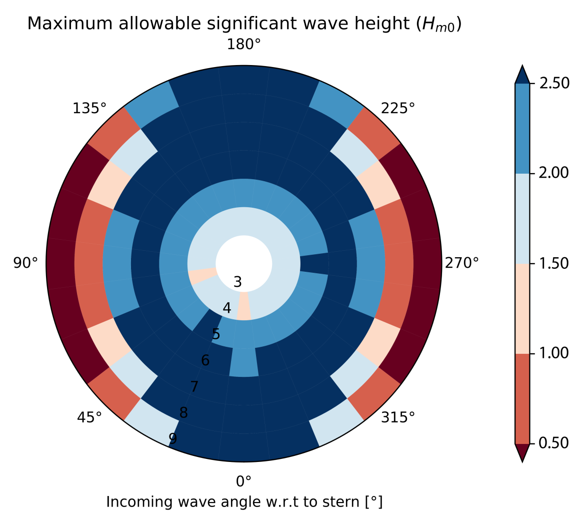


Fig. 4.2 – An example of the allowable conditions expressed in terms of the significant wave height, peak wave period and encounter wave angle.

The operational limits expressed in terms of (vessel) response motions were established on expert opinion's and the above mentioned criteria. Also, because the launch and recovery operations require the Deep Dig-It trenching tractor to be hoisted through the splash zone, the governing current velocity does affect the limiting conditions. Nonetheless, in this study, the workable limits (derived above and established by expert opinion's) correspond to a zero current velocity. Therefore, permitting the simulations to neglect the effects of currents on the workability.

4.2.3 Prevailing wave climate

The representative wave climate for this region was accessed through two resources. First, hourly wave datasets were retrieved from DHI's MetOcean Data Portal. This dataset covers the years 1990 to 2019 and is generated based on global wind data by DHI's MIKE 21 Spectral Wave Model (SW). From this dataset, both wave spectra time-series and time-series of the spectral parameters were retrieved.

However, since the construction of export cables for the Hollandse Kust Zuid (HKZ) project took place in 2020, an additional source of wave data was approached. To cover this time period, hourly ERA5 data was used. ERA5 provides hourly estimates (following a reanalysis) of oceanic climate variables on a 30 kilometre grid. The ERA5 dataset is derived from advanced models that use a vast amount of historical records to produce global estimates. Nevertheless, it provides only time-series of the (discriminated) wind-sea and swell spectral parameters. Therefore, the wave spectra over the period 2019 - 2020 were reconstructed using the JONSWAP wave spectrum and the cosine directional spreading model.

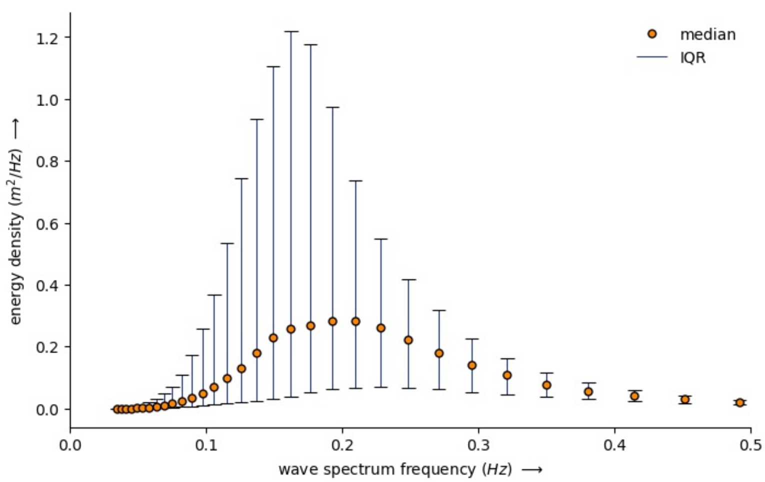


Fig. 4.3 – Distribution of the wave energy density over the frequency bands.

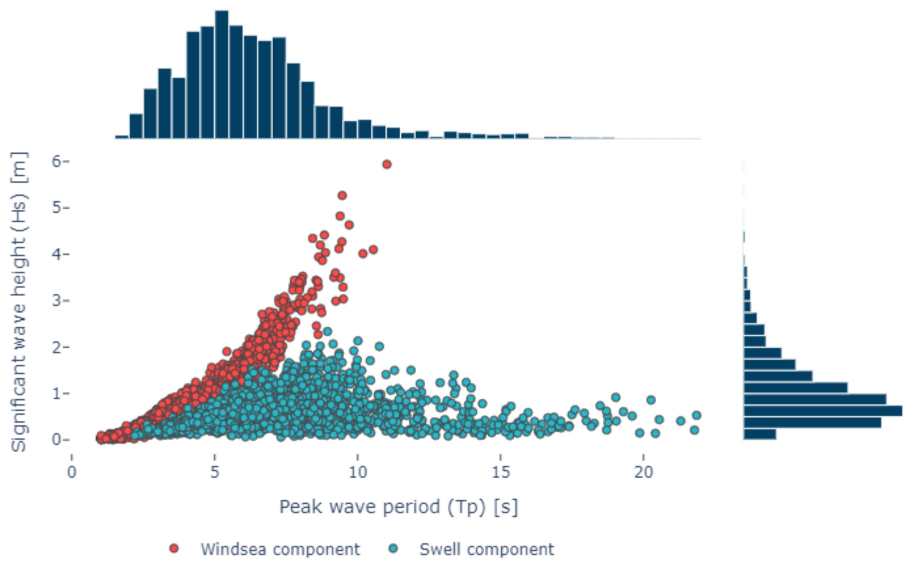


Fig. 4.4 – Distribution of spectral wave parameters in the North Sea (52.01N, 3.97E).

4.2.4 Project estimates

In order to study the effects of using the underlying model assumptions, ten-thousand (10,000) repeated simulations were run with varying start dates over 1990 to 2020. The start dates with hourly incremental time-steps were selected based on a uniform probability distribution to obtain an evenly distributed probability of being selected. After every simulation, the start date, estimated project duration and weather downtime related delays were collected.

From this collection, the empirical cumulative probability distribution (ECDF) of the project duration was computed using Eq. (4.1). The result is illustrated in Fig. 4.5.

$$\hat{F}_n(x) = \frac{1}{n}\sum_{i=1}^{n} 1\{X_i \leq x\} \tag{4.1}$$

In which,

$$1\{X_i \leq x\} = \begin{cases} 1 & \text{if } X_i \leq x \\ 0 & \text{otherwise} \end{cases} \tag{4.2}$$

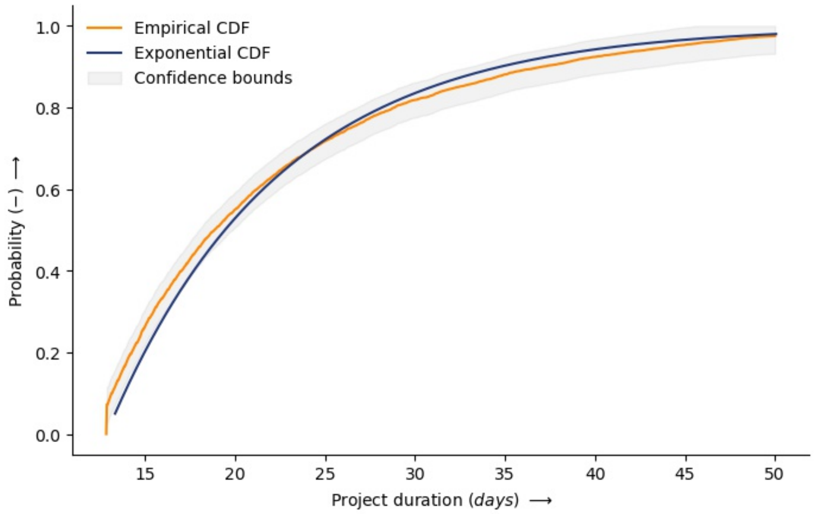


Fig. 4.5 – Cumulative distributions of the estimated project durations.

Often, many simulations are required to obtain a good estimate of the actual distributions (e.g. 10,000 simulations). Therefore, in order to quantify how well the above empirical cumulative distribution functions describes the "true" ECDF, confidence bands are provided using the Dvoretzky-Kiefer-Wolfowitz (DKW) inequality (Eq. (4.3) and Eq. (4.4)).

$$LB(x) = \max\left(\hat{F}_n(x) - \sqrt{\frac{1}{n}\ln\left(\frac{2}{\alpha}\right)}, 0\right) \tag{4.3}$$

$$UB(x) = \max\left(\hat{F}_n(x) + \sqrt{\frac{1}{n}\ln\left(\frac{2}{\alpha}\right)}, 1\right) \tag{4.4}$$

In Fig. 4.5, it is illustrated that the resulting ECDF fits within the five percent confidence bounds (i.e, $\alpha = 0.05$). Therefore, the sample size of the collection is considered statistically large enough to approach the "true" ECDF. Moreover, an exponential (continuous) distribution (Eq. (4.5)) was fitted to the sample set to illustrate the accuracy of theoretical probability models. Based on the figure, it appears that the project duration can be described by an exponential probability model.

$$p(x) = \lambda e^{-\lambda x} \tag{4.5}$$

It must be stressed, however, that the above distribution represents the probability of the project duration for any arbitrary start date during the year. As a result, the figure lacks information regarding the seasonality effects. Instead, non-parametric distributions (box plots) of the project durations were developed and illustrated per month of the start date (Fig. 4.6).

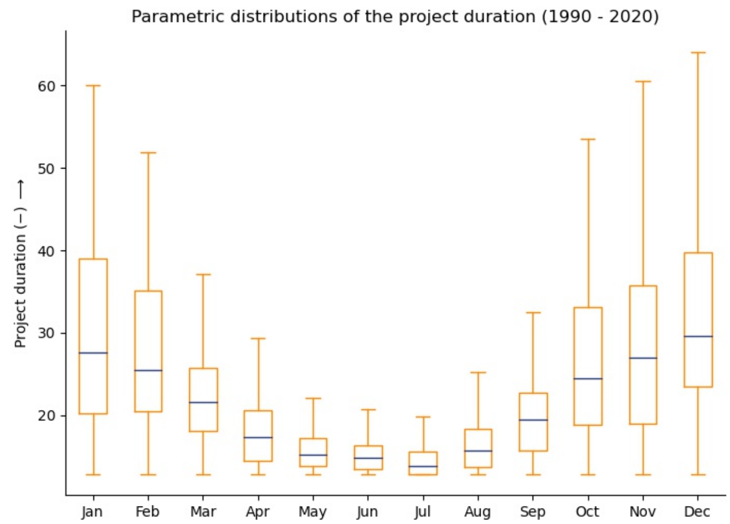


Fig. 4.6 – Non-parametric distributions of the project duration grouped by month.

In the above figure (Fig. 4.6), the seasonality effects are illustrated. As one can expect for the North Sea region, the (workability) conditions are less favourable during the winter period. As a consequence, the expected project duration is significantly longer for operations starting during the winter period (with respect to the summer months). Also, it appears that there is much more variation during the winter months. Hence, estimates of the project duration during this period are, inevitably, much more uncertain.

4.2.5 Workability estimates

Scatter workability

In an attempt to highlight the fundamental differences between the allowable sea state based method and response motion based method, the workability was assessed using the statistical scatter model first. For both approaches, time-series of characteristic parameters (i.e. significant wave, peak wave period, heave motion, etc.) were derived from the metocean wave dataset. Through a transformation step, these time-series were transformed into a *binary workability sequence* as discussed in Section 2.3.

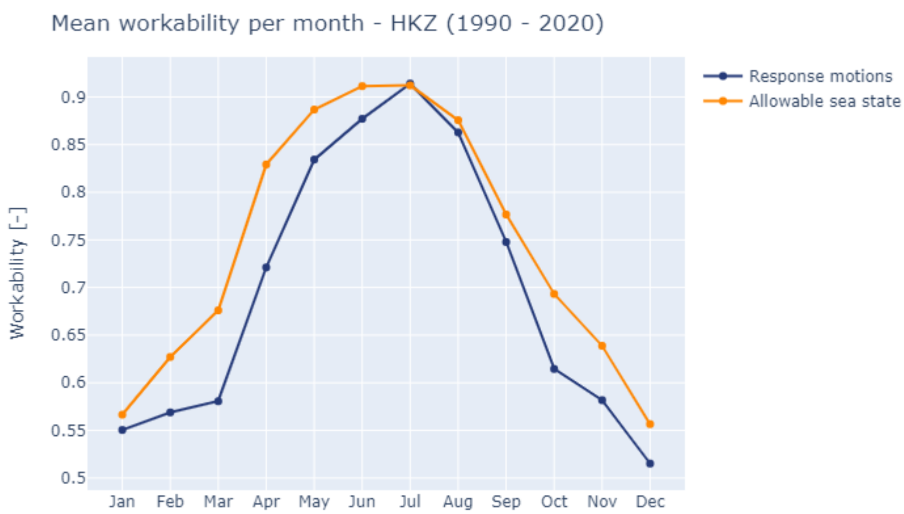


Fig. 4.7 – Workability at the Hollandse Kust Zuid (HKZ) based on the launch and recovery operational limits and the scatter approach.

During this transformation, the vessel was, in both approaches, aligned with the mean wave direction, therefore neglecting the optimisation step that allows to reduce the response motions (Section 3.2). After the transformation, the binary sequence data was grouped by months to which the monthly averaged workability was computed using Eq. (4.6).

$$\bar{x} = \frac{1}{n}\sum_{i=1}^{N} x_i \tag{4.6}$$

In Fig. 4.7, an evident dissimilarity is observed between both estimating methods. In particular, beyond the summer months, the response motion based method appears to provide less favourable workability conditions. In order to gain an understanding of the cause leading to the differences, the contribution of each response motion limit to the downtime was inspected using probability theory (Eq. (4.7)). This is illustrated in Fig. 4.8.

$$\begin{aligned} P(D) = \quad & P(A) + P(B) + P(C) - P(A \wedge B \wedge C^c) \\ & -P(A \wedge B^c \wedge C) - P(A^c \wedge B \wedge C) - P(A \wedge B \wedge C) \end{aligned} \tag{4.7}$$

Where D refers to the downtime event, A to the condition that the heave limit has been violated, B to the condition that the roll limit has been violated, and C to the condition that the pitch limit has been violated.

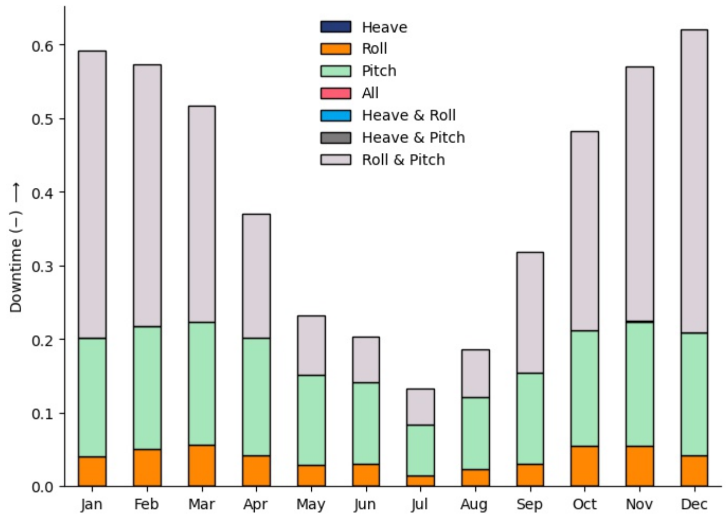


Fig. 4.8 – Contribution of the different threshold levels to the weather downtime, and therefore workability.

The image above reveals that the predominant cause of weather downtime related delay is particularly ascribed to the violation of the pitch motion limit. Moreover, the data from the figure also suggests that the roll motion limit has been violated on multiple occasions. The latter is a rather striking result because it indicates that, although the vessel was positioned towards the mean wave direction, it has encountered waves from the side that caused excessive roll motions for which the operations were claimed to be not workable.

This result implies that as a result of the two commonly used assumptions in workability assessment models (discussed in Section 3.1.1), a significant part of the weather downtime is ignored (almost 10% of the weather related downtime in March).

Persistence statistics

Likewise, the two approaches were used in a time-domain workability assessment model to highlight the differences. Through a weather window analysis on the binary workability sequences (obtained for the launch and recovery operations of the Deep Dig-It trenching tractor), workable periods were obtained. Then, the durations of the workable weather windows were computed and the windows were, subsequently, grouped by the month of the start date. Following, for each corresponding month, non-parametric distributions (box plots) of the window durations were obtained. This is illustrated in Fig. 4.9.

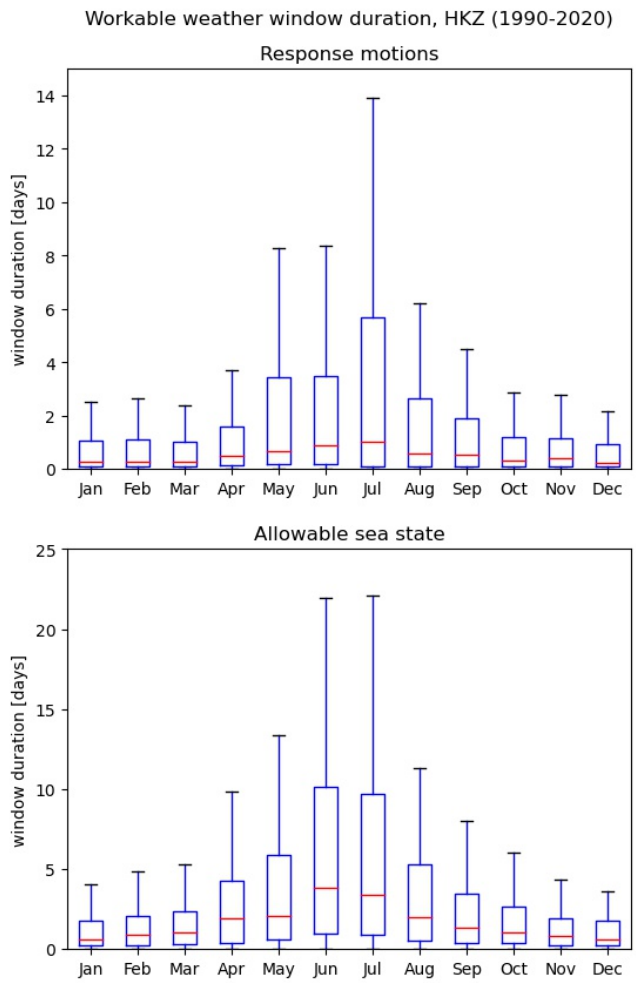


Fig. 4.9 – non-parametric distribution of the workable weather window durations given the operational constraints that correspond to the launch and recovery operations.

From the image, it becomes evident that the allowable sea state approach produces more frequently longer workable periods. That is to say, the probability to encounter "long" workable weather periods is greater for the allowable sea state approach compared to the response motion approach. Therefore, the data from the figure implies that the workability is less favourable for the response motions based method.

Nevertheless, because the launch and recovery operations often do not require particularly long workable weather windows (2 — 3 hrs), the workability is presumably dominated by the duration of waiting on weather events. Therefore, waiting on weather events related to the launch and recovery operations were derived using the same approach as mentioned above, however, for windows in which the weather conditions are insufficient. This is illustrated in Fig. 4.10.

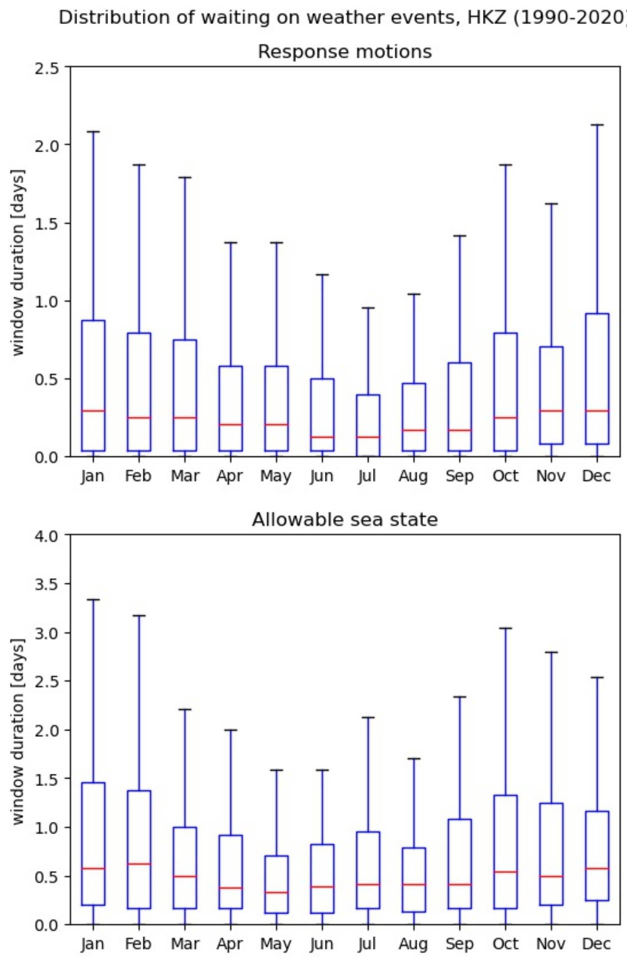


Fig. 4.10 – Distribution of the duration of waiting on weather events based on the launch and recovery operations.

The above figure shows that the allowable sea state based method also generates longer durations of the waiting on weather events (almost twice as much). Hence, although the method offers more often workable weather windows, once the encountered weather conditions do not allow for commencement, the probability to encounter long waiting on weather events is greater compared to the response motions based approach.

Because in logistics optimisation tools the goal is to identify bottlenecks (long delays) and resource utilisation, discrete-event simulation will show how the above findings affect the logistic operation.

Discrete event simulation

After simulating the installation process over 10,000 times with varying start dates ranging from 1990 to 2020 (Section 4.2.4), workability estimates were derived per simulation. The data was, subsequently, grouped by month and non-parametric distribution (using box plots) were obtained. The results are shown in Fig. 4.11.

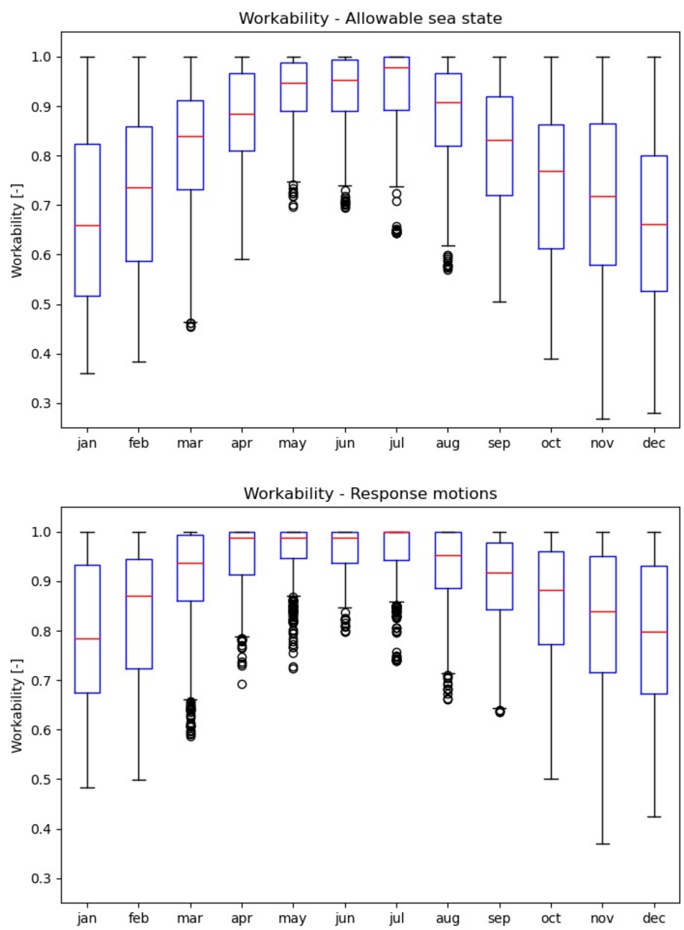


Fig. 4.11 – Non-parametric distributions of the workability following the workability assessment model as discussed in Section 3.2

From Fig. 4.11, it appears that the workability estimates are more favourable for the response motion based method. In particular, during the winter period, the response motion based method generates up to 10% more favourable workability conditions. This result is somewhat counter-intuitive. However, it must be stressed that during these simulation runs, the vessel's heading was optimised in order to obtain the least response motions. Because a common approach is to position the vessels such that it's bow is headed towards the mean wave direction (MWD) and in order to compare it with previously found results, identical simulations were run using this approach.

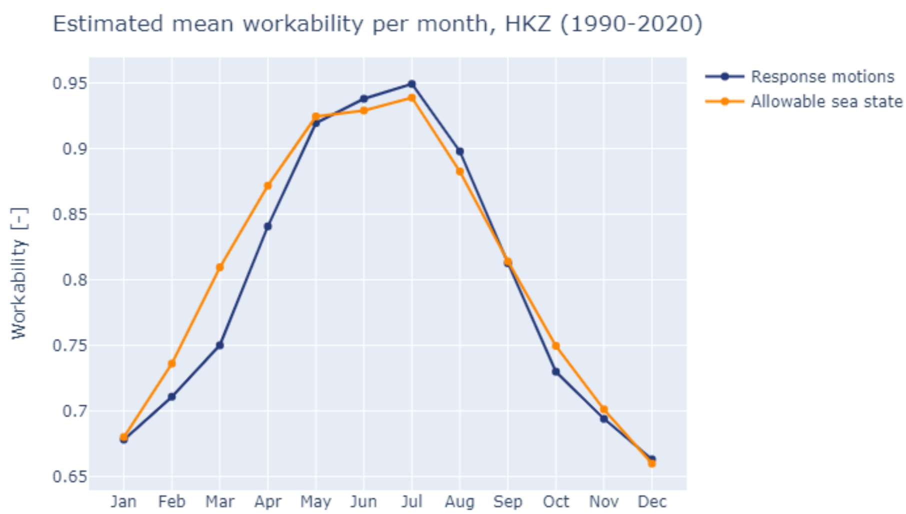


Fig. 4.12 – Mean workability per month when positioning the vessel towards the mean wave direction.

As a result of this approach, the workability decreases substantially and becomes, during the winter period, more favourable for the allowable sea state based method.

4.2.6 Failure analysis

In an attempt to support the "waiting on weather" decisions made by the model, observations of the significant wave height were extracted from the wave database for those periods in which the model identified not workable conditions. The retrieved values are referred to as the *point of failure* and help to identify at which critical values the model decides to let a time-step "fail" (i.e. is not workable). Simultaneously, wave height observations were extracted from the wave data base during periods in which the activity log registered waiting on weather events. For both significant wave height sample sets, empirical cumulative density distributions and quantile-quantile plots were drawn. These are shown in

Fig. 4.13 and Fig. 4.14, respectively.

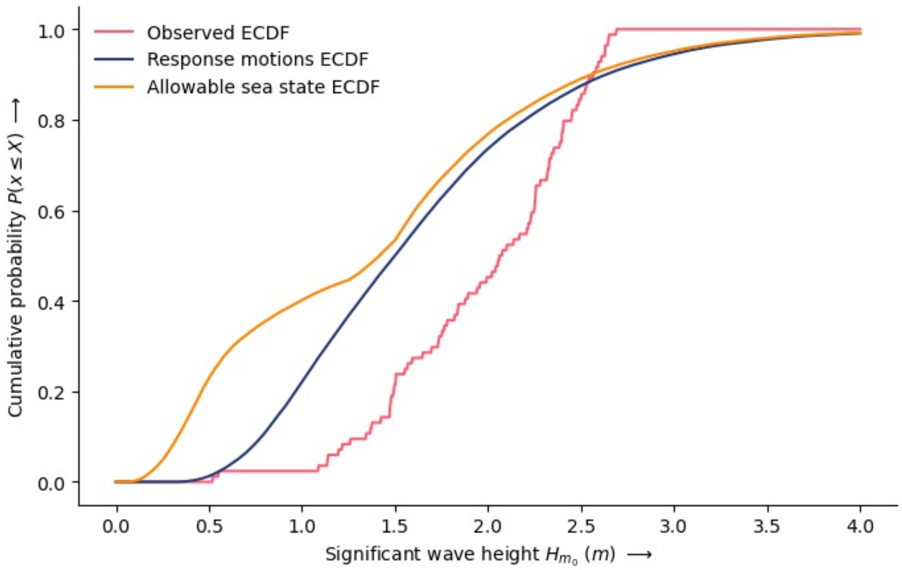


Fig. 4.13 – Empirical cumulative distributions of the *point of failure* expressed in the significant wave height at which the simulated and realised operations experienced weather downtime (operational failure).

The data from the above chart illustrates that allowable sea state based method states on several occasions not workable conditions for small values of the significant wave height. It was found that this is related to the abrupt change of the allowable sea state limit. That is, because the workable limit analysis derives operational limits for a range of peak wave periods, the allowable value of the significant wave height outside of that range is deliberately set to zero. As a result, small values of the significant wave height that correspond to long wave periods (for instance swell waves with frequencies above 10.00 seconds) will trigger the model to declare not workable conditions. Interestingly, the image indicates that this issue is resolved using the response motion based method.

Furthermore, the figure illustrates that both the response motion and allowable sea state based methods impose up to a certain degree more strict limits. It follows that fifty percentile limit corresponds to a wave height of approximately 1.50 meters. In contrast, the corresponding observed wave height is nearly 2.25 meters. However, it must be stressed that due to the limited waiting on weather events during the Hollandse Kust Zuid (HKZ) offshore wind farm project, the corresponding sample size of the critical values observed during operational failure is rather small. As a consequence, the resulting empirical cumulative distributions of the observed values only describes a fraction of the conditions that result in weather downtime.

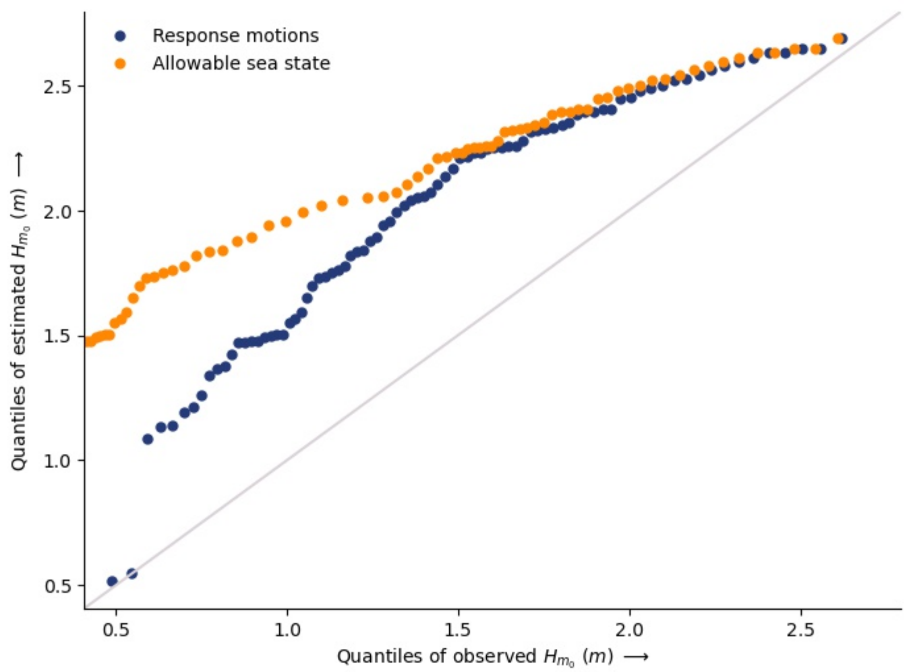


Fig. 4.14 – Quantile-Quantile (q-q) plots of the significant wave heights during the observed and estimated waiting on weather events.

In the above graph, it is illustrated that the models predict at a rather calm sea state operational failure compared to the observations. Besides, as mentioned above, the response motions based method appears to describe the not workable conditions more accurately at smaller values of the significant wave height. Most likely because low wave frequencies (0 to 0.10 Hz) are not accounted for during the workable limit analysis.

4.3 Borssele III&IV

The Borssele III&IVoffshore wind farm project was chosen in addition to the Hollandse Kust Zuid (HKZ) case. The Borssele III&IV offshore wind farm is located approximately 24 kilometers of the coast (refer to Chapter B of the appendix) and consists of 77 wind turbine generators (WTGs). The case study is particularly interesting for this research because of the type of weather downtime experienced on site. It was found that during the mating process — in which the turbine blades are connected with the hub and nacelle — tower oscillations were that significant that it became impossible to “mate” the blades and hub. Therefore, ultimately resulting in weather downtime.

Fig. 4.15 – Coupling of the turbine blades with the nacelle from the Aeolus (HLV) self-elevating unit at Borssele III&IV offshore wind farm.

However, more interesting, it was not the oscillating motions of the load (the blades) that caused the delay, but the tower structure’s oscillations. It became apparent that the towers frequently oscillated considerably during rather “ideal” weather conditions. These oscillations were ultimately related to the wave excitation of the natural frequency. In particular short-crested waves, that are characterised by a wave period of 3 to 4 seconds, forced the structure to oscillate at its natural frequency. Hence, stimulating the structure to resonate.

4.3.1 Installation campaign

At the time of the construction of the Borssele III&IV offshore wind farm, Van Oord deployed the Aeolus (HLV) to install the turbine structures. According to the onboard activity log, the corresponding work method consisted of (1) transit to port, (2) the transfer of the structural components from port to deck, (3) transit to the construction site, (4) (dynamic) positioning, (5) jacking up, (6) installation of the tower component, (7) installation of the hub and nacelle, (8) the mating process of the blades with the hub, and (9) jacking down.

4.3.2 Operational limits

Because the activity log recorded mostly weather downtime related delays as a consequence of the excessive tower oscillations, it was chosen to impose only operational limits on the blade mating process. The corresponding limits were expressed in terms of the horizontal displacement amplitude of the turbine structure at the height of the hub and were established based on field experience[2]. Moreover, the allowable sea state conditions were derived using the response amplitude operator of the tower structure (Fig. 4.16). Therefore, the operational limits are, for both the allowable sea state and response motion based method, entirely identical. Hence, the case only illustrates the uncertainties that arise from describing the offshore state by only two parameters (H_{m_0} and T_p).

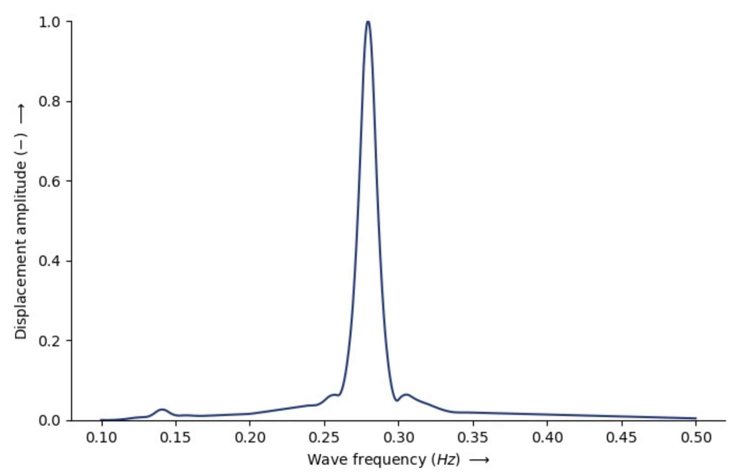


Fig. 4.16 – The response amplitude operator of the tower structure.

[2]The workable limit (in terms of the displacement amplitude) was determined in consideration with the operators that worked on site.

4.3.3 Workability estimates

Scatter workability

A similar approach as the Hollandse Kust Zuid (HKZ) case study was used to illustrate the differences of both approaches for the Borssele III&IV case study. For this case, however, operational limits were imposed on the blade root mating process, for which the maximum oscillating tower motions were set at X centimeter horizontal displacement amplitude. After computing the displacement amplitudes using the response amplitude operator, the binary workability sequence was computed using the workable limit. Simultaneously, the binary workability sequence of the allowable sea state method was computed based on the observed wave heights and period. Based on the corresponding months and years of the data points, non-parametric distributions of the workability were obtained. In order to compare both methods, the mean values were obtained from the non-parametric distributions. This is illustrated in Fig. 4.17.

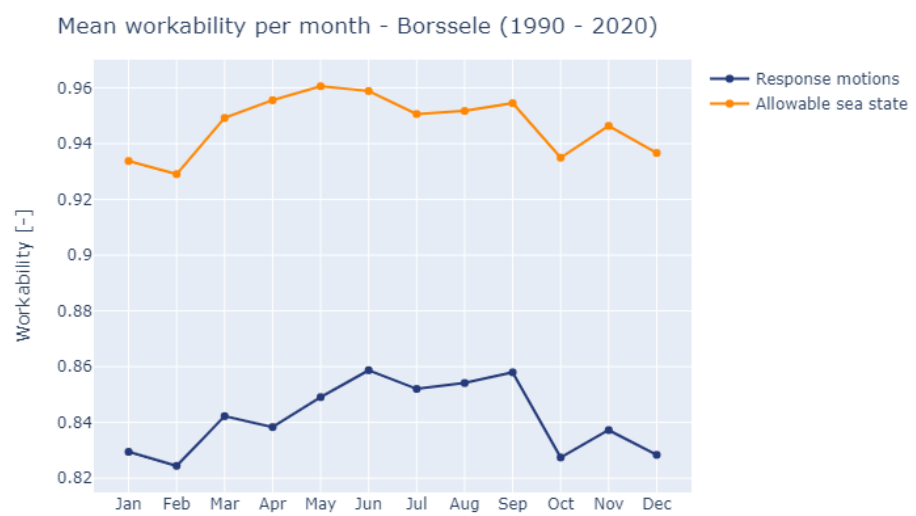


Fig. 4.17 – Workability of the blade root - hub mating process using the scatter workability model.

From the figure, it can be seen that both approaches yield different results. Equally to the previous case, these results show that response motion based approach generates less favourable workability results. Because the operational limits of both approaches are identical, these results imply that describing the offshore environment only by means of two characteristic parameters (the significant wave height and peak wave period), causes the models to neglect a significant part of the weather downtime.

Persistence statistics

In Fig. 4.18, the persistence model results of Borssele III&IV offshore wind farm are presented.

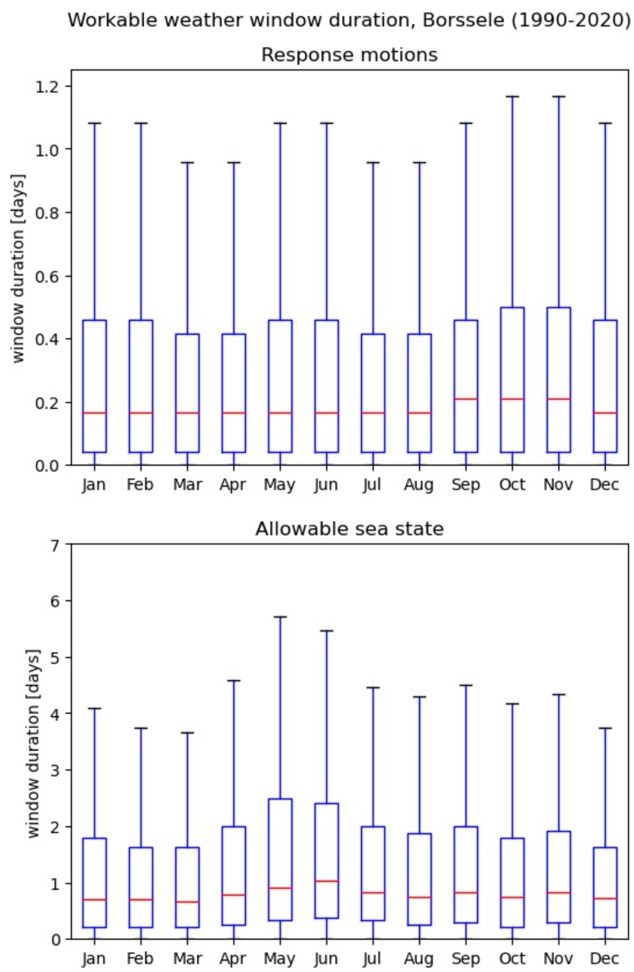


Fig. 4.18 – Non-parametric distribution of the workable weather window durations.

From the image it appears that, also for this case, the allowable sea state based method generates considerably more favourable workability conditions. However, more interesting is that the results show little to no dependence on seasonal variation. It is believed that the governing wave climate that triggers the tower oscillating motions occurs throughout the year uniformly. Especially, because the natural frequency of the structure corresponds to small wave frequencies. Hence, the presence of unfavourable motions does not rely on “extreme” events, but occur more occasionally. This is illustrated in Fig. 4.19.

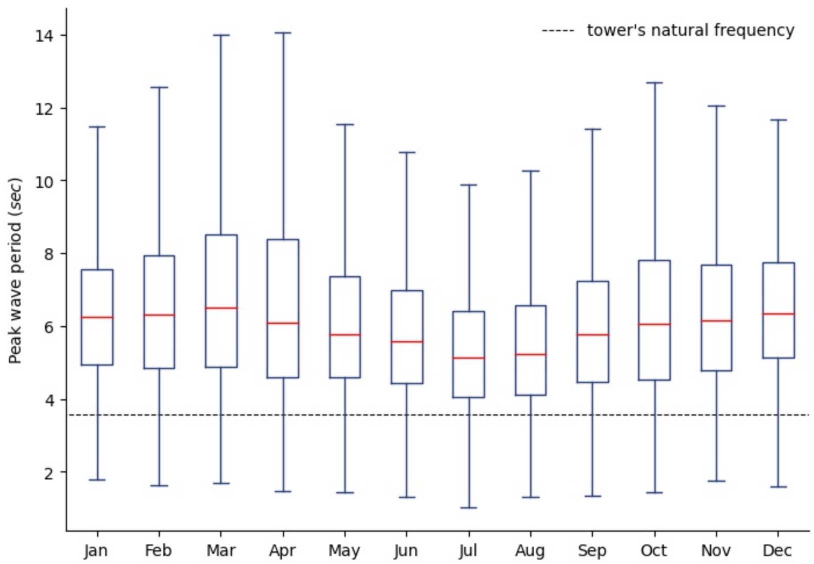


Fig. 4.19 – Non-parametric distributions of the peak wave period. Note that the interquartile range (IQR) remains relatively equal throughout the year.

From the above image, it is found that the peak wave period meets the natural frequency somewhere between 15 - 25% of the time. This range remains fairly equal throughout the year. As a result, the weather downtime related delays are not particularly dependent on seasonality. Nevertheless, the corresponding wave height still needs to be considerably in order to cause excessive tower motions.

Discrete event simulation

In Fig. 4.20, the workability results generated by the *workability assessment model* are presented for the Borssele III&IV case study. Also for this case study, it is found that the response motion based method estimates less favourable workability conditions.

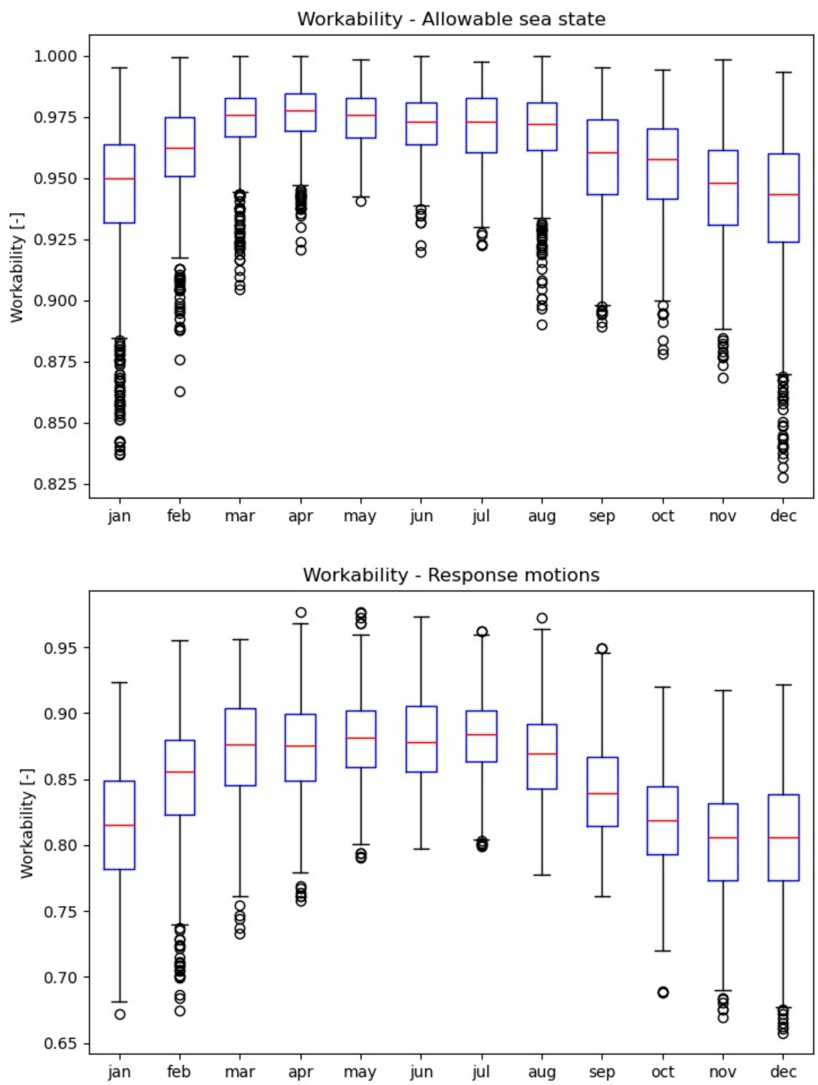


Fig. 4.20 – Non-parametric distributions of the workability of the Borssele III&IV case study.

4.3.4 Failure analysis

The point of failure (i.e. the value of the significant wave height for which a time-step was considered not workable) was also examined for the Borssele III&IV case study. Again, observations of the significant wave height were extracted from the wave database for those periods in which the model identified not workable conditions. In the same way, wave height observations were extracted from the wave data base during periods in which the activity log registered waiting on weather events. Correspondingly, for each of the significant wave height sample sets, empirical cumulative distributions and quantile-quantile diagrams were drawn. These are provided in Fig. 4.21 and Fig. 4.22, respectively.

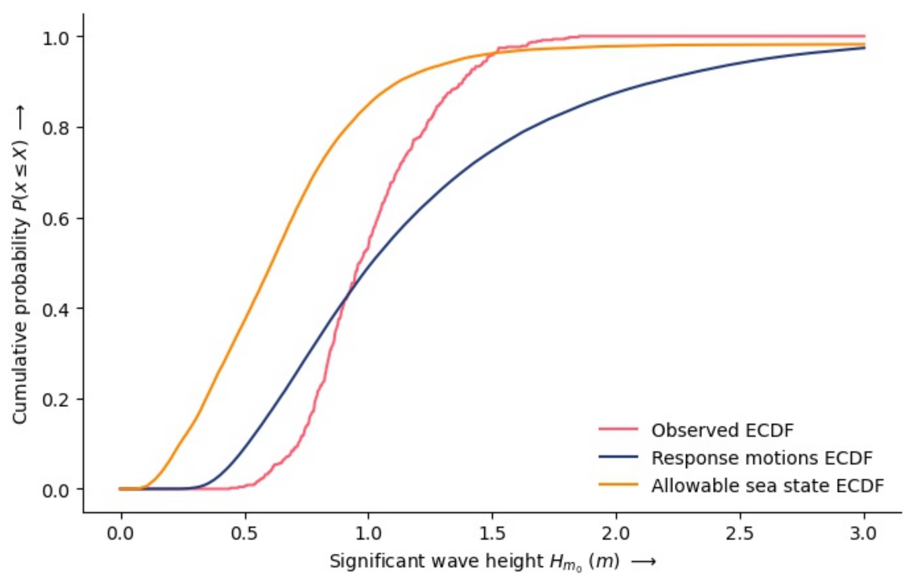


Fig. 4.21 – Empirical cumulative distribution functions of the significant wave height observed during waiting on weather events

In the above plot, it is shown that the significant wave height observations that caused weather downtime during construction are sampled around a 50-percentile value of 1.00 [m]. Nevertheless, both estimating models indicate at an earlier state not workable conditions and terminate the installation at significant wave heights lower than 1.00 [m] (with respect to the p50-value). Besides, it appears that the allowable sea state method imposes a slightly stricter limit in terms of the significant wave height.

Although, these results are counter intuitive with respect to the workability results shown in figure Fig. 4.20, one must notice that it is believed that the problem occurred predominately for a small range of wave frequencies (3.40 [s] —

3.70 [s]). Therefore, any wave component that has a frequency which is close to the natural frequency needs enough energy to produce considerable response motions. For instance, a regular wave component with a frequency at 3.70 [s] needs a height of 1.00 [m] to obtain tower displacements of 0.05 [m].

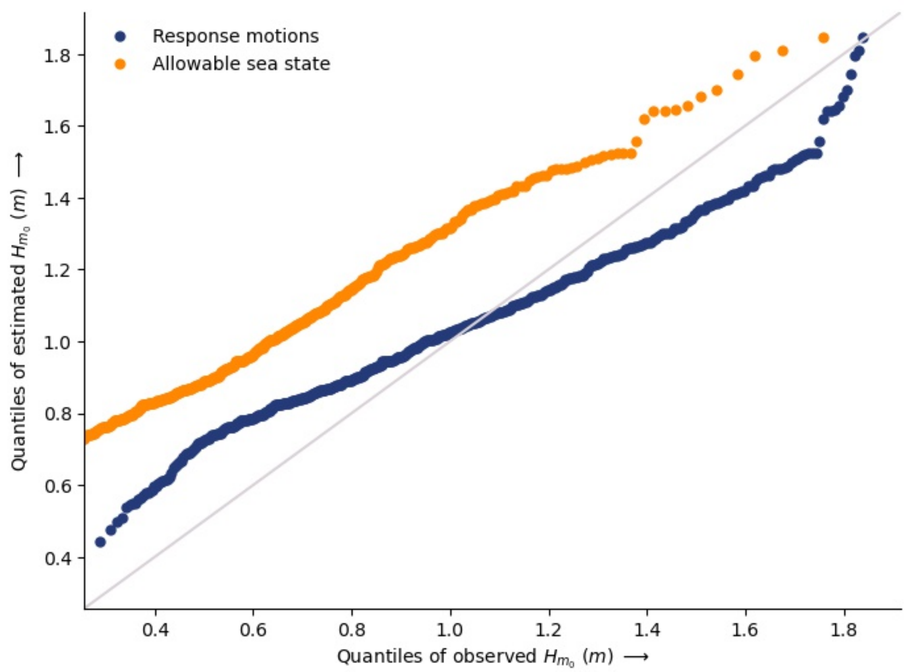


Fig. 4.22 – Quantile-Quantile diagrams of the significant wave height observations during waiting on weather events.

Chapter 5

Discussion

5.1 Research findings

In reviewing literature, it was established that uncertain estimates of the workability are the principal cause of substantial operational risks, and therefore construction expenses. A reduction of the operational risks benefits the industry and the development of offshore renewable energy. Therefore, this study set out to improve the reliability of workability estimates. Hence, the main research question raised in the introduction section was:

> "How can the reliability of workability estimates involved in the planning and engineering stage of an offshore wind farm installation be improved?"

Below, the key research findings of this study are summarised and interpreted.

In the first place, the literature study of this research (Chapter 2) identified two underlying model assumptions that are often used to model and estimate the workability. These being:

1. The significant wave height and peak wave period adequately describe the two-dimensional wave energy distribution of a (directional) wave field.
2. The wave conditions associated with weather downtime are sufficiently described by the two characteristic parameters following a workable limit analysis

However, research regarding the workability lacks clarity on the appropriateness of implementing these assumptions and the accuracy of existing modelling approaches.

To study the appropriateness and accuracy of using these assumptions, this research presented an alternative logistics optimisation model that integrates response motions of vessels and turbine structures into the weather window analysis of the coupled hydrodynamic model. Subsequently, the model was implemented on two recently realised offshore wind farm projects operated by Van Oord.

Following the two case studies, the most important finding of this study is perhaps that the current approach adopted by the industry potentially overestimates the true workability and therefore imposes unnecessary operational risks. This study found two possible explanations for this result.

The first possible explanation for this result might be that the two-dimensional (2D) wave energy distribution describes the wave field more accurately and therefore exposes additional wave conditions that result in weather downtime. Because the allowable sea state method applies an unimodal one-dimensional wave spectra to model the wave conditions, it may not necessarily describe bimodal or multimodal sea states properly. This was also emphasised by Garcia-Gabin (2015). Therefore, because of the loss of detail, the model might not have been able to identify critical sea states. In contrast, the response motions modelling approach maintains the two dimensional wave energy distribution. Therefore, the model is able to describe the wave conditions in more detail and potentially enables it to identify weather downtime conditions more often.

Support for this explanation was, in particular, provided by the results from the Borssele III&IV case-study. In the Borssele III&IV case-study, the operational limits in terms of the allowable sea state and response motions were essentially identical. Therefore, the only differences between both modelling approaches existed in the representation of the offshore environment. Nevertheless, the case study found a significant decrease of the workability.

Additional proof for this explanation was provided by the results from the Hollandse Kust Zuid (HKZ) case-study. In Fig. 4.8, the contribution of the response motion limits of the MPI Adventure to the monthly weather downtime was illustrated. Despite that the model aligned the vessel (for this analysis) with mean wave direction (MWD), the study found that both pitch and roll motions are mostly accountable for the occurrence of weather downtime. However, because of its alignment with the mean wave direction, one expects roll motions to occur only if wave components encounter the vessel at an angle. To capture this motion behaviour, one must at account for the propagation direction of the independent wave components. Therefore, these results highlight an important feature of the response motions modelling approach.

Another possible explanation for this research finding is that allowable sea state operational limits inadequately describe the sea state conditions that result in weather downtime events. That is, because the workable limit analysis establishes operational limits based on an unimodal sea state, it may well be possible that those workable limits do not apply to multimodal sea states. This problem was also acknowledged by Acero & Li (2018).

Nevertheless, the model validation results from the Hollandse Kust Zuid (HKZ) case-study (Figs. 4.13 and 4.14) showed that the wave conditions causing weather downtime are to a certain degree similar for both modelling approaches. However, because of the fact that the allowable sea state limits were only derived for a finite range of wave frequencies, the approach claimed on a number of occasions not workable conditions where in practice the operators would allow for commencement. This problem is resolved by means of the response motions based approach, however, it does not provide support for the above explanation.

In fact, it appears that the allowable sea state modelling approach is (slightly) more conservative in terms of the acceptable maximum significant wave height. Therefore, one expects to find more favourable workability conditions for the response motions approach. However, the failure analysis of both case-studies also showed that the response motions modelling approach is more accurate in identifying critical sea states. Therefore, these findings suggest that the reliability of workability estimates can be improved by integrating the response motions.

Furthermore, this study found in Section 4.2 that adjusting the vessel's heading to generate the least response motions provides the possibility to optimise the workability to be more favourable compared to positioning the vessel towards the mean wave direction.

5.2 Interpretation of the findings

Based on the research findings discussed in the previous section, it can be stated that the two underlying model assumptions applied in most workability models give rise to inaccurate workability estimates. Consequently, project estimates such as the project duration and corresponding costs become uncertain and increase the risks of economic loss due to unexpected weather downtime events.

Moreover, because these model assumptions are often implemented in (DES-based) logistic optimisation tools, the reliability and performance of operation scheduling studies is affected. As a result, limited space is available for the optimisation of the logistics operation. However, in literature the optimisation of the logistic operation is described as the most effective approach to fundamentally decrease operational costs. Therefore, the findings of this study highlight the importance of accurately describing the offshore environment, and therefore, workability.

5.3 Implications of the findings

In this thesis, the main objective was to improve the reliability of workability estimates. Therefore, this study aimed at identifying the weaknesses of today's workability modelling approaches, describing the implications following from these weaknesses and addressing them accordingly. It was shown that by integrating response motions into the workability analysis provides the possibility to improve the reliability of workability estimates and to optimise the logistic operation of the construction process. Therefore, the results of this study may help others to better understand how engineering decisions on the logistic operation affect the workability and therefore the performance of the installation process.

5.4 Limitation of the findings

The findings in this report are subject to at least four limitations. These are explained below.

First, despite that the results of this study appear to be consistent with previous studies, due to the lack of "actual" data on the workability, it is at this moment not possible to provide constructive evidence to support the claim that the response motion based modelling approach is more accurate than the allowable sea state based model.

Moreover, the results of this study were computed for an offshore environment in which wind and current do not exist. However, the workability issues encountered at sea were also affected by the wind and current. For instance, the limits corresponding to the launch and recovery operations of the Deep Dig-It trenching tractor through the splash zone are a function of the current. Especially, because drag forces should be accounted for.

Besides, because the current study focused only on offshore wind farm projects realised in the North Sea region (in particular of the Dutch coast), the effects of multimodal spectra that were shown in the results, may be considered limited (due to the governing wave climate). Therefore, it is expected that these effects become more evident for projects located in coastal regions that are affected by both wind-sea and swell waves on more frequent occasions.

Also, to derive weather windows, it was chosen to compute the significant response motion amplitudes from the response spectra (the average of the highest one third). Alternatively, following reliability theory, the exceedance probability of occurrence could have been used to describe the occurrence of a failure event. Consequently, it is expected that workability results found in this study are less strict compared to the application of exceedance probability.

5.5 Recommendations

Currently, the operational limits are based on a workable limit analysis. However, through an iterative process (calibrating the workability model with workability observations), the actual operational limits — that relate to the field conditions and experience of onboard personnel and the operators — can be determined. This sort of calibration, however, requires appropriate data to be available.

Furthermore, in the current study, it was tried to assess the accuracy of workability models. However, because of the sheer size and extreme complexity of marine operations, it is complicated to obtain proper validation methods. Therefore, future research is recommended to address the validation and possibly calibration of workability models.

Moreover, as stated in the model assumptions section (Section 3.2.4), current decisions of the model (to initiate the activity) are based on the true values of the response motions. However, during the actual process, this is often based on forecasts which can introduce uncertainties. As a result, it is possible that operations are delayed whilst they could have been executed. Therefore, future research is recommended to study the effects of hindcasting and decision-making processes on the resulting weather downtime and project duration.

Also, it is recommended to include the possibility in scenario simulation models to execute the activity at a slower rate in case that is possible. This implies that the workability is not longer described by two states. Therefore, a not-workable state may be workable, but imposes a certain amount of delay.

Finally, response amplitude operators are a function of the structural mass. Hence, during a marine operation, the properties of the response amplitude operators may potentially change. This will affect the estimated response motions. Hence, future research is recommended to address the change in dynamic response of floating equipment as a consequence of a change in response amplitude operators.

Chapter 6

Conclusion

6.1 Answers to research questions

This study set out to address the substantial installation costs associated with the construction of an offshore wind farm. Therefore, the study aimed to improve the reliability of workability estimates to reduce operational risks and to allow for optimising the logistics of marine operations. Hence, throughout the research, the main objective was to obtain an answer to the question:

> *"How can workability estimates involved in the planning and engineering stage of an offshore wind farm installation be improved?"*

Below, answers to the subset of research questions are provided first. After presenting answers to the sub-questions, the main research question is addressed.

6.1.1 Sub-questions

1. *What methods exist in literature for estimating the workability of marine operations?*

In the literature section, it was found that three types of workability assessment models exist that provide support for determining the workability of marine operations. These are: (1) strictly statistical models, commonly known as the scatter model, (2) time-domain models that in order to derive the workability account for the persistency of certain offshore conditions and (3) scenario simulation models that allow to model the installation activities that define the marine operation and simulate the weather related delay of those respective activities.

Moreover, according to den Uijl (2018), scenario simulation models are likely to be the most accurate method for estimating the workability. That is because they allow to model multiple (sequential) installation activities that may or may not be *weather restricted*. Besides, it is believed that these types of models respect the seasonality and the persistency of the offshore environment. The latter is in literature frequently referred to as the most crucial parameter for indicating the occurrence of weather downtime.

2. *What are the weaknesses of today's state-of-the-art workability models?*

Following the literature study, this study found that current workability models describe the sea state in at most two spectral parameters, the significant wave height (H_s) and peak wave period (T_p). Therefore, these models rely on two underlying model assumptions. These being:

1. The significant wave height and peak wave period adequately describe the two-dimensional wave energy distribution of a (directional) wave field.
2. The wave conditions associated with weather downtime are sufficiently described by the two characteristic parameters following a workable limit analysis

However, in a number of studies, researchers acknowledged that this approach could introduce uncertainties into the workability analysis. Therefore, this study set out to investigate their impact on workability estimates and the accuracy of the modelling approach.

3. *What are potential implications of utilising the underlying model assumptions during the weather window analysis?*

By integrating response motions of vessels and turbine structures into the workability analysis, this thesis revealed that conventional state-of-the-art workability models potentially overestimate the true workability. It is believed that characterising complex sea states into one-dimensional uni-modal wave spectra results in more favourable wave conditions. Therefore, the model is unable to identify critical complex sea states that cause weather downtime. Hence, the resulting workability estimates are more favourable.

4. *How accurate describe allowable sea state limits the conditions experienced at site that result in weather downtime?*

Based on the results from the failure analysis, this thesis found that allowable sea state limits are more conservative than experienced at site. However, as stated in Chapter 5, due to the lack of observation data, it is not possible to provide constructive evidence for this claim. Nevertheless, on the basis of the available data, this thesis has shown that a response motions based modelling approach is (in certain cases) more accurate in describing the limiting conditions.

6.1.2 Main question

On the question of *"How can workability estimates involved in the planning and engineering stage of an offshore wind farm installation be improved?"*, this study identified two commonly used model assumptions. These being: (1) the wave energy distribution of a 2D wave field can adequately be characterised by the significant wave height and peak wave period, and (2) the operational limits of marine activities may be expressed in terms of these characteristic parameters following a workable limit analysis.

Furthermore, this research work aimed to investigate their impact and appropriateness (in terms of accuracy). This thesis found that conventional state-of-the-art workability models potentially overestimate the true workability. In particular, this study found that reducing the two-dimensional (2D) distribution of the wave energy into two characteristic parameters (the significant wave height and peak wave period) of a one-dimension (1D) unimodal wave spectrum results in underestimating the weather downtime, and therefore, overestimating the workability. Therefore, because these models are often adopted by the industry for planning and engineering purposes, the potential modelling and data errors may contribute to unexpected costs and poor performance of the selected installation strategy.

Instead, this study presented an alternative model that integrates response motions of vessels and turbine structures into the weather window analysis. This approach has at least two major advantages:

1. The encountered sea states are described in full detail, and therefore, the approach does not generalise complex sea states that consists of multiple wave components. Hence, the wave energy distribution is maintained.
2. The operational limits are established from the multibody system dynamics and are therefore independent of wave motion. Consequently, the approach excludes uncertainties involved in characterising the wave conditions.

It was shown that, by means of this modelling approach, the model was able to expose not workable conditions that were previously not accounted for. Therefore, it appeared that the approach is more accurate compared to the allowable sea state method.

Appendices

Chapter A

Response amplitude operators

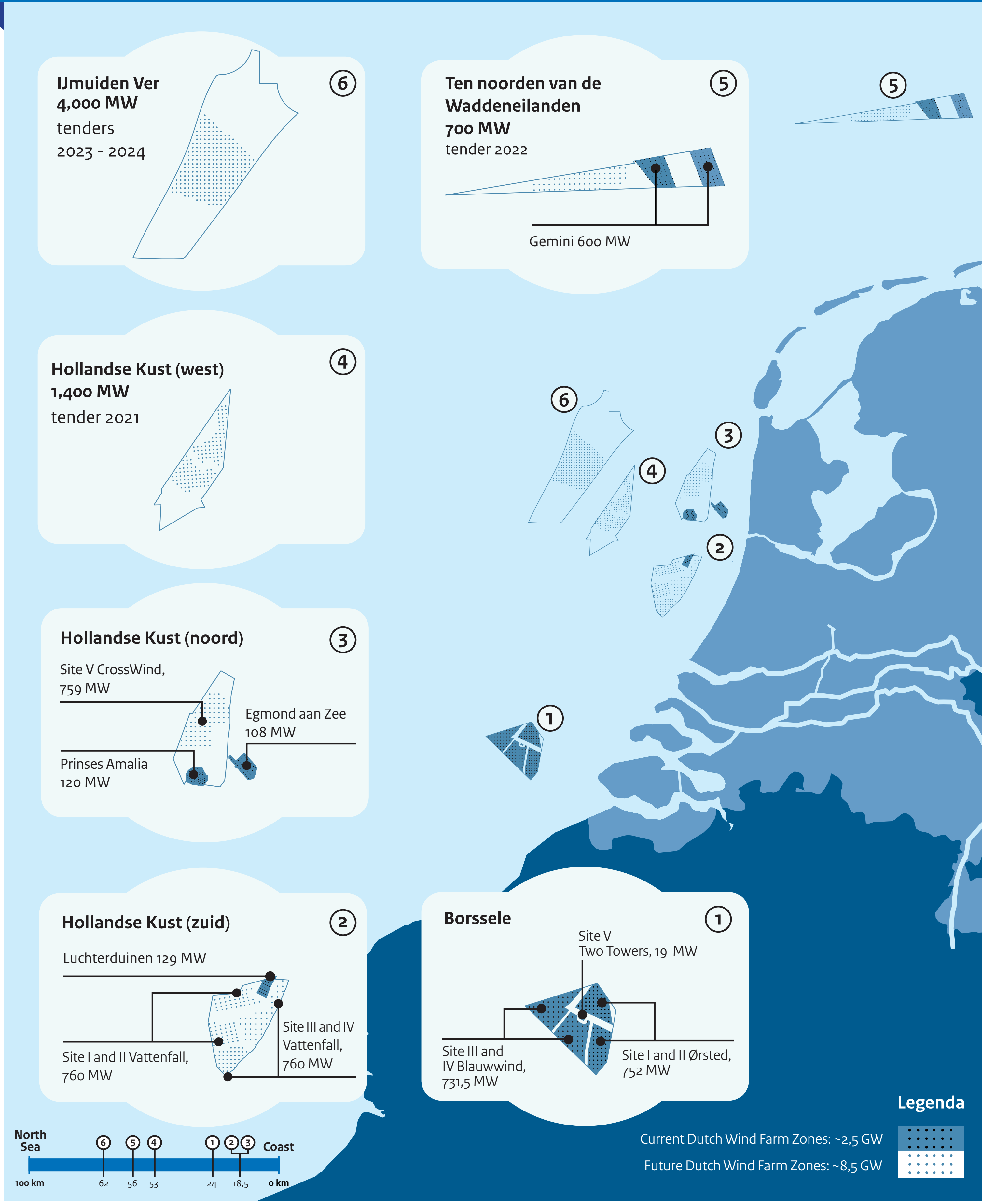
A.1 MPI Adventure

On the following pages, the response amplitude operators of the MPI Adventure used in the study are displayed.

Chapter B

Dutch offshore wind farm zones

Dutch Offshore Wind Farm Zones



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