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Helene Seyr

Stochastic Wind Park Modelling and Maintenance Scheduling under Uncertainty

Doctoral thesis

Helene Seyr

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To a future, where female scientists are so common that girls don't need role-models anymore.

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Abstract

In this thesis, my main objective was to enable improved decision making for the scheduling of maintenance for offshore wind farms. The decisions depend on many factors which are subject to uncertainty.

The factors were studied in this thesis and it was identified where variations and uncertainty should be accounted for. Subsequently, an in depth analysis of two factors was conducted. A set of indicators were defined, which can be used to monitor a wind farm's performance in terms of production, reliability, maintenance, finances and safety. The presented indicators enable the comparison of different maintenance strategies.

Weather was identified as an influential factor. Different methods for weather modeling have been presented and discussed as well as the influence of weather forecasts studied. The duration of maintenance actions - the repair time - was also identified as influential to the decision making. Multiple ways to incorporate the repair time into decision support models have been presented and discussed. The included case studies confirm the importance of including the variation of the repair times as an input to maintenance scheduling models.

Following the identification and investigation of influential factors, a novel method for decision support has been presented. The included case study indicates a possible alternative maintenance strategy for future energy prices.

The findings from the previous chapters were integrated into a serious game that can be both used as a teaching tool for newcomers to the wind industry and as a general outreach tool. The thesis concludes with recommendations for future work.

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Preface

This thesis is submitted to the Norwegian University of Science and Technology (NTNU) for partial fulfillment of the requirements for the degree of philosophiae doctor.

The work leading to this thesis has been carried out at the Department of Civil and Environmental Engineering at NTNU, under the supervision of Prof. Michael Muskulus as the main supervisor and Prof. Jochen Köhler from the Department of Structural Engineering at NTNU as the co-supervisor. Part of the work was prepared during two secondments, at Simis AS, Trondheim and ForWind - Center for Wind Energy Research, Carl von Ossietzky Universität Oldenburg, Germany. The co-supervisors during the secondments have been CEO Paul Thomassen, PhD at Simis AS and Prof. Martin Kühn at the University of Oldenburg.

The doctoral work is part of the AWESOME project, which has received funding from the European Unions Horizon 2020 research and innovation programme under the Marie Skłodowska-Curie grant agreement No 642108.

Acknowledgment

As you, dear reader, are certainly aware, hardly anything in life is ever achieved alone - as is true with this thesis. I had help along the way and thanks are in order.

Prof Michael Muskulus has been my main supervisor during my PhD. Through you I have gained valuable insight into the workings of academia and your advice has had an important influence on the publications I have achieved during this PhD. Prof Jochen Köhler has been my co-supervisor. I did not have to rely on your supervision much, but you always showed interest and gave me new ideas whenever we had the chance to talk about my work. Dr Paul Thomassen from Simis AS has hosted my industrial secondment and shown me the reality of working in a start-up. You were one of the first persons who had to cope with my (luckily improving) Norwegian skills, thank you for understanding me and for not switching to English. Prof Martin Kühn from Forwind at the University of Oldenburg has enabled my academic secondment in Germany. I enjoyed the working environment and gained many new contacts through this opportunity.

I would also like to thank Prof Anne Barros from the Department of Mechanical and Industrial Engineering at NTNU for all the time and effort she spent in addition to teaching the course "Maintenance Optimisation" to guide my work.

I would like to thank Prof Julio Melero for initiating the AWESOME project. The colleagues and friendships I gained through this ITN are very valuable to me. Lisa, Ravi, Estefania, Maik, Lorenzo, Elena, Laura, Manos, Jannis, Nurseda, I will always remember the hours and days we spent together in specific courses, workshops and at conferences.

My stay in Oldenburg has gained me new friends, I would like to thank everyone who helped me adjust at Forwind and get oriented in Oldenburg. I would like to especially thank Matthias Wächter for providing me with an interesting problem, literature and for answering questions I had about the Langevin model. Laura, Luis, Augusto, Marijn for making my stay in

Germany fun and for your friendship.

The work environment in “the PhD basement” with other PhD-students and Post-docs from the marine group was very motivating. I would like to thank everyone who has contributed to many interesting discussions at lunch and at our salary beer.

Special thanks go to my wind group “siblings”: Gordon Stewart for always bringing fun into our shared office and for providing advice, both concerning PhD life and English language. Sebastian Schafhirt for advice and help getting settled into the academic life. Lisa Ziegler and Wojciech Popko for being awesome office mates. My “big sister” Tu Ying for helping me understand emails and navigating the communication with supervisors. My “brother” Lars Einar Stieng for lighting up my days with nerdy jokes and funny references. I am very grateful to both of you for being great office mates and for helping me with all kinds of challenges during my PhD - our Friday meetings will always be something I look back to and I am very happy that we continue to chat across fjords and timezones.

Arun Kamath, you have welcomed me to the marine group and even though you are a “cousin” from the wave group, I have always seen you as a big brother. Thank you for all your advice, both professional and private. Thank you and your wife Lauren for always welcoming me into your home during my stays in Trondheim in this final phase of my PhD - I am certain I will visit again!

The wind energy community is small and yet I have had the chance to meet many amazing people at conferences and seminars. I am especially thankful for my friendship with some brilliant researchers who have supported me during my final years of the PhD. I would like to thank the “windy girls” Becky, Elena, Estefania, Eva, Laura, and Sophia for all the support and encouragement.

I want to also thank my friends back in Austria, Georg, Gregor, Hannah, Michi, Nora, Valli and Judith who have also supported me during my PhD journey. I am grateful that you found the time to meet up with me during my short visits during Christmas or summer holidays.

Finally, I want to thank my partner and best friend Michi for supporting me throughout the last years. You have helped me to stay grounded in life, preventing me from becoming mad and keeping balance in life. Thank you for putting up with my often irregular working hours, making sure I eat breakfast (and other meals) and for always being there for me. It turns out, renovating a house can be a good balance to writing this thesis.

Helene Seyr
Molde, April 2020

Publication List

List of Appended Papers

Paper 1:
Seyr H, Muskulus M. Decision Support Models for Operations and Maintenance for Offshore Wind Farms: A review. *Applied Sciences*, **9**(2):278, 2019.

Paper 2:
Seyr H and Muskulus M. Safety indicators for the marine operations in the installation and operating phase of an offshore wind farm. *Energy Procedia*, **94**:72–81, 2016.

Paper 3:
Gonzalez E, Nanos EM, Seyr H, Valldecabres L, Yren NY, Smolka U, Muskulus M and Melero JJ. Key performance indicators for wind farm operation and maintenance. *Energy Procedia*, **137**:559–570, 2017.

Paper 4:
Seyr H and Muskulus M. Interaction of repair time distributions with a weather model. *Proceedings of the 29th International Congress on Condition Monitoring and Diagnostics Engineering Management COMADEM*, 2016.

Paper 5:
Seyr H and Muskulus M. Value of information of repair times for offshore wind farm maintenance planning. *Journal of Physics: Conference Series*, **753**:092009, 2016.

Paper 6:
Seyr H, Barros A and Muskulus M. The Impact of Maintenance Duration on the Downtime of an Offshore Wind farm - Alternating Renewal Process. *International Journal of Condition Monitoring and Diagnostic Engineering Management*, **21**(3):27–30, 2018.

Paper 7:
Seyr H and Muskulus M. How does accuracy of weather forecasts influence the maintenance cost in offshore wind farms?. *Proceedings of the Twenty-seventh (2017) International Ocean and Polar Engineering Conference ISOPE*, 2017.

Paper 8:
Seyr H. and Muskulus M. Using a Langevin model for the simulation of environmental conditions in an offshore wind farm. *Journal of Physics: Conference Series*, **1104**:012023, 2018.

Paper 9:
Seyr H and Muskulus M. Using a Markov Decision Process to evaluate different maintenance scheduling strategies for offshore wind farms. *Energies* **12**:2993, 2019.

Paper 10:
Dornhelm E, Seyr H and Muskulus M. Vindby - a serious offshore wind farm design game. *Energies* **12**:1499, 2019.

List of Additional Papers

Paper 11:
Seyr H, and Muskulus M. Operation and maintenance models for offshore wind farms - mathematical structure and techniques. *Proceedings of the 12th EAWE PhD Seminar on Wind Energy in Europe*, 2016.

Paper 12:
Seyr H, Barros A and Muskulus M. The Impact of Maintenance Duration on the Downtime of an Offshore Wind Farm - Alternating Renewal Process. *Proceedings of the 30th Conference on Condition Monitoring and Diagnostic Engineering Management COMADEM*, 2017.

Paper 13:
Gonzalez E, Valldecabres L, Seyr H and Melero JJ. On the effects of environmental conditions on wind turbine performance: an offshore case study. *Journal of Physics: Conference Proceedings.*, **1356**:012043, 2019.

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Glossary

Abbreviations

AR AutoRegressive

ARMA AutoRegressive - Moving-Average

CTV Crew Transfer Vessel

DSCR Debth-Service Coverage Ratio

DSS Decision Support System

EBITDA margin Earnings Before Interest, Taxes, Depreciation and Amortization margin

ECMWF European Centre for Medium-range Weather Forecasts

GUI Graphical User Interface

KPI Key Performance Indicator

KS Kolmogorov-Smirnov

LCOE Levelised Cost Of Energy

LLCR Loan Life Coverage Ratio

MA Moving-Average

MC method Monte Carlo method

MDP Markov Decision Process

MTBF Mean Time Between Failures

MTTF Mean Time To Failure

MTTR Mean Time To Repair

O&M Operations and Maintenance

OPEX Operational Expenditures

OWE Offshore Wind Energy

OWF Offshore Wind Farm

OWI Offshore Wind Industry

OWT Offshore Wind Turbine

PDF Probability Density Function

SI Safety Indicator

WF Wind Farm

WT Wind Turbine

Nomenclature

L_p Production loss

d Constant delay

$d(t_{rep})$ Delay function dependant on the required time for repair

h_s Significant wave height

p_a Annual failure probability

t_{rep} Time required to complete a repair

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Chapter 1

Introduction

1.1 Background

The world's need for energy is rising due to population growth and a higher average living standard. At the same time, global initiatives against climate change and pollution have lead many countries to have the goal to lower their emissions of CO_2 and other greenhouse gases and pollutants. Therefore the demand for electricity from renewable energy sources energy is rising. One such renewable source of energy is wind energy [1]. On land, construction sites are limited. Wind parks need open space with regular and high winds. Open areas are scarce in some countries and are preferably used for agriculture or housing. Additionally, many open space regions are enclosed by mountains, causing the wind to be influenced by the local geography. The surface roughness causes lower mean wind speeds, variations in wind speed with the height (wind shear) and higher turbulence intensity. In addition, wind parks have environmental impacts both on wildlife and humans [2]. The shadows caused by large structures, such as wind turbine towers, can also have an influence of the yield of agricultural areas. The public opinion on having wind parks in view is split, construction of wind parks close to cities often causes public commotion.

Building wind farms offshore therefore has many advantages over onshore installations. The wind speeds are generally higher, the wind shear is less pronounced and the wind farm can be built out-of-sight of settlements. Therefore the demand for energy from offshore wind parks is rising and the offshore wind industry is one of the fastest growing industries in the world [3]. One of the problems offshore wind is facing, is the high costs of operations and maintenance, which account for up to a third of the total cost of energy [4]. This means that up to a third of the costs for each unit of electrical power produced is due to maintenance. Lowering theses costs can make offshore wind more profitable for wind farm operators and in the long run decrease electricity prices for customers and reduce global CO_2 emissions.

The maintenance costs include the cost for spare parts, workers, transport vessels and production losses due to downtime. These contributors to maintenance costs can be divided into direct and indirect cost factors. The cost of spare parts is a direct cost, as the maintenance provider sees these as an expense in their finances. The same can be observed for vessel costs (both vessel hire and vessel purchases), and worker salaries. An indirect cost are the losses due to downtime. While the downtime can be measured directly as the number of hours the turbine or farm is in a non-operational state, the lost production can only be estimated based on the turbine specifications and wind conditions during the downtime. Preventive maintenance is a collective term for all types of maintenance conducted before the occurrence of a fault or failure. Types of preventive maintenance are age-based maintenance, where the maintenance is conducted at a certain component "age" (usually measured in hours/days of operation), time-based maintenance, where the maintenance is conducted at fixed time intervals (independent of the operational time) and condition based maintenance, where the state (or condition) of a component is measured (with e.g. vibration sensors) and the maintenance scheduled when a certain threshold is crossed. Maintenance that is conducted following a fault or failure is called corrective maintenance.

In the last decade, a rising number of researchers have worked to lower the maintenance cost for offshore wind. Different approaches have been followed, including condition monitoring [5] and condition based maintenance [6]. When conducting condition monitoring, specific parameters of a machine - in this case a wind turbine or a specific turbine component - are monitored in order to access the condition of it. For wind turbines, temperature or vibration measurements are often used. Recently, also operational data (SCADA) [7] are used for condition monitoring and failure prediction. Condition monitoring of the turbines gives a better overview of the turbine status and hence increases the detection rate of failures before they occur. When failures are detected ahead of time, preventive maintenance can stop failures from happening. Unexpected downtime and production loss is then reduced, leading to an overall drop in the maintenance costs. In addition to reducing the occurrence of unplanned, corrective maintenance, another angle of improvement is the scheduling of the corrective maintenance itself. Scheduling maintenance can be challenging offshore, due to adverse weather conditions [8, 9]. In the last years, several researchers developed models for improving maintenance scheduling in offshore wind parks [10, 11, 12, 13, 14, 15, 16]. All of the models have their limitations as partly discussed in [14] and [13]. However, so far the models have mainly been analyzed by persons involved in the process of generating the model. This means no external evaluation of the models has been conducted, as the only existing comparison case study [14] was conducted by the model authors. Since the current models can be improved, as stated by some authors, this is the starting point for this thesis.

This thesis studies the factors influential to maintenance scheduling and how they are currently used and modelled. The weather and uncertainties in the weather have been extensively studied by meteorologists and most maintenance scheduling models include the influence of the weather in modelling the Operations and Maintenance (O&M). However, the uncertainties are almost exclusively included in the modelling, by conducting scenario studies, as these are straightforward to model and implement. Based on different input scenarios, the model output can be compared. However, with scenario studies, only the investigated scenarios can be compared and the usefulness of the study depends strongly on the researcher's ability to include relevant scenarios. Only discrete "steps" in the variation of the model inputs can be considered. Additionally, when investigating uncertainties in multiple input variables, the set on scenarios becomes extensive. Depending on the model used, the evaluation of the scenarios can become challenging in terms of calculation power and time. An example of this from Offshore Wind Farm (OWF) design where it is almost impossible to investigate all scenarios in a reasonable amount of time are the load case scenarios used when designing the foundations and substructures for OWFs. Instead of scenario studies, building a model that is able to include the uncertainty in the inputs can be an alternative. With such a model, it would be possible to draw the uncertainty in the model inputs through the whole model, such that a statement on the uncertainty can become part of the model output. In this thesis, three approaches are investigated that are capable to include uncertainty without the use of scenario studies. Uncertainties in other factors than the weather, such as the repair duration or travel time to the Wind Farm (WF) are not as extensively studied and many model authors choose to not include them. In this thesis, in addition to the weather, repair time duration and it's uncertainty is studied as an influential factor.

The objective of this thesis is to develop novel maintenance strategies including the uncertainty in information, e.g. by including weather forecasts with limited accuracy and incomplete information about turbine status. It is also an objective to include uncertainty in areas other than the weather.

Bayesian statistical decision theory will be used to derive optimal strategies for maintenance scheduling under such conditions, and will be contrasted with stochastic modelling approaches. The findings are finally composed into a serious game that has the aim of demonstrating the complexity of running a wind farm to potential end users, decision makers and the general public. With this game it will be possible to create awareness for the advantages and disadvantages of offshore wind energy. This game is freely available as an outreach activity and learning experience.

1.2 Research objectives

The main objective of this study is to improve the decision making for offshore wind farm maintenance, based on the assumption of uncertainties in the influential factors. The following sub-objectives are defined:

- To identify those influences on offshore wind farm maintenance that are subject to variation and where the uncertainty about this underlying variation has to be considered in maintenance modelling.
- To find a method that is able to include these uncertain inputs to support the decision of a maintenance strategy.
- To define indicators that can be used to monitor the effectiveness of a new maintenance strategy.
- To create a dissemination tool that can be used to increase the knowledge about offshore wind farm maintenance in the general public and to spread awareness about the challenges in offshore wind farm maintenance.

1.3 Scope and limitations

The identification of influential factors is done through a review of the relevant literature on the topic of OWF maintenance scheduling. Existing decision support models and tools are reviewed to determine the inputs used and the factors required for maintenance modelling are collected. The complete collection of factors is included in Paper A.1, a selection of the most common factors and their definitions in included in the main part of the thesis in Chapter 2.

One of the investigated models was used as a starting point for more detailed investigations of the influential factors. The original model was implemented in Matlab and published in [10]. This model was used in the case study presented in A.7. In the later case study presented in Paper A.5, the same model was implemented and modified in Python. The case study in Paper A.6 is based on an analytical model for the delays due to sea state [17]. In Paper A.8, a simple stochastic process was applied. Papers A.4 and A.9 each introduce and apply a method that had not previously been used for the investigated application. Paper A.10 includes a separate literature review concerning serious games, while the previously identified factors are used as a given input and not reviewed separately.

Detailed investigation of all of the identified factors is out of the scope of the thesis and the study focuses therefore on two of the identified factors. Multiple models and methods to include uncertainties and variation in those factors are investigated. The thesis discusses the benefits and drawbacks of the investigated methods for modelling the investigated factors. Evaluation of the methods' usefulness when applied to modelling other factors than the ones investigated, is out of the scope of the thesis.

In the case studies investigating the influential factors, different assumptions are made about the inputs to the model.

- While failures are included in all of the included case studies, only random failures, based on a constant failure rate are used. This choice is based on the availability of failure rate data. Constant failure rates can be assumed for electrical components, as they do not experience fatigue and degradation. For mechanical components, the assumption of a constant failure rate poses a limitation, as the failure behaviour changes over time for those components. The results of the studies in this thesis therefor do not apply to components during their early phase of operation shortly after installation, or towards the end of their lifetime. Since the maintenance during the early-life of Wind Turbines (WTs) is often covered by the manufacturer, this limitation was deemed manageable. Towards the end of WT life, investigations regarding possible lifetime extensions become relevant, which are outside the scope of this thesis.

- Investigations regarding the repair time depend on the availability of data. Since only mean repair duration values are available in the literature, in the case studies the distributions of the repair time are assumed. Different possible distributions have been studied to account for variation in the results due to variation in the type of distribution.

- While most of the case studies in this thesis include mobilization and travel time, the study presented in Paper A.8 only includes the downtime and does not distinguish between wait time and repair time.

- The influence of external factors has been limited to the weather and sea state conditions in the published articles. While also other factors, like vessel collisions or legal restrictions, might influence the operation of an OWF, including these influences is outside the scope of this thesis.
- Legal constraints, like work time and rest laws, are omitted in all of the analyses. This is mainly due to the fact that laws vary between the different countries where OWFs are being operated. Finding the appropriate work time constraints comprises a lot of literature review work in multiple languages and was deemed outside the scope of the thesis. Additionally, limits due to work time restrictions can be bypassed by providing worker accommodations at the WF site. It was therefore chosen to omit these restrictions in the case studies.
- Electricity prices are in general assumed or estimated based on publicly available data. The prices are also assumed to be constant during the duration of the case studies.
- Constraints and prices for maintenance vessels and cranes are based on publicly available data where possible and estimated or assumed otherwise.
- In order to reduce the influence of assumed prices and costs to the results of the analyses, price-independent indicators, such as downtime and availability, are used for comparison whenever possible.

Identification of indicators for monitoring was done by collecting and explaining the indicators identified in the relevant literature. In addition to the literature review, interviews with industry representative were conducted in preparation for Paper A.3. The usefulness of the indicators has been evaluated, providing a suggested set of indicators for a standardized definition. Some of the identified indicators are used in the further investigations of the thesis, where appropriate. Applying and evaluating all of the indicators is out of the scope of the thesis, which is mainly focusing on indicators monitoring performance and reliability.

The dissemination tool presented in the thesis is a fully functioning prototype. The full development, as well as validation with a large group of test participants and distribution of the game are outside of the scope of the thesis.

1.4 Thesis structure

This thesis is written as a collection of research articles and the ten articles included in the appendix should be considered part of the thesis. The eight chapters of the main part serve as an introduction and summary of the research work. The main results of the appended articles are included in the different chapters of the thesis, Figure 1.1 presents an overview of the structure and how the individual research articles fit into it.

Chapter 1 includes an introduction to the topic, the research objectives and thesis structure.

Chapter 2 contains an analysis of the factors influential to the maintenance of offshore wind farms. The factors that have to be considered when scheduling the operation and maintenance tasks are presented and discussed. This chapter covers the main results from Paper 1 that can be found in A.1. The influence of variation in two of identified factors is studied in depth in Chapters 4 and 5. Identified factors are used as input to the investigations in Chapters 4, 5 and 6 as well as included in the dissemination tool presented in Chapter 7.

Chapter 3 presents indicators that can be used to monitor the changes a new maintenance strategy implies on an existing wind farm. The indicators cover performance, reliability, maintenance, finances and safety. This chapter summarizes the results of Papers 2 and 3, which can be found in A.2 and A.3. Some of the indicators identified in this chapter are used to evaluate maintenance strategies in the case studies in Chapters 4, 5 and 6. Some of them are also included as player feedback in the serious game presented in Chapter 7.

Chapter 4 investigates the weather, one of the factors that were identified in Chapter 2. Ways to model weather for different applications are discussed and the importance of the weather forecast is investigated. This is a summary of Papers 4 and 5, appended in A.4 and A.5. Some results from Papers 1 and 10 are also included.

Chapter 5 includes investigations of the repair time, which was another factor identified in Chapter 2. The influence of the repair time on maintenance modelling is studied. Chapter 5 is a summary of the results presented in Papers 6, 7 and 8, which are appended to the thesis in A.6, A.7 and A.8.

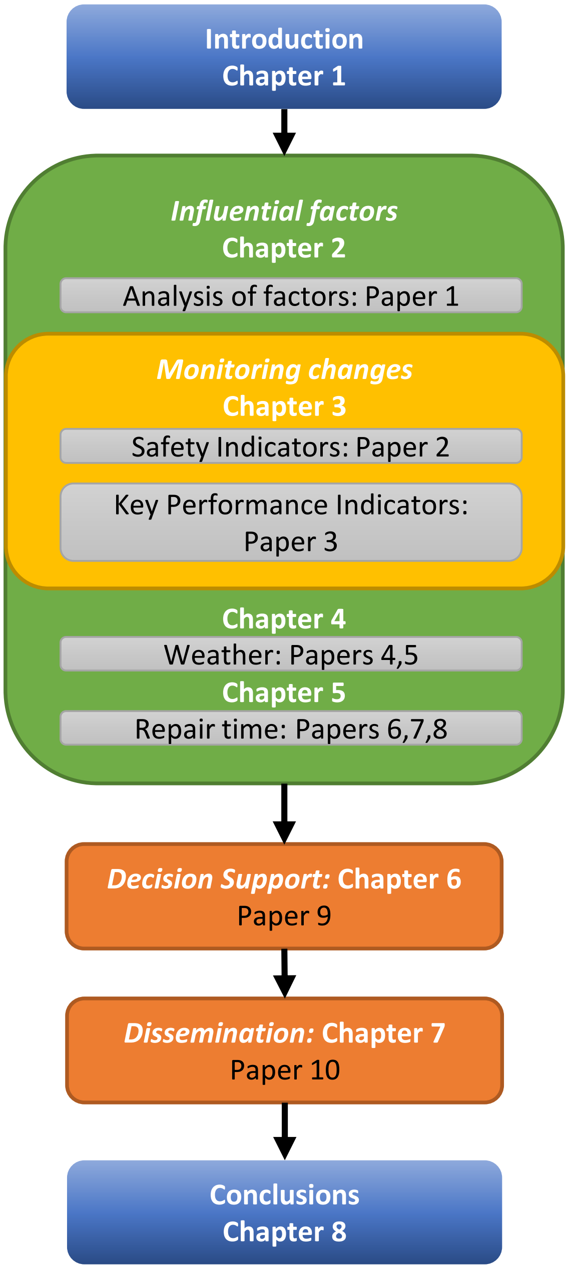


Figure 1.1: Structure of the thesis.

Chapter 6 presents the concept of decision support. It discusses how the existing tools reviewed and studied in the previous chapters, can be used to support decisions. Chapter 6 also presents a novel way to evaluate maintenance strategies. This chapter contains the results of Paper 9, which can be found in A.9.

Chapter 7 contains information about dissemination of research results as well as describing the usefulness of serious games. The chapter also includes a description of a prototype of a serious game for wind farm design and operation, which has been published in Paper 10, appended to this thesis in A.10. The prototype of the game is based on the investigations presented Paper A.1 and in Chapters 2 and 4.

Chapter 8 concludes this thesis, highlights the contributions and includes recommendations for further work.

Chapter 2

Factors influential to maintenance scheduling

2.1 Overview

In this chapter, the factors that are influential to the O&M of an OWF will be presented. Many different factors have been mentioned in the literature, as presented in paper A.1 Table 1. In the following chapter, these factors will be described and their importance discussed. Since I do not want to preempt any ranking of the factors, they are presented in alphabetical order. Some factors which are related are grouped together.

2.2 Financial factors

Electricity market price

In order to profit from producing electricity from wind energy, the WF operator needs to sell the electricity to a utility provider or directly to a customer. As with most commodities, the supply and demand of electricity regulate the market price which is therefore fluctuating both intra-daily and with the season. Both competing WFs, solar power plants, hydro power plants and thermal power plants provide electricity to the grid and during conditions with e.g. high winds and sunshine the high supply will decrease the market price. During peak consumption hours - usually the early morning or late afternoon - high demand increases the price. As a means to support electricity production from renewable energy sources, many countries have implemented feed-in tariffs - guaranteeing a fixed compensation for electricity production independent of the market price.

Transportation costs

The cost of transportation of spare parts, equipment and personnel will influence the financial performance of a WF asset. Different vessel types will inflict different costs and the number mobilizations also has an influence on the total transportation cost. When modelling and planning the O&M of an OWF, minimizing the transportation cost will be one aspect of optimization. The costs of mobilization as well as the hourly costs for a vessel vary with the vessel type. The different types of vessel are discussed in "fleet composition".

Downtime costs and production losses

Downtime cost is a term used to describe all costs that are inflicted due to WT or WF downtime. Downtime is all time during which the WF or WT is not supplying electricity to the grid, due to it not being in an operational state, which can have different reasons [18]. Naturally, failures that lead to a turbine stop cause (unplanned) downtime. This is the main cause of downtime, as considered by [9]. However, for Offshore Wind Turbines (OWTs) also some preventative maintenance actions that require the turbine to stop, such as blade inspections or repairs, can inflict (planned) downtime. In the case studies provided in Chapters 4 and 5, only downtime due to faults is considered, and other maintenance actions are omitted from the case studies. Time periods, where the WT does not supply electricity, due to the weather being outside its operational limits, i.e. below cut-in wind speed or above cut-out wind speed, are not included in the downtime. In order to value the loss of production during downtime, often the production losses are estimated. It is not possible to calculate the production losses exactly, as the available energy during downtime can only be estimated. Combining wind speed measurements with the turbine's power curve provides a way to estimate the amount of electricity that would have been produced during the downtime of the WT. When considering the production losses for a WF, the number of turbines can be multiplied with the production losses for a single turbine in order to estimate the WF production losses. This simplified calculation neglects variation in the energy production throughout the WF, due to e.g. the WF layout and wake effects.

Spare parts and logistics

Spare parts and logistics are mentioned as a factor by [11, 16, 19, 20]. When repairing or replacing a WT component, usually spare parts are required.

Some maintenance tasks can be completed without spare parts, such as inspections or lubrication, where generic equipment can be used. Some spare parts have very long lead times. When an unexpected failure occurs requiring such a part, this can lead to an extended downtime and therefore high production losses. For warehouse logistics, the maintenance service provider needs to balance keeping the necessary spare parts on stock while simultaneously reducing warehousing costs such as rent, utilities, insurance and personnel costs.

2.3 Maintenance

Repairs and repair time

In order to return a faulty component to an operational state, some repair or replacement action needs to be taken. Repairs are conducted on repairable systems, while replacements are used for non-repairable systems. To summarize both repairs and replacements, the term restoration has been suggested [21]. Often however, the term 'repair' is used to describe a maintenance task, for both repair and replacement. The duration of the maintenance task, often referred to as the repair time, plays an important role when scheduling maintenance. Naturally, different types of repairs (or restorations) will require different amounts of time.

Maintenance crew

Maintenance crew is a term used to describe the collective of maintenance personnel. The size and composition of this crew can have an influence on the repair time and is therefore investigated in some models. Crew transfer times with vessels play a role in maintenance planning as well as the work shift organization and shift length. Depending on the amount of personnel a maintenance service provider has employed, worker availability can limit the scheduling of maintenance, due to work shift length and required repair times.

Types of maintenance and maintenance strategy

Maintenance does not only cover repair, but also routine inspections and tasks such as lubricating bearings or oil change [18]. Time-based preventive maintenance can be scheduled for components that need to be switched out periodically. When inspections lead to the detection of a condition that might lead to failure, condition based maintenance is conducted. Failures can also be detected ahead of time by condition monitoring systems. When it comes to a failure or fault, corrective maintenance needs to be scheduled to restore the component. The maintenance strategy, mentioned as an influential factor by [10, 22], concerns the choice of maintenance types to consider for the WF in question. Not all models consider all of the different maintenance types, inspections are often not considered. Paper A.1 provides information about which types of maintenance are considered in which models in Table 3.

2.4 Transportation

Fleet composition

Three main options exist for the vessel choice for O&M, Crew Transfer Vessel (CTV), crane vessel and helicopters. CTVs are mostly used to transport maintenance crew to and from the wind farm. They can operate during waves with up to 1.5m significant wave height [23]. When the significant wave height is higher, CTVs cannot transport workers due to safety reasons. When heavy lifting operations need to be conducted during maintenance (e.g. replacement of a gearbox or blade), a crane vessel is needed. Lifting operations can only be conducted when wind speeds are below 10 m/s [14]. Helicopters might be used for maintenance technician access, however these are generally quite expensive, so often helicopters are only used for emergency evacuations. Often, a combination of vessels is used in any given WF, with varying numbers of each vessel type. Three options exist for acquiring vessels. They can either be bought be the maintenance service provider, chartered for a fixed time period or chartered on the spot. The different types will invoke different costs. The benefit of having many vessels available at all times is that maintenance or a repair can be scheduled immediately using a vessel that is available. The drawback however is that during periods with little or no maintenance activities, idle vessels will imply costs.

Mobilization and transfer time

Mobilization time is the time it takes between the decision to use a vessel until the vessel is ready at the harbor. The mobilization time depends on the type of vessel hire contract, location of the vessel crew and the time it takes to fuel the vessel before departure. Transfer time for the vessel or technicians is the time it takes the vessel to reach the WF after leaving port.

The transfer time will depend on the type of vessel, vessel speed and the weather conditions.

Transport strategies

Transport strategies can both include the strategic decisions about transport types and specific vessel routing decisions. The different types of and choice of vessel types is discussed in "fleet composition" above. Vessel routing strategies are in the most general sense of the type of the traveling salesman problem. A wind farm operator needs to decide how to route the existing vessels to accomplish either as many maintenance tasks in one route as possible, or to accomplish the completing of the most economic profitable maintenance tasks. [24, 25, 26] present models for vessel routing.

2.5 Reliability

Condition monitoring systems

Condition monitoring systems are used to monitor the status of some component installed in a turbine. As an example, vibration sensors can be used to monitor bearings - as they wear, the vibration patterns will change and a failure can be detected ahead of time [27]. Temperature sensors or current signature analysis [28] can help estimate the remaining life in electrical components. Also operational data from the SCADA-system can be used to detect abnormal turbine conditions [29].

Damage

Damage, mentioned by [30], is the accumulation of fatigue or other degradation prior to a fault or failure. Damage models are especially needed when considering preventive maintenance. Condition monitoring offers a way to gauge the damage caused by repeated loading of e.g. rotating parts in the gearbox.

Failures

Failures of turbine components will cause a turbine to shut down its operation such that no electricity is generated. Cable faults or substation failures can cause the whole wind farm to be disconnected form the grid such that the produced electricity cannot be distributed to the consumers. This will in most cases also lead to the turbines shutting down operation as a safety measure. As a wind farm operator earns money by selling the produced electricity all kinds of turbine downtime need to be avoided as much as possible. Different turbine components have different probabilities of failure occurrence. Substructures are designed to last the whole lifetime of the wind farm without any failures. Moving equipment such as bearings have a higher wear and will therefore fail more often. Many maintenance models use annual failure rates to estimate the probability of failure. The failure rates as usually calculated based on observations, collected during turbine operation. Examples of data sources for failure rates are [31, 4]. Depending on the type of turbine component, the probability of failure may change during the lifetime. For electrical components, a constant failure rate can be assumed and the failures are therefore uniformly distributed. For mechanical components that experience fatigue, the bathtub curve is often used to visualize the changing failure rate explained by early-operation-failures and end-of-life failures [18]. For those components, the failures will be distributed differently over time. It is more likely to have failures in the first years of operation, mostly due to manufacturing flaws or incorrect installation. After this initial phase, the failures will be approximately uniformly distributed, with only random failures occurring. Towards the end of the expected life, the probability of failure will rise again, this time due to the wear during operation.

Reliability

Reliability has been mentioned by [32] and [33]. In general, reliability can be defined as the probability of success, i.e. (1 - probability of failure) [34, 18]. Reliability of a component is the item's ability to perform its required function [21], i.e. successful operation of a specific component. Turbine reliability concerns the success of operating the turbine as a system, i.e. the turbine's ability to produce electricity, and depends on the reliability of the turbine components [18]. WF reliability will measure the success of the complete WF as a system, including cables and substations in addition to the WTs.

2.6 Weather

Wave height

For OWFs, wave height conditions at the WF location and between the WF and maintenance base have an influence on the accessibility. As technicians and spare parts need to be transported to the turbine location ahead of maintenance actions, the wave height conditions need to be such that vessels transporting these can access the WF. Often the significant wave height h_s, defined as the mean wave height of the highest third of the waves [35], is used to describe the local wave height conditions. The significant wave height is a results of the aggregation of different wave phenomena like wind driven surface waves, storm surges and tidal waves.

Wind speed

Wind speed is a driving factor for the energy production of WTs. Depending on the turbine type, electricity generation typically begins at a so-called cut-in wind speed and increases (non-linearly) until the rated power is reached. In most modern turbines, pitch control systems are used to achieve a constant rotor speed during changing wind speed conditions. When the wind speeds are higher than are needed to achieve the rated power, the control systems of the turbine come into play, keeping the energy production constant. Additionally, wind speed influences the loads experienced by the turbine, both during operation and during idle times. Often, wind speed is measured at hub height and usually the 10-minute aggregated wind speed is collected.

Weather windows

The time intervals during which the weather and sea state conditions, like the significant wave height, stay below a given threshold are referred to as weather windows in this thesis. During these weather windows, access to the WF with vessels and WT maintenance are possible. The length and frequency of weather windows have an influence on the optimal maintenance strategy for maintenance scheduling.

Weather forecast

Weather forecasts are predictions of the weather and sea state conditions in the future. They can include temperature forecasts, wind speed forecasts and wave height forecasts. Predictions are always subject to some form of uncertainty and the influence of the accuracy of weather forecasts on the O&M is being investigated in Chapter 4.

Seasonality

With seasonality, usually the change of weather throughout the year (seasons) is described. Usually, harsher weather persists during the winter months, with higher average wind speeds, higher waves, higher frequency of storms occurring and generally colder temperatures [36]. This influences the production - higher wind speeds will generally lead to higher power extraction. The higher wind speeds however also lead to faster wear of turbine components and more frequent storms will increase the probability of failure occurrence. Simultaneously, the higher waves and occurrence of storms limit the opportunities for maintenance access. Due to these differences in weather between seasons, many operators choose to schedule regular inspections and other non-condition-based maintenance actions during the summer months.

Metocean data

The word Metocean is a combination of the words meteorology and oceanography, and is used to describe the combined environment of meteorological factors, like wind speed and humidity, and oceanographic factors, like surface waves, ice conditions and salinity, at a given (offshore) location. Metocean data therefore is a collective term for observations and measurement of these factors. In order to take the metocean conditions into account when taking a decision, data is needed. Different sources of both meteorological and oceanographic data exist - also in the public domain. Examples for data are presented in [37].

2.7 Wind farm properties

Accessibility

Accessibility, mentioned by [19, 20, 32, 38], describes how difficult it is to gain access to the WF. For onshore WFs, the availability and quality of access roads would fall under this factor. For OWFs, local weather conditions, such as significant wave height or average wind speeds have an influence. Also the distance from a maintenance base or shore have an influence on the availability of an OWF.

Turbine power rating and production

When constructing a WF, the owner can usually choose between a multitude of different turbine type from different manufacturers. Each turbine type will have unique properties, such as rotor size, tower height, power rating and characteristic power production curves. The rated power of a turbine gives the limit of the generator output. Currently installed OWFs have turbines with power ratings between 4 MW and 8 MW [39].

Wind farm layout

A wind farm usually consist of multiple turbines, which are installed in geographical proximity and connected to the grid through a common connection point. Theoretically, each turbine in the WF can be of a different type - also one-turbine farms are possible. In practice, most OWFs consist of 50 to 100 WTs of the same type [40, 41]. Within a WF, multiple turbines are spaced in relative close proximity. In order to optimally use the wind resources in a given location, the layout and spacing of turbines is important. Each turbine extracts energy from the wind and creates a so-called wake. In this wake, the wind speeds are lower compared to the air around. Over distance the wakes disperse as the air in the wake is mixed with the surrounding air masses. Higher turbulence will reduce the time it takes to disperse the wake. When deciding the WF layout, often the predominant wind direction is taken into consideration when spacing the turbines. Other geographic restrictions, such as water depth, soil quality, international shipping routes and protected natural areas need to be considered.

Wind farm location

The location of an OWF has an influence on multiple WF parameters. The distance from shore determines the travel time of vessels from port to the wind farm. Water depth at the wind farm location will influence the choice of substructure. Not all substructures experience the same degradation, which will have an influence on structural failure modes. Naturally, the wind farm location also impacts the climate and WFs at different locations will experience different weather.

2.8 Summary of the influential factors

The factors influential to maintenance scheduling can be summarized in the categories of financial factors, maintenance, transportation, reliability, weather and wind farm specific factors.

Regarding financial factors, some authors [42, 15, 10, 43, 19, 44] consider production losses due to downtime, while [45, 42, 15, 13, 12, 46, 11, 43, 16, 19, 44, 20, 38] (also) include maintenance costs in form of vessel hire, spare parts or worker salary.

Regarding the maintenance, the literature distinguishes different types of maintenance. Preventive maintenance is conducted on a fixed schedule to prevent failures from happening. It is included in the models and analyses by [23, 12, 47, 11, 43, 16, 19, 44, 38]. Condition-based maintenance is similar to preventive maintenance conducted to prevent failures. It is, however, based on the condition of the system instead of a fixed schedule. Condition-based maintenance is considered in the models by [12, 19, 48]. Corrective maintenance must be carried out after a fault to return the component to a state in which it can perform its required function. Corrective maintenance is included in the models by [10, 12, 11, 43, 16, 19, 44, 38].

In terms of transportation, the routing of vessels has been studied in [23, 30, 49, 25, 24, 50], while [51, 8] optimize the fleet size and composition.

In order to represent the reliability of components and turbines, many authors choose to include some form of failure modelling. Condition monitoring is studied by [45, 52, 53, 54, 55, 56]. Damage accumulation or time dependent failure rates are included in [30, 15, 46, 11, 47, 16, 19, 6, 44, 57, 58, 38, 48]. Different stochastic processes with failure rates are used by [10, 42, 15, 13, 12, 11, 47, 8, 43, 16, 59, 19, 60, 57, 38, 61].

The weather is widely recognised as an influential factor and is used as an input to the decision support models by [42, 15, 10, 13, 12, 11, 8, 43, 16, 59, 19, 60, 54, 62, 63, 38, 50]. Many models include weather generation models, which are based on Markov chain models [64, 65, 66, 15, 10, 67, 12, 8, 68], auto-regressive models [42, 13, 43, 69], or statistical methods [46, 17, 59, 60]. The weather as an influential factor is studied further in Chapter 4, where also the different options for weather modelling will be presented and further explained, as well as an alternative modelling method introduced.

In addition to the summarized explanations provided in this chapter, Paper A.1 provides details about the literature and models mentioning them, as well as details on how they are included in the individual models.

Chapter 3

Indicators to monitor changes

3.1 Background and motivation

As this thesis is concerned with the modelling and possible improvement of OWFs, it is necessary to define some measure that can be used to evaluate the performance of an OWF under a given maintenance strategy. This is useful in order to be able to assess and compare different policies, both among each other and comparing the performance of the same strategy under different circumstances such as WF location, electricity market prices, turbine types, and laws. A Key Performance Indicator (KPI) is defined by [70] as "a metric, measuring how well an organisation or an individual performs an operational, tactical or strategic activity that is critical for the current and future success of the organisition" [70]. KPIs are used in many industries, such as the financial sector [71] or health care [72], to measure the progress towards a set goal. In order to be useful, a KPI must be relevant, portraying information that is useful to the stakeholders. The KPIs need to be specific, i.e. it should be clear which property or value is being observed and how this can be done. Furthermore, the KPI needs to be measurable in either a qualitative or quantitative way. In order for the KPIs to be useful when investigating different WFs or maintenance policies, they need to be comparable. In order to follow up on the performance of one WF over time, KPIs which are traceable in time - ideally on different timescales - are necessary. Ideally, the KPIs should be standardized - leaving no room for uncertainty or individual interpretation - so that different stakeholders can use the same KPIs and benchmark their own assets' performance to the state-of-the-art in the industry. Finally, the whole set of KPIs should be both complete and minimal - including the fewest possible number of KPIs, which still cover all necessary areas of interest.

The necessary properties presented above have been defined in Paper A.3, and a set of suggested indicators presented. The topic of Safety Indicators (SIs) was omitted, as these had been separately presented and discussed in Paper A.2. Paper A.3 also includes more information about the background of KPIs and details how the individual indicators where defined. In the following, the indicators fulfilling the suggested properties are presented, sorted into five categories: performance, reliability, maintenance, finance and safety. As Paper A.2 did not include an analysis of the SIs to assess them based on the recommended properties from Paper A.3, this analysis is included in Section 3.2.5.

3.2 Indicators

Here, the indicators for each of the five categories are presented. For the performance, reliability, maintenance and finance, the indicators fulfilling the suggested properties are presented. More indicators have been discussed in paper A.3. For the SIs, the indicators presented in paper A.2 are presented and grouped based on their fulfillment of properties from Paper A.3.

3.2.1 Performance

Time-based availability

The time-based availability is the fraction of total time where the turbine is in an operational state [73]. This indicator is not part of a standard, however technical definitions exist that can be used to standardize.

Energy-based availability

The energy-based (also production-based) availability is the ratio between the actual production and theoretical possible production [74]. As it is impossible to accurately define the available energy, this indicator is not measurable. Existing approaches are based on calculations using a power curve. Although more difficult to assess, the energy-based availability provides an intuitive and more objective indicator for asset comparison than the time-based availability.

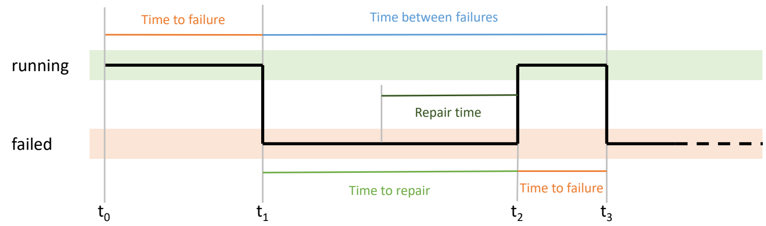


Figure 3.1: Visualization of time to failure, time between failures, time to repair and repair time.

3.2.2 Reliability

Mean time between failures and failure rate

The Mean Time Between Failures (MTBF) calculates as the ratio of the number of failures per operating time [21, 18]. Its reciprocal is the failure rate, often provided as annual failure probability. This indicator could be standardized as soon as a comprehensive wind turbine taxonomy is defined in order to distinguish different turbine components. The example in Figure 3.1, shows the occurrence of two failures at t_1 and t_3. The time between failures includes the time to repair (t_1 to t_2) and time to failure (t_2 to t_3). The MTBF however is based on the operating time [21], calculated as the sum of the times to failures: $(t_3 - t_2) + (t_1 - t_0)$.

Mean time to repair and repair rate

The Mean Time To Repair (MTTR) describes the average time it takes to return a WT or turbine component to an operational state after a failure or fault [21, 18]. It can be calculated as the ratio of the total time of restoration per number of failures. Figure 3.1 shows one repair taking place between t_1 and t_2. It should be noted that the time to repair includes wait and travel times in addition to the repair time. Similar to the failure rate, the repair rate is the reciprocal of the MTTR. Again, this indicator can easily be standardized once a standard WT taxonomy is defined.

Mean time to failure

The Mean Time To Failure (MTTF) is used for non-repairable systems similar as the MTBF is used for repairable systems [34, 18]. A non-repairable system only fails once - the MTTF provides the average time until this failure.

3.2.3 Maintenance

Number of interventions per WT

The number of interventions per turbine is a count of maintenance actions conducted in the WF, divided by the number of turbines. With higher WT reliability, fewer interventions are expected. However, counting the number of interventions does not capture information about the duration and costs of an intervention.

Percentage of corrective maintenance

The percentage of corrective maintenance provides information about the share of corrective maintenance in the maintenance-mix of the WF. Since corrective maintenance usually imply higher costs than inspections and preventive maintenance actions, this indicator provides information useful to gauge the effectiveness of O&M policies.

Percentage of schedule compliance

The percentage of schedule compliance provides the ratio of tasks that are completed within the scheduled time as a percentage of the total number of tasks. This indicator can be used to assess the quality of maintenance planning. [75] includes this as indicator O22.

Percentage of overtime jobs

The percentage of overtime jobs is the ratio of overtime hours to planned work hours per worker and size of the maintenance team. This indicator provides information about the quality of maintenance planning and can be used as an indicator to ensure worker health. [75] includes this as indicator O21.

Labor costs versus total maintenance costs

The percentage of labor cost as part of the total maintenance costs provides insight into the effectiveness of maintenance execution. The general consensus in the industry is that qualified personnel - albeit higher in wages- is needed to ensure a good ratio of labor costs. The labor cost as a percentage of total maintenance cost is divided into indicators E8 and E9 in [75].

Total annual maintenance cost versus annual maintenance budget

An indicator comparing the total annual maintenance cost with the annual maintenance budget gives information about the quality of maintenance planning and might be used to detect potential for improvement.

3.2.4 Finance

Operational expenditures

The Operational Expenditures (OPEX) include all costs of operation a WF, both O&M costs including scheduled and unscheduled maintenance, and other costs like taxes, rent and insurance [76]. By normalizing this indicator by the installed capacity, this indicator can be used to compare cost-effectiveness between WFs.

Earnings before interests, taxes, depreciation and amortizations margin

The Earnings Before Interest, Taxes, Depreciation and Amortization margin (EBITDA margin) [76] describes the percentage of earnings that remain after covering the OPEX and can be used to track changes in earnings when implementing a new maintenance strategy.

Loan life coverage ratio

The Loan Life Coverage Ratio (LLCR), calculated as the ratio between the net present value of cash flow and the amount of debt [77], provides information about the solvency of a WF - i.e. measuring the ability to pay back debt.

Debt-service coverage ratio

The Debth-Service Coverage Ratio (DSCR) is the ratio between the net operating income and the amount of current debt obligations [77]. It measures the ability to cover debt payments with the earnings. Similar to the LLCR, this indicator provides information about the solvency, provided on a yearly basis rather than lifetime basis.

Levelised cost of energy

The Levelised Cost Of Energy (LCOE) takes into account the installed WF capacity, WF lifetime, annual energy production, capital expenditures, OPEX and discount rate to inform about the financial status of a WF. As the LCOE takes into account many financial influences, it is very popular when aiming to compare the financial output of a WF and improving its performance.

3.2.5 Safety

In this section, the safety indicators presented in paper A.2 are presented and discussed. A pre-selection of the indicators was done in order to focus on the indicators that are not provided by other KPIs, and to ensure that the SIs fulfill the properties defined in A.3. None of these indicators are standardized yet. Again, the order of indicators is not meant as a ranking and is therefore alphabetically.

Incidents during lifting or due to falling objects

The number of incidents during lifting operations or incidents involving falling objects as percentage of the total maintenance task with lifting operations provides information about the worker safety during these operations. This indicator can be e.g. used to compare the safety of workers at WFs with different safety procedures.

Incidents during work at height

The number of incidents during work at height as a ratio of all maintenance actions at height gives an indicator of the worker safety during work at height. The indicator can be used to compare different safety procedures and worker training.

Incidents with electrical equipment

The number of incidents during work with electrical equipment as percentage of total maintenance actions involving electrical equipment gives an indicator to monitor worker safety and compare different safety and training routines.

Incidents with mechanical equipment

The number of incidents during work with mechanical equipment as a percentage of total maintenance tasks performed on mechanical equipment gives an indicator to monitor safety procedures, training routines and worker safety.

Presence of a boat-landing structure

The presence of a specialized boat landing structure lowers the risk of incidents during turbine access and it can be monitored with this categorical indicator.

Quality of documentation

Number of incompletely filled worksheets out of all worksheets returned. Correctly filled worksheets can help in improving the performance of the WF. If the maintenance technicians do not fill the worksheets correctly, information might be lost.

Safety zone violations

The number of safety zone violations as a ratio of all vessel accesses to the wind farm enable to track the risk of collisions between vessels and structures. The number should track both vessels that aim to access the WF and external vessels. Usually external vessels will need to hold a specified distance to the turbines, while WF vessels have to follow rules, like to set their course slightly to the side of the structure to avoid collisions.

Technician experience

The work experience of a technician in either work hours or years provides information about the worker experience and helps measure both worker safety and cost-effectiveness.

Transport incidents

The number of incidents during transportation with a vessel (helicopter or boat) as a ratio of the total number of personnel transports aids in monitoring the worker safety during WF access and returns to port.

Weather restriction violations

The number of times the wave height and wind speed restrictions for worker transport are violated as a percentage of the total number of accesses, gives information about the worker and equipment safety during transport.

3.2.6 Summary about indicators

This chapter presented a summary of the indicator properties defined in Paper A.3, as well a selection of the indicators presented in Papers A.3 and A.2.

For the KPIs, only those indicators that were deemed useful and fulfilling the necessary criteria presented in Paper A.3 have been presented in this chapter. A more extensive list of possible indicators as well as details on how they are defined in standards and how they are currently used in the wind industry can be found in Paper A.3.

For the SIs, a selection of the indicators that were discussed in Paper A.2 has been presented here. I have chosen to present those indicators that are useful for a wind farm operator or a worker representative (e.g. union representative) in order to have a quantifiable means to compare different maintenance service providers and maintenance quality between WF assets. None of the presented SIs are standardized, though their definitions allow for standardization, should the industry be interested to do so.

Chapter 4

Weather

4.1 General remarks

The weather has been identified as a factor influential to the O&M of OWFs as has been presented in Chapter 2. It is therefore included in many of the existing O&M models. Some researchers choose to use recorded weather data, while others choose to model the behaviour of certain weather parameters. The three main choices for the simulation of weather conditions are (Gaussian) statistics, AutoRegressive - Moving-Average (ARMA) processes and Markov processes [66].

Historical weather data was used by [16] and [38]. Sources for weather data have been presented and discussed in Paper A.1. Popular publicly available data sources include [78, 79, 80, 81] and [82]. [60] and [46], fit Weibull statistics to their wind speed data and use the distribution to resample observations for their models. [17] use a Weibull distribution as an input to their model. [19] follows the same method for wave heights and a Rayleigh distribution.

Different kinds of ARMA models are used by [13], [43] and [69]. Markov chain models are widely used, including [10], [15] and [12]. In the following chapter, the ARMA and Markov chain methods will be presented and discussed as well as an alternative approach to weather modelling introduced.

In the scheduling of maintenance, weather forecasts are used to predict the weather conditions during the maintenance task and to avoid compromising worker safety. In the final section of this chapter, the importance of weather forecasts is studied.

4.2 Autoregressive - moving-average models

AutoRegressive - Moving-Average (ARMA) models are used in time series analysis to represent stationary (or weakly stationary) stochastic processes [83]. ARMA models can be used to understand a given time series and to predict future values. The models' parameters can also be used to generate a new time series based on the observed data. An ARMA process is a combination of an AutoRegressive (AR) process with a Moving-Average (MA) process.

An AR process can be understood as a linear regression of the current time series value against the historical time series values and the current error term. The order of the process indicates the number of steps into the time series' history that are used for the regression, while the model parameters function as weights for the historical values.

The MA process is a linear regression of the current time series value against the mean of the time series and the historical error terms. The order of the process indicates again the number of steps the process looks back into the series' history and the process' parameters serve as weights for the error terms.

An ARMA process, combining an AR and a MA term and can be described by

$$X_t = c + \varepsilon_t + \sum_{i=1}^{p} \varphi_i X_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i}, \tag{4.1}$$

where φ_i are the parameters of the AR, and θ_i the parameters of the MA process. The order p of the AR term and order q of the MA term are used to classify the order of the combined ARMA(p, q) process.

AR models are used by [42] for both the wave height and the wind speed. For the wave height, the AR process is of order 20 and for the wind speed of order 2. A multivariate AR model is used by [13] to model correlated wave heights and wind speeds. Also [43] use a multivariate AR model, with which they are able to maintain persistence, seasonality and correlation between the different weather parameters. Generalized AR models with conditional heteroskedasticity were presented by [69].

ARMA models have the advantage that they can be used for forecasting as well as time series generation. They will in most cases require fewer parameters than a Markov chain model and can be used for any type of time series. However, in the given application, estimating and updating them is not as straight forward as with the Markov matrix.

Table 4.1: Weather data - comparison of model fit. Data is ERA-interim data from [79], Model is the Markov chain model implementation from A.5 based on that data, and Reference is the model implementation from [85] based on the same data.

	Data	**Model**	**Reference**
Mean wave height [m]	1.67	1.66	1.69
Standard deviation wave height [m]	0.08	0.12	0.11
Mean wind speed [m/s]	8.07	8.07	8.15
Standard deviation wind speed [m/s]	0.31	0.41	0.38

4.3 Markov chain weather modelling

Markov chain models are stochastic processes that fulfill the Markov property, assuring that one state only depends on its predecessor, explained by e.g. [84]. They consist of states and the transition probabilities between them. Markov chain models are used for wave height modelling in a number of O&M models, including [15, 10] and [12]. Paper A.1 includes a description and example of a Markov chain. The model from [10] was used in Papers A.5 and A.7 and in adapted forms in Papers A.9 and A.10. It will be described in the following in a bit more detail.

[85] presents a discrete time Markov chain model for the simulation of the significant wave height h_s. The transition probabilities for the Markov chain are derived from discretizing the average frequencies of transitions between the observed data after sorting the data into bins. Seasonality is achieved by using separate matrices with transition probabilities for each calendar month. In addition to the Markov chain model for the wave height [85] derive a correlation matrix for the wind speed from the same dataset. The correlation matrix provides the probability of each wind speed for a certain wave height.

One of the possible challenges with including seasonality in a Markov chain model in the presented way is the switch from one month's transition matrix to the next. If no transition probability exists in the matrix of the new month for the last value from the first month, the first value of the second month can not be calculated. When using a Markov chain model with multiple transition matrices, one needs to define how these situations should be treated by the model.

Paper A.5 includes an investigation of the performance of the Markov chain model, similar to the investigations in [85], comparing the data, the model from [85] and an alternative implementation for data from the European Centre for Medium-range Weather Forecasts (ECMWF) [86]. Table 4.1 summarizes the statistics of the comparison. The mean values are represented slightly better with the new implementation, however with a slightly higher standard deviation around the mean.

A similar approach is used in Paper A.10. Here, the wave height is modelled with a Markov chain, in one hour steps. The wind speed is derived using a correlation matrix - also in one hour steps. To achieve a higher resolution of the wind speed, 10-minute mean wind speeds are sampled from a Gaussian (Normal) distribution defined by the hourly mean wind speed obtained from the correlation matrix and a fixed standard deviation value for 10-minute wind speeds within the hour, which was calculated from the available data prior.

4.4 Langevin weather modelling

Paper A.4 presents an alternative method for the generation of artificial weather data. The Langevin process is a stochastic process governed by the Langevin equation

$$\frac{\mathrm{d}X}{\mathrm{d}t} = F(X,t) + G(X,t,\Gamma) \tag{4.2}$$

This stochastic differential equation includes a deterministic term $F(X,t)$ and a stochastic term $G(X,t,\Gamma)$. These are often called drift and diffusion function and depend on the first and second Kramers-Moyal coefficients $D^{(1)}(X)$, $D^{(2)}(X)$

$$F(X,t) = D^{(1)}(X)\tau \tag{4.3}$$

$$G(X,t) = \sqrt{D^{(2)}(X)\tau}\ \Gamma_t \tag{4.4}$$

where τ is a time-increment and Γ_t are the stochastic forces. The coefficients depend on both the observation X and time t.

Langevin equations were fitted to wind speed data by [87]. [88] used a Langevin approach to model turbulent wind. [89, 90] applied the approach to ocean waves. Both [89] and [88] have shown that the process can be described by

$$\frac{\partial P(X)}{\partial t} = \left(-\frac{\partial}{\partial X}D^{(1)}(X) + \frac{\partial^2}{\partial X^2}D^{(2)}(X)\right)P(X) \tag{4.5}$$

the Fokker-Planck equation. The Kramers-Moyal coefficients can then be defined as

$$D^{(n)}(X) = \lim_{\tau\to 0}\frac{1}{n!\tau}M^{(n)}(X,\tau) \tag{4.6}$$

Table 4.2: Statistics of the wave height simulations based on the FINO 1 data.

Wave height	Mean	Maximum	SD
Data	1.44	9.77	0.93
Simulation (a)	1.44	8.62	0.93
Seasonal simulation (b)	1.51	7.49	0.92

where τ is a time increment and $M^{(n)}(X,\tau)$ is the conditional moment of the Langevin processes' trajectory in time, with respect to τ as shown by [91].

For the analysis in Paper A.4 the software 'R' with package 'Langevin' [92] was used to first estimate the Kramers-Moyal coefficient functions $D^{(1)}(X)$ and $D^{(2)}(X)$, and subsequently to generate a time series of observations based on the estimated coefficient functions.

Three slightly varied approaches were carried out in Paper A.4 (a) a simulation based on one Langevin process, (b) a seasonal simulation based on twelve Langevin processes - one for each month, and (c) a seasonal simulation based on 6 h-data. In the following, I will focus on simulations (a) and (b).

Table 4.2 presents mean, maximum and standard deviation (SD) for the significant wave height for the FINO 1 data set and simulations (a) and (b). Both (a) and (b) are able to replicate the statistics of the data well, with (a) performing slightly better than (b).

Figure 4.1 shows the distribution of the wave heights over one year for the data from FINO 1, and for the simulations (a) without and (b) with seasons taken into account. Simulation (b) that was based on separate Langevin equations for each month results in a distribution of the wave heights that is closer to the distribution of wave heights in the data.

For O&M, weather windows are important and therefore the persistence of wave heights below threshold of 1.5 m was investigated in Paper A.4. It is visualised in Figure 4.2 for the FINO 1 data set and simulations (a) and (b). Simulation (a) without seasonal effect under-predicts the lengths of weather windows, while the simulation with seasonal effect (b) over-predicts the lengths. The Kolmogorov-Smirnov (KS)-distance between the persistence curve of the data and simulation (a) is about double the KS-distance of simulation (b). However, neither of the simulations show a

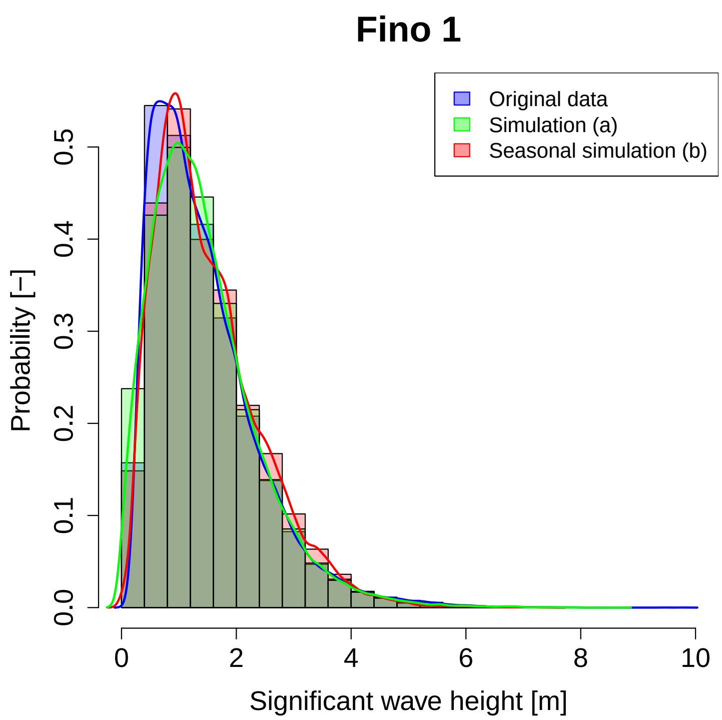


Figure 4.1: Distribution of the wave heights over one year for the FINO 1 data, simulation without (a) and with (b) a seasonal effect.

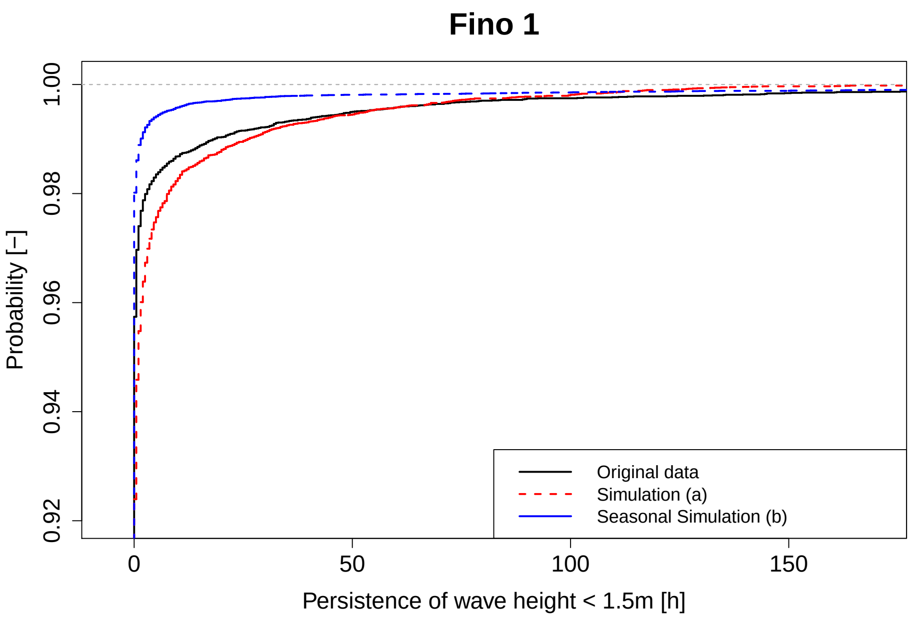


Figure 4.2: Persistence of wave heights below 1.5*m for the location of FINO 1. The data is compared to the simulation without (a) and with (b) seasonal effect.*

significant difference from the persistence of the data set.

4.5 Influence of the weather forecast

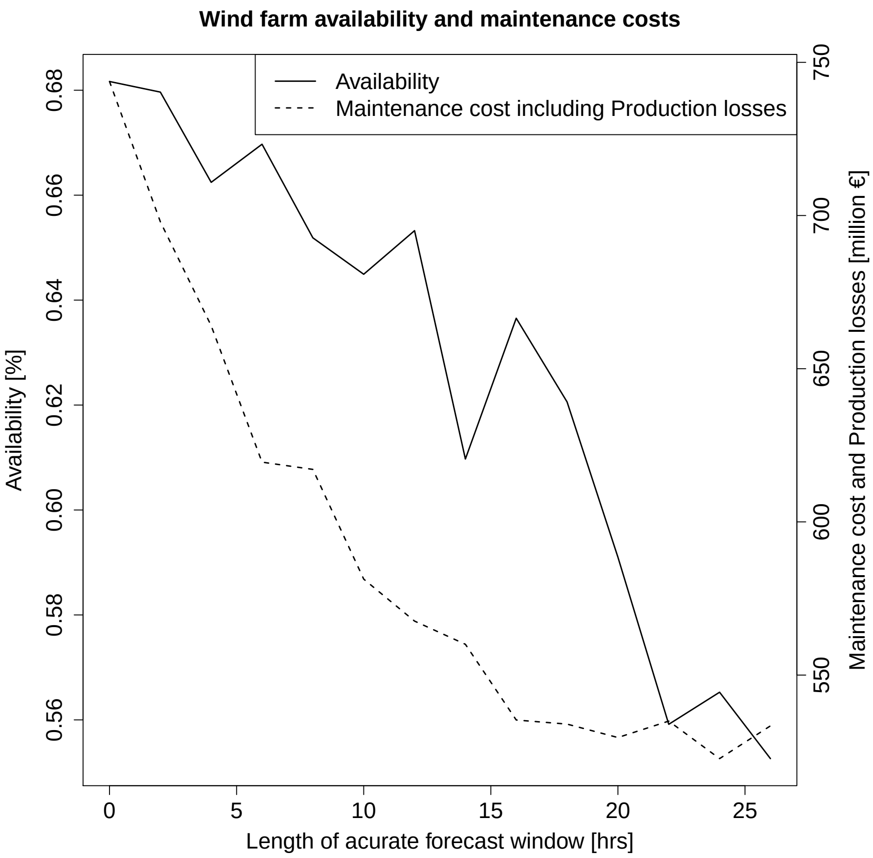
The influence of the weather forecast on the maintenance scheduling has been studied in Paper A.5. This is done by varying the length of the prediction window (look-ahead time) for which it is assumed the forecast is completely accurate. A simulation model, based on a Markov chain wave height model, was used. The maintenance strategy from [10], the power curve from [93] and component properties, like repair time and number of workers needed, from [31] were used as input to the simulation, as well as weather data from ECMWF [79].

Figure 4.3 shows the interpolated results for the availability and the total maintenance costs including the losses due to forfeited production, for different lengths of accurate weather forecast. It can be seen that the availability decreases with the forecast length, which is due to the applied maintenance strategy. At the same time, Figure 4.3 also shows a steep decrease in the total maintenance costs. When the forecast window is increased to 10 hours, availability decreases by 4 percentage points, while the total maintenance costs are reduced by 21%. Allowing for a slightly reduced availability can therefore lead to significantly lower costs of maintenance. For the investigated strategy, a moderate forecast length can help reduce the number of repairs started that need to be interrupted immediately due to bad weather. Strategies where the decision to access the WF is dependent on the predicted weather, for example immediately starting repairs that can be completed during the predicted weather window, might see additional improvements with longer forecast lengths. It should be noted that the overall low values for availability (68% in absence of a weather forecast) are due to the assumed location of the wind farm in the case study. The weather data, taken from the location of the planned WF “Dogger Bank”, has a mean significant wave height of 1.67 m. The limit for the significant wave height in the case study was set to 1.5 m, which is below the mean significant wave height. Together with investigated maintenance strategy, where repairs are not started when the limit predicted to be exceeded within the forecast window, this explains the low values for availability presented in Figure 4.3.

4.6 Conclusions about weather

In this chapter, the weather as a factor influential to maintenance scheduling has been investigated. In addition to providing sources of weather data, three options for weather modelling have been presented. The ARMA models combine forecasting and time series generation. They rely on fewer parameters than the Markov chain models. However, estimating and updating the model parameters is not as straight forward and requires more input from the model designer. To fit a Markov chain model is very straightforward. The only decision that has to be taken by the model builder, is the step size for binning the data. When using multiple Markov chains to represent seasonality in the simulation, the transition between them needs to be defined. This is especially important, when some of the Markov chains do not contain transitions between all possible states, as the model could end up in a state without a transition probability. The transition probabilities represented by the Markov chain can not only be used in Markov chain simulation, but can additionally be used as input to stochastic models, like the Markov Decision Process (MDP) presented in Paper A.9 which is presented in Chapter 6. The Langevin process, a stochastic process including deterministic and stochastic terms, is not yet widely used. Some publications used it for wind speed modelling. Paper A.4 investigated a Langevin process as a means to model both wave height and wind speed and achieved a good replication of the data properties, both in terms of statistics and persistence. In addition to the weather, the availability and reliability of a weather forecast also influences the decision process in maintenance scheduling. The analysis in Paper A.5 has shown that weather forecasts can help reduce the maintenance cost. Depending on the maintenance strategy this can have the drawback of a (slightly) reduced availability.

Figure 4.3: Interpolation of the mean availability and mean total cost of maintenance for different forecast lengths. The forecasts lengths are multiples of the 2 hour step size.



Chapter 5

Repair time

5.1 Constant repair time

A very simple, data-based approach for modelling repair time is to use the Mean Time To Repair (MTTR) as an estimate for the maintenance duration. The MTTR can than be included in models, requiring the technicians to be present at the turbine for a fixed amount of time. When considering weather windows, the MTTR can provide a minimum weather window necessary for repair. Using the MTTR in maintenance models is straight forward, as there is exactly one repair time value to consider that never changes. It is possible to update the MTTR, when new data becomes available. For researchers, information about repair times is hard to come by, as many wind farm operators and maintenance service providers choose to keep their data confidential. A few publications of summarized repair data exist by researchers that were able to access data.

[94] provide repair time data for onshore wind turbines provided through discussions with operators and technicians. The attempt to verify the provided numbers with maintenance logs was not possible due to inconsistency in recording format. [94] present repair time values for major components with repair times greater than 2 hours and assume that all other maintenance tasks are covered during general service hours. Five turbine sizes are distinguished in [94], ranging from 750 kW to 2.5 MW. Compared to currently installed offshore wind turbines, these turbine ratings are relatively low, so when using the repair time data provided by [94] this should be taken into consideration.

[31] provide data from approximately 350 OWTs. They present average repair times and the average number of technicians required for repair. The turbine data has been collected during the turbines' early life, 68% of

the turbines are between three and five years old, and 32% are older than five years. Failures that occur only during late turbine life might not be well-represented, due to a lack of observations. It might be that the average repair time is calculated based on very few observations. Since the underlying data is not provided by [31], this cannot be verified. The repair time numbers are presented for 19 different WT components and for three different failure types each. The average number of repair technicians needed is presented for the same 57 component-failure combinations. The repair time presented by [31] is the time the maintenance personnel spends at the turbine conducting repair. Transfer and preparation times are not included in the repair time numbers.

[95] present WT downtime data for onshore wind turbines. Unfortunately, the data has been normalized for confidentiality reasons. Additionally, the downtime data does not only include the repair time itself, but also wait times due to different reasons. Therefore it is not as useful as we would like for the current application.

By calculating the MTTR or average repair time from the maintenance data, all information about underlying variations in the repair duration is lost. On the other hand, maintenance planning becomes more straight forward, when a constant repair time is assumed. A constant repair time equal to the repair time presented in [31] was used in paper A.5 to evaluate the influence of the weather forecast. Furthermore, the four maintenance models [12, 13, 15, 16] compared in [96] all use constant repair times.

5.2 Variable repair time

As this thesis in concerned with WF modelling and maintenance scheduling under uncertainty, it seems natural to also investigate uncertainties and variations in the repair duration. Additionally, since the existing models [12, 13, 15, 16] all use constant repair time, no previous investigations into the repair time exist. In the sensitivity study from [96], different repair time values were investigated with these models.

A simple way to include a variation in the repair time in the maintenance scheduling models, are Monte Carlo methods. Multiple simulations are conducted, with a slightly varied repair time in each simulation run. The values to choose for the individual simulations can come from data observations such as the data set [31] used in their analysis. In the absence of publicly available repair time data, the MTTR can be used as a starting point to define repair time distributions. When defining distributions, the repair time for each simulation run can then be randomly drawn from the pre-defined distribution.

An alternative to using Monte Carlo simulations are (closed-form) analytical models. These models do not rely on drawing random realizations, rather the repair time distribution can be fed into the model as an equation. An example of a closed-form model is the model presented by [17], presenting a method to calculate the maintenance delay due to sea state. Closed-form models have the advantage of (mathematical) simplicity and the avoidance of simulations can save calculation time and computing power. However, not all phenomena can be simply described by closed-form models. Additionally, when working with closed form expressions operations such as inverting or integrating a function can only be performed when certain predicaments are met. Sometimes it will be necessary to perform transformations that require a function be e.g. invertible or integrable. In order to invertible, a function needs to be bijective. To be integrable, the function needs to be continuous. If these conditions are not met, no analytic solution can be found and one needs to resort to numerical methods again.

5.2.1 Production losses due to repair time and weather delay

In paper A.6, the closed-form model for the delay due to sea state [17] was taken as a starting point. MTTR values from [94] were used, as well as an exponential distribution based on these same values. The exponential distribution was chosen, as it only depends on the mean value, which was the only information available from the data. The Probability Density Function (PDF) of the repair time is

$$f(t_{rep}; \lambda) = \lambda \mathrm{e}^{-\lambda t_{rep}} \chi_0(t_{rep}), \tag{5.1}$$

$$\text{where } \lambda = \frac{1}{\text{MTTR}} \text{ and } \chi_0(t_{rep}) = \begin{cases} 1 & \text{for } t_{rep} \geq 0 \\ 0 & \text{for } t_{rep} < 0 \end{cases}.$$

In a first step, the expected production loss was calculated without considering any delay caused by the sea state. The production loss L_p is a function of the repair time

$$L_p(t_{rep}) = g(t_{rep}) = C \cdot t_{rep}, \tag{5.2}$$

C represents a cost-constant , based on the installed capacity, capacity factor and feed-in-tariff.

Given the PDF for the repair time from equation 5.1 and the production loss L_p, the expected production loss over one year is

$$E(L_p | t_{rep} = MTTR) = MTTR \cdot C \cdot p_a, \tag{5.3}$$

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Table 5.1: Expected delay and production loss for constant delay d and delay due to sea state $d(t_{rep})$ from [17]. To have a comparable value for the production loss L_p, unit-free values are presented. For failure probability data, [9] was used.

Component	$E[d(t_{rep})]$	$d(E[t_{rep}])$	$\frac{E[L_p \mid d(t_{rep})]}{C}$	$\frac{E[L_p \mid d(\mathrm{MTTR})]}{C}$
Gearbox	917.5	286.0	103.8	40.4
Pitch system	20.9	17.4	8.5	7.4
Electronics	11.9	11.2	11.3	10.9
Units	hrs	hrs	unit-free	unit-free

Next, the distribution of the repair time was combined with a constant delay d. With the repair time t_{rep} equal to the MTTR, the expectation of the production loss L_p calculates to

$$E(L_p|t_{rep} = MTTR) = (MTTR + d) \cdot C \cdot p_a, \tag{5.4}$$

where p_a is the annual failure rate of the investigated component and C is a cost-constant as before. The production loss function defined with the delay function from [17] is

$$L_p(t_{rep}, d(t_{rep})) = C \cdot (t_{rep} + d(t_{rep})) \tag{5.5}$$

This function cannot be inverted and therefore the expected value cannot be calculated analytically as before. Monte Carlo simulation was used to evaluate the expected production loss given this delay.

The results for the delay and production loss calculations are shown for three WT components in Table 5.1. The expected delay, dependent on the distributed repair time $E[d(t_{rep})]$ shows higher values than the constant delay, dependent only on the MTTR $d(E[t_{rep}]) = d(MTTR)$ for all three investigated components. It can be observed that for the generator replacement, the variation between those two values is quite large, $E[d(t_{rep})]$ is more than three times $d(E[t_{rep}])$, while for the electronics system, the delays show less than 10% difference between considering the distributed repair time and constant repair time. For the production losses L_p, similar observations can be made. For the generator replacement, which has a long MTTR, the production loss L_p for the constant repair time is less than half of the production loss for the distributed repair time.

Figure 5.1 provides a visualisation of these results for the example of the pitch or hydraulic system. It can be seen how the distribution of the repair

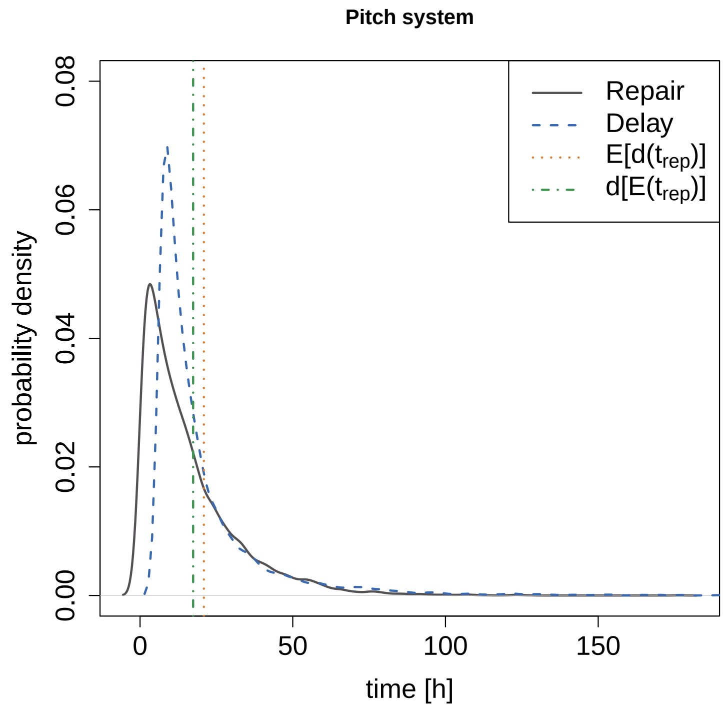

Figure 5.1: The distributions of the repair time (black line) and delay (blue dashed). The horizontal lines represent the expected delay (yellow dotted) and the delay based on the MTTR (green dash-dotted).

time influences the distribution of the delay time. Additionally, the figure shows both the delay caused by the MTTR $d(MTTR)$ and the expected delay when considering the repair time distribution $E[d(t_{rep})]$ as vertical lines.

In general, this study has shown that variations in short repair times have little influence on the overall delay, whereas a variation in the repair of components with a higher MTTR has a larger influence on the delay. A recommendation for additional work is to investigate repair times and failure rates for larger turbines, as will be shown in the following section. Additionally, collecting repair time data from an operating wind farm and investigating the statistical properties, like mean and variance as well as fitting a distribution is recommended.

5.2.2 Value of information of repair times

In Paper A.7, the influence of variations in the repair time to the WF availability and the production losses has been studied. For the study, the maintenance scheduling model from [10] was chosen as a starting point. The Markov chain weather model was modified to use weather data from the location of the Dogger Bank WF, provided as reanalysis data from the ECMWF. The mean repair time data from [31] was used to calibrate an exponential distribution. The exponential distribution can be defined with only one parameter, defined as the inverse of the mean, as can be seen from 5.1. As no information about the nature of the actual distribution around this average repair time was available, this exponential distribution was used as a basis for further analysis. The exponential distribution was again used as it is the simplest way to model random time to an event, while having a fixed value for the variance. The log-normal distribution depends on two parameters and is a natural candidate for modelling non-negative random processes where the variance is known. As the variance for the duration of the repair time is unknown, the exponential distribution served as a a starting point for investigation for the variance. Subsequently, a log-normal distribution was fitted, defined by the mean and variance provided by the exponential distribution. In order to investigate repair time distributions with larger and smaller variance, the variance in the log-normal distribution was doubled in one case and halved in the other case. The PDF for the log-normal distribution is

$$f(t) = \frac{1}{t} \cdot \frac{1}{\sigma\sqrt{2\pi}} \exp\left(-\frac{(\ln t - \mu)^2}{2\sigma^2}\right), \tag{5.6}$$

where μ =MTTR is the mean and σ^2 the variance. In the case study, the value for σ^2 are σ^2 = MTTR^2, $\sigma^2 = 2 \cdot$ MTTR^2, and $\sigma^2 = 0.5 \cdot$ MTTR^2.

In the original model presented by [10], the repair time for each component was set to the MTTR. In order to incorporate the distribution of the repair time, in paper A.7, the value for the repair time is randomly generated according to the repair time distribution for each occurring failure. The case study set up in paper A.7 was a wind farm with 100 turbines, using the power curve from the NREL 5-MW reference turbine [93], annual failure rates and MTTR from [31], two different vessels types with five CTVs and one crane vessel, and 25 operation years. Two KPIs are evaluated; the mean annual lost production in MWh and the mean (time-based) wind farm availability in percent. The mean annual lost production was calculated based on the weather during downtime and the power curve provided by [93]. The same kinds of repair time distribution were used for those components that require a CTV for repair and for those that need a crane vessel, based on the component specific parameters from [31]. The simulation was performed using the same distribution for all components, and repeated using deterministic repair time values for one type of component and varied repair time for the other component.

Table 5.2 shows the mean annual availability of the WF over 25 simulation years for the different scenarios. The most important observation is that the availability decreases, when variation is added to the repair time. The leading cause seem to be the turbine components which require a CTV for repair. These are the components with high failure rates where failures occur more often. This result differs from the analysis presented in paper A.6, where the larges influence on the delay was shown to come from the components with the longest repair times. It can therefore be assumed that the influence of the delay in scheduled maintenance outweighs the delay due to sea state in this model. It can be observed that the mean WF availability increases for the cases with a deterministic repair time for CTV components and variable repair time for the crane components. This is most likely due to the very low failure rates for the component repairs that require a crane. Due to the positive skewness of the repair time distributions, a low value is more likely for a single realization of repair time. Due to the very low failure rates for these components, few realizations are observed which are likely not sufficient for the repair time to average out close to the mean value. The lower repair time in turn leads to shorter downtime and hence an increased availability of the WF.

In Figure 5.2, the distribution of the mean annual production loss per turbine is presented for the first five of the simulation scenarios. Here, the

Table 5.2: This table shows the mean wind farm availability in percent for 13 different scenarios of repair time distributions. In all scenarios, the mean is equal to the mean time to repair. The variance of the log-normal distribution is set equal to the variance of the exponential distribution ($\sigma^2 = (1/\mathrm{MTTR})^2$). For the log-normal distributions with increased and decreased variances, the variance is doubled for the increased variance and halved for the decreased variance.

Repair time distribution for CTV components	Repair time distribution for crane components	Mean WF availability in percent
Deterministic	Deterministic	76.7
Exponential	Exponential	43.7
Log-normal	Log-normal	49.1
Log-normal, $2\sigma^2$	Log-normal, $2\sigma^2$	40.7
Log-normal, $0.5\sigma^2$	Log-normal, $0.5\sigma^2$	57.8
Deterministic	Exponential	77.6
Deterministic	Log-normal	78.2
Deterministic	Log-normal, $2\sigma^2$	76.9
Deterministic	Log-normal, $0.5\sigma^2$	76.8
Exponential	Deterministic	42.6
Log-normal	Deterministic	47.9
Log-normal, $2\sigma^2$	Deterministic	40.8
Log-normal, $0.5\sigma^2$	Deterministic	55.1

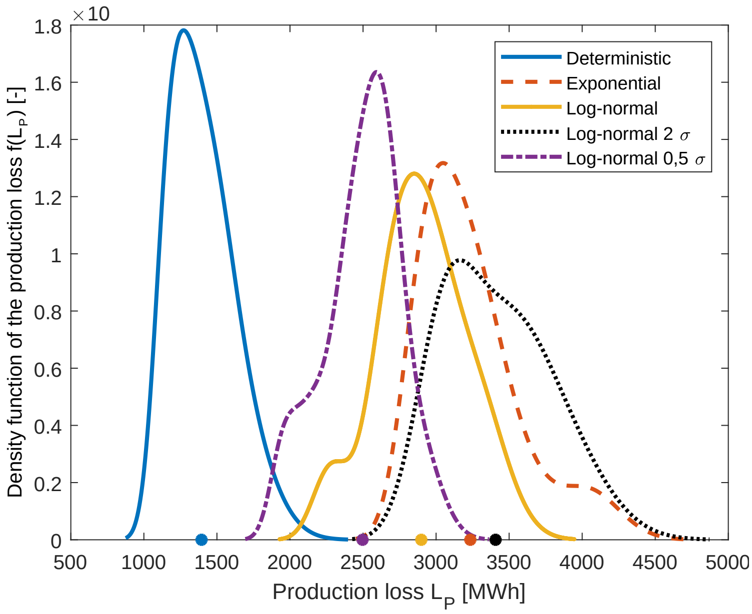

Figure 5.2: The distributions of the annual production loss per turbine in MWh for a deterministic (blue line), exponential distributed (red dashed), log-normal distributed (yellow line), log-normal with double variance distributed (black dotted) and log-normal with halved variance distributed (purple dash-dotted) repair time.

repair times for all components come from the same type of distribution, both component repairs that require a CTV only and those requiring a crane vessel. The density functions in the plot have been fitted with Kernel density estimation, leading to the smooth curves presented in the plot. Like with the availability, it can be seen that using a variable repair time as opposed to using a deterministic repair time influences the production losses. When the repair time distribution has a large variance, also the values for production losses show a larger variance.

5.2.3 Repair time distributions in a closed form model

In paper A.8, the distribution of the WT downtime based on the repair time and failure distribution is investigated. The study was based on the theory of alternate renewal, combined with the previous investigations of the influence of repair time distributions. An alternate renewal process describes a process where the two states "running" and "failed" alternate. In order to switch between the two states, a failure or renewal take place. A failure turns a component from "running" to "failed", while a renewal returns it from "failed" back to "running". No wait times are included in the alternate renewal process and it is assumed that both the duration of the operation X_i of a component as well as the duration of the downtime Y_i of the component are random, following a given distribution. An example of an alternate renewal process is displayed in Figure 5.3.

In principle, any kind of distribution can be used - in paper A.8, a constant failure rate as well as a constant repair rate were assumed, leading to an exponential distribution, with a probability density as presented in 5.1. In the following the PDFs for the occurrence of a failure and a repair will be denoted with $f(t, \lambda)$ and $g(t, \mu)$ respectively.

The distribution of a sum of n operation durations $X_1 + \ldots\ X_n$, is calculated as the n-th fold convolution of the PDF

$$F^{(n)}(t) = F^{(n-1)}(t) * f(t) = \lambda^n \mathrm{e}^{-\lambda t} \frac{t^{n-1}}{(n-1)!}. \tag{5.7}$$

To calculate the distribution of the downtime $D(t)$, an event "$D(t) \leq x$" is defined. The total downtime $D(t)$ is the sum of all downtimes during $[0, t]$ and has the probability

$$P(D(t) \leq x) = \sum_{n=1}^{\infty} P\left(Y_1 + \ldots Y_n \leq x | N(t-x) = n\right) P(N(t-x) = n) \tag{5.8}$$

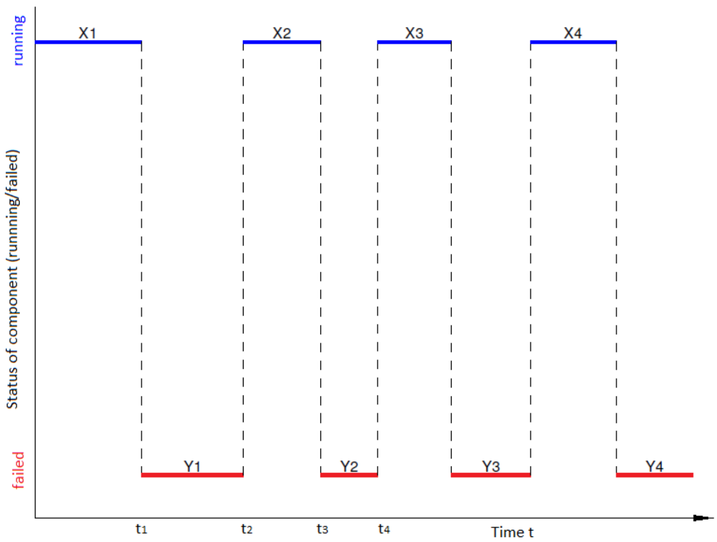

Figure 5.3: An example of an alternate renewal process. The X_i present the operational time, while the Y_i represent the downtime. The process switches from operational to failed at times $(t_1, t_3, \ldots)$ and back at times $(t_2, t_4, \ldots)$

The probability of having exactly n failures, is equal to the process being between t_{2n-1} and t_{2n}, therefore having a total operational time between $X_1+X_2+\cdots+X_n$ and $X_1+X_2+\cdots+X_{n+1}$. The probability $P(N(t-x) = n)$ can be simplified with 5.7 to

$$P(N(t-x) = n) = F^{(n)}(t) - F^{(n+1)}(t). \tag{5.9}$$

Analogously to the distribution of a sum of operation durations, the distribution of the total repair duration conditional on the number of failures n can be calculated as the n-th fold convolution of the PDF $g(t)$ as

$$P\left(Y_1 + \ldots Y_n \leq x | N(t-x) = n\right) = G^{(n)}(x) = \mu \mathrm{e}^{-\mu x} \frac{x^{n-1}}{(n-1)!} \tag{5.10}$$

By plugging the simplifications from Equations 5.9 and 5.10 into Equation

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Component	Failure rate λ [failures per annum]	Mean time to repair $\frac{1}{\mu}$ [hours]
Gearbox replacement	0.154	231
Pitch system minor repair	0.824	9
Conductor/ Circuit breaker/ Relay system	0.326	4

Table 5.3: Parameters used for the visualization of the downtime distribution.

5.8, the distribution of the downtime $D(t)$ finally calculates as

$$
\begin{aligned}
P(D(t) \leq x) &= \sum_{n=1}^{\infty} P\left(Y_1 + \ldots Y_n \leq x | N(t-x) = n\right) P(N(t-x) = n) && (5.11)\\
&= \sum_{n=1}^{\infty} G^{(n)}(x) \left(F^{(n)}(t) - F^{(n+1)}(t)\right) && (5.12)\\
&= \mathrm{e}^{-\mu x - \lambda(t-x)} \sum_{n=1}^{\infty} \frac{\mu^n \lambda^n x^{n-1} (t-x)^{n-1}}{(n-1)!(n-1)!} \left(1 - \lambda \frac{t-x}{n}\right) && (5.13)\\
&= \mathrm{e}^{-\mu x - \lambda(t-x)} 2\sqrt{\lambda} \left(\sqrt{\mu x (t-x)}\, I_0 + (x-t)\sqrt{\lambda}\, I_1\right). && (5.14)
\end{aligned}
$$

I_0 and I_1 are the modified Bessel functions [97, Chapter 14] of the first kind, of order 0 and 1 respectively.

The probability distribution from 5.14 is visualized for the pitch and conductor system in Figure 5.4. Since no simple method for the visualization of multi-dimensional downtime exists, the distribution was numerically evaluated for possible downtime lengths up to 365 hours, with a resolution of 1 hour. A surface plot was fitted for visualization. Data for the MTTR and failure rates was taken from [31], the values are shown in Table 5.3

It can be seen that the most probable downtime lengths are lower than the total time of observation. This can be best seen for the conductor system, where the "ridge" in the surface indicates the highest probabilities.

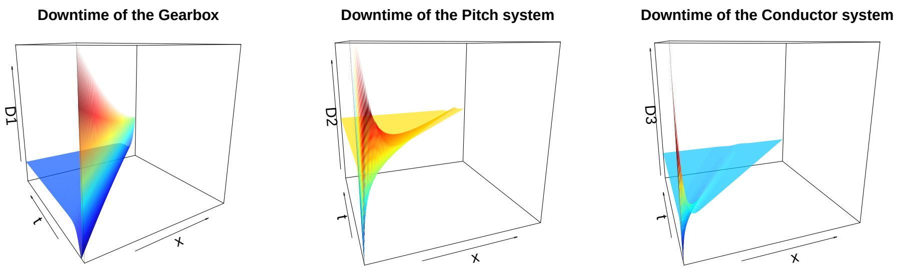

Figure 5.4: Distribution of the downtime for three different wind turbine components. From left to right: Gearbox replacement, Pitch system minor repair, Conductor/Circuit breaker/Relay system.

5.3 Conclusions about repair time

The observations collected in this chapter show that indeed the variation in repair time has an influence on different KPIs, like the time-based and energy-based availability. Paper A.6 shows that the variation in repair times has a higher influence on the delay due to sea state for those components, where the mean repair time is higher. Paper A.7 shows that variation in the repair time for repairs requiring a CTVs have a higher influence on the availability and production losses, possibly due to higher failure rates. In the framework investigated in Paper A.7, the maintenance scheduling has a more pronounced influence on the WF availability and production losses than the delay due to sea state. Paper A.8 confirms that the variation in repair time influences the downtime, and presents an approach to calculate and visualize the distribution of downtime dependent on the repair time and failure rates.

All of the studies agree that it is most important to account for variations in the repair time for WT components with a long repair time, small maintenance crew and without the need for a crane, as these repairs show the highest influence on the overall WT availability.

Due to the lack of publicly available repair time data, all observations should be taken mostly as a guide for future investigations. The next logical step for investigating repair time variations is to acquire repair time data and use this to investigate the nature of actual repair time distributions. These should then be used when modelling OWF O&M instead of the single values used today. Ideally this integration will be done in closed-form models similar to the ones explored in Paper A.6 and Paper A.8.

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Chapter 6

Decision support

6.1 Introduction

It was previously established in Chapter 2 that there are a multitude of factors that are influential to OWF O&M planning. I have also shown the importance of taking into account unforeseen variation in the different factors with the examples of the weather and repair time in Chapters 4 and 5 respectively. It is no surprise that stakeholders and decision makers can feel overwhelmed when trying to take into account all of the necessary factors. Taking an informed decision based on the multitude of influential factors can be challenging for human decision makers and often Decision Support Systems (DSSs) are used to facilitate the decision process. As was explained in Paper A.1, DSSs are being used in many industries today. The first DSSs were developed shortly after the invention of modern computers - [98] presents the historical development and [99] summarizes the types of DSSs. For the decisions in Offshore Wind Energy (OWE), model-driven decision support is the most relevant type of DSS. The different stakeholders in the Offshore Wind Industry (OWI) have been analysed in Paper A.3. For O&M decision making, the maintenance service provider is the main stakeholder involved. In case the WF operator is not outsourcing the maintenance but conducting it themselves, the operator also becomes a stakeholder interested in decision support.

Paper A.1 reviewed and summarized the state of the art of DSS. In the paper it was shown that most of the published DSSs rely on Monte Carlo methods (MC methods). The DSSs repeat the same simulations with input that is varied through random sampling, to account for variations and uncertainty in the input factors. The model used in Papers A.5, A.7 relies on MC methods. The MC method was also used for the case study presented in A.6.

Paper A.9 presents a method that can be used to compare different scheduling policies under a corrective maintenance strategy. In contrast to most of the alternatives, this method does not require simulations and the expected values for different KPIs can directly be compared between the different policies. The method will be explained on the example of the case study presented in Paper A.9 in the following Section 6.2.

In the decision support framework, and specifically in the context of the decision process used in Paper A.9, the term 'policy' is used to describe the set of rules used in the decision making process [100]. The 'policy' governs the decision and provides rules to decide what to do in previously encountered (or investigated) situations. In the case study, the policy is applied in case of a component fault that requires corrective maintenance. The decision regarding the order in which components or turbines are repaired, and the decision to use a corrective maintenance strategy over a preventive or condition-based approach, are not governed by the policy. The case study presented in the following chapter assumes a corrective maintenance action for a single turbine and focuses on policy governing the WT access.

6.2 Markov decision process

The method used in Paper A.9 is called a Markov Decision Process (MDP). A Markov Decision Process (MDP) is a stochastic control process that can be seen as an extension of a Markov chain, adding actions and rewards. The MDP can be represented by the tuple: $(\mathcal{S}, \mathcal{A}, \mathcal{P}, \mathcal{R}, \gamma)$, where $\mathcal{S}$ is a set of states, $\mathcal{A}$ a set of actions, $\mathcal{P}$ the transition probabilities between states, given actions, $\mathcal{R}$ a reward function, and γ a discount factor.

The states $S \in \mathcal{S}$ are tuples of the form $S = (\text{location}, \text{wave height}, \text{repair time left}, \text{steps waited})$, where 'location' can take on either of the values 'port' or 'turbine'. The significant wave height ('wave height') takes values in steps of 0.4 m between 0 m and 10.4 m. The 'repair time' starts off with an initial value, specific to the turbine component that is investigated. In the following I am presenting the results for a major blade repair, with 21 h mean time to repair, so the values for the 'repair time' range from 0 to 21 in steps of 1 h. The 'steps waited' also take steps of 1, starting at 0 and ranging up to 3 depending on the policy. Table 6.1 shows the possible values for the parameters of the state.

Table 6.2 summarizes the set of actions $\mathcal{A} = \{\text{stay, wait, reset wait time, go out, repair, return}\}$ and details what effect the action has on the parameters of the following state. The actions 'wait' and 'reset wait time' are only used in some of the policies.

The transition probabilities $\mathcal{P}$ depend on the transition probabilities of the significant wave height values which are calculated based on the weather data from FINO 1. The reward function $\mathcal{R}$ is used to evaluate different aspects of the maintenance policies. To evaluate the influence of the policy change on the expected downtime of the turbine, a penalty is used for the steps it takes to end up in a repaired state. To calculate the expected production losses, the reward function $\mathcal{R}$ represents a penalty of the production losses. These are calculated based on the correlation of wind speeds and wave height and a linearized power curve for the NREL 5 MW turbine [93]. Discounting is not used and hence the discount factor set to $\gamma = 1$.

In addition to the Markov decision process that describes how the system works, we have a set of policies Π. A policy π can be understood as a decision maker's rule for choosing one of the possible actions $a \in \mathcal{A}$ in each state. In paper A.9 three types of policies are investigated, the (a) go-right-away policy, (b) wait-n-steps policies and (c) h m-limit. In policy (a), as soon as the wave height is below 1.6 m - the h_s threshold for CTV access - the CTV is sent to the WT. The travel time is 1 h, which corresponds to one step in the MDP. Once the CTV arrives at the WT, the repair is conducted as long as the wave height stays below the threshold. The repair is interrupted and the CTV returns to port when h_s crosses above 1.6 m. The travel time back to port is again 1 h. The repair is cumulative and can be resumed after an interruption, without losing progress. Restrictions to working hours of the maintenance crew are not taken into account in the policy. Policy (b) presents an alternative to accessing the wind farm as soon as the weather allows. In this policy, the CTV waits a fixed number of one, two or three hours respectively before accessing the WT. The number of hours waited is fixed for each policy, independent of the observed weather. All other aspects of the policy remain as before. The third policy (c) introduces a second wave height threshold for the CTV access. The original limit of 1.6 m is used for the decisions to start and interrupt the repair (returning to port), while the

Table 6.1: The different parameters of the states and their possible values.

Parameter	**Possible Values**
Location	$\{port, turbine\}$
Wave height [m]	$\{0, 0.4, 0.8, \ldots, 10, 10.4\}$
Repair time [h]	$\{0, 1, 2, \ldots, 20, 21\}$
Steps waited	$\{0, 1, 2, 3\}$

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Table 6.2: The actions and how they influence the next state.

Action	Parameters of the following state
stay	
wait	steps waited +1
reset wait time	steps waited = 0
go out	location = turbine
repair	repair time −1
return	location = port

new limit is used for the decision to access the WT. The alternative limits investigates are 0.8 m, 1.2 m, 2 m, 2.4 m and 2.8 m with all other aspects remaining the same.

Combining a MDP with a fixed policy, results in a Markov chain. This is because all of the actions are defined by the policy and one is left with only the transition probabilities between states. In a Markov chain the value of each state S_i can be calculated based on the reward of that state and based on the values of states that can be reached. This done by solving the linear equation system defined by

$$V(S_i) = \mathcal{R}(S_i) + \sum_j P_{ij} V(S_j), \tag{6.1}$$

where P_{ij} is the transition probability between state S_i and S_j from $\mathcal{P}$. These equations 6.1 are known as the Bellman equations. To investigate the result of an investigated policy, the value V of the starting states is of interest. The starting states are those states with repair time equal to 21 h in the example. Due to the different state parameters, multiple starting states exist and their values are weighted with the probability of occurence of this starting state, before averaging the value.

In the given framework, it is expected that policy (a) go-right-away will be the most economical option, as it leads to the fastest resolution of a failure. Figure 6.1 shows the total cost due to downtime for a major blade repair, for the nine investigated maintenance policies. It confirms that go-right-away is the most economical option for an electricity price of 30.84 Euro-cent (Germany 2017, from [101]), hourly vessel costs of 287.5 € (calculated from daily cost from [14]), hourly worker costs of 55.3 € (calculated from annual worker salary) and vessel mobilization costs of 1000 € (similar to [96]). Paper A.9 indicated that for a lower electricity price, alternative policies might surpass policy (a) in terms of total costs.

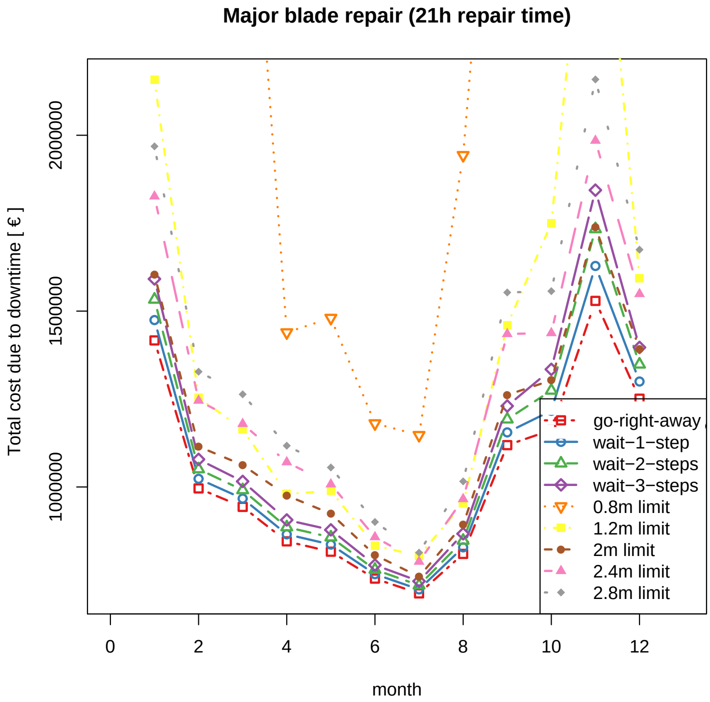

Figure 6.1: Results for the total costs for the major repair of a turbine blade. Policy (a) go-right-away is the cheapest option independent of the season.

6.3 Conclusions about decision support

Paper A.1 explained DSS and summarized the state of the art in DSS for the O&M of OWFs. A DSS is some form of model or rulebook that can be used by a decision maker in order to simplify the decision process. The existing DSS for the OWI rely on MC method. Paper A.9 presented the MDP as a useful alternative to MC method. The MDP was then used in a case study in Paper A.9, summarized in this chapter. In addition to validating the method, the case study showed that under a (hypothetical) lower electricity market price, alternative scheduling strategies will be more economical than the currently optimal strategy.

Chapter 7

Outreach and dissemination

7.1 Motivation

The motivation for outreach and dissemination is two-fold. On the one hand, there is a need to recruit more researchers and professionals in the field of OWE. On the other hand, public knowledge about and support from the general public for the field should be increased.

In order to captivate the full potential of OWE as part of the energy mix, the support of innovation and training, as well as the enhancement of synergies are priority measures according to [102]. In order to support training and more specifically to improve innovation by utilizing synergies between different academic and engineering fields, training tools are needed that enable engineers and researchers from other fields to rapidly gain insight into the OWE sector, without spending years studying from textbooks. This will not replace more thorough studies of the engineering models, but rather enable easy access to the main concepts - sparking discussions and possible collaborations.

Concurrently, the current momentum of environmental awareness in the general public can be used to build appreciation of the importance and contribution of OWE as share of the energy mix. Many misconceptions about wind energy exist in the general public [39] and high electricity prices are a reason for concern in many European countries.

In order to address both groups, a serious game (Vindby) was developed and presented in Paper A.10. In this chapter, the main content of the paper will be summarised, the concept of serious games introduced and the prototype presented.

7.2 Serious games

Serious games provide an alternative learning strategy, supplementing the existing teaching and learning techniques like textbook reading and studying in groups. Therefore, they provide an additional method for learners to explore the topic of OWE. [103] defines a serious game as *a digital game created with the intention to entertain and to achieve at least one additional goal* - known as the characterizing goal. According to [104], the effectiveness of the serious game as a teaching tool is influenced by how much the player enjoys the game play. Therefore, designing an immersive and fun game is equally important as the game mechanics and engineering principles behind the simulations. While engineering simulation models often focus on accuracy and ordinary games focus on entertainment, a serious game falls between the two. For training purposes, the game is expected to represent the subject matter correctly, including realistic details to educate the users about the subject.

In order to balance the accuracy of the engineering models with fun in the game play, the game prototype presented in Paper A.10 is the results of multiple iterations of game design and testing. The internal tests focused on the accuracy of the presented results regarding scale, weather simulation and playability. Different feedback mechanisms have been implemented and tested to achieve playability in the prototype. The prototype can be understood as a fully functional serious game for the offshore wind farm design and operation. However, to achieve improved immersion, the game interface should be developed in collaboration with dedicated game developers and user interface experts.

7.3 Vindby - the game

Vindby - the prototype presented in Paper A.10 provides a fully functional serious game for both needs detailed in the motivation. It can be used as a training tool for researcher and engineers as well as a dissemination tool targeted to the general public. The characterizing goal for training purposes is to improve the players' technical judgement of offshore wind farm design and operation. The characterizing goal for outreach purposes is to improve the players' sentiment towards the OWE industry and to introduce basic terminology. Vindby aims to be technically as accurate as possible, while teaching about the technology choices in the offshore wind industry. Existing games concerned with wind energy topics, like [105] and [106] do not provide the same level of technical details.

7.3.1 Framework and implementation

The objective of the game presented in Paper A.10 (Vindby) is to reach one of five game goals by building wind farms in a virtual sea within a predefined budget and time frame. Each game goal has a different difficulty, and the game duration varies.

Depending on the selected game goal, different game dynamics, such as solve and collect can be observed. The game does impose a time limit to reinforce real-life constraints on wind energy. However, the game is slow paced, does not require quick reactions and can be paused at any moment to aid with learning.

The game elements used in Vindby are rewards, resources, scoring, story, chance and strategy. Rewards are used for player motivation, resources are limited and their availability made visible to the player. The scoring indicates the player's progress towards the selected game goal, while the story aids with immersion. Chance is included to make each play-through unique, demonstrating real-life uncertainty. The player is free to choose any strategy they like, allowing for comparison and demonstrating that there is no single perfect solution that solves all challenges equally.

The game mechanics include game rules that guide the player as well as internal procedures that determine the structure of the game. The game space in Vindby is a virtual sea grid, including 100 unique cells with individual properties. The game time is measured in calendar dates to represent realistic timelines. Two examples of game rules are related to money and reaching the game goal. The player must not run out of money - in that case the game is automatically lost. When the initially selected game goal is reached, the game is won. While these game rules are already set from the beginning, additional mechanics are added throughout the game, including rewards and penalties for different actions as well as unveiling of additional design options.

The prototype was implemented in the object-oriented programming environment of Python 3.6. The game consists of a main game loop, where the game continuously cycles through input, update, and render steps. One cycle through the game loop takes one real-time second, but can represent one in-game hour, week or month. To enable different in-game speeds and ensure compatibility with variable machine capabilities, a time delay is added to the game loop when necessary.

7.3.2 Content and design

The game content in Vindby includes the design and operation of offshore wind farms. The topics integrated into Vindby are variations in the weather, wind farm design, operation and maintenance, energy demand, costs, stakeholder influence and optimization.

Weather modelling is included in the game content to improve the players' knowledge about the influence of the weather on the energy production, constriction and maintenance. In Vindby, significant wave height and mean wind speed are included. Both factors are used to determine weather windows for construction and maintenance access, whereas only wind speed is used to determine the power production. The Markov chain weather model used in Vindby has been presented and discussed in 4.

One of the fundamental activities in Vindby is the design of WFs. The design includes choices on the wind farm site selection, choice of turbine model and number of turbines, type of support structure, grid integration, lifetime extension and decommissioning. Not all aspects are included in equal detail, a focus was put on turbine technology, and support structure types and their requirements.

A second aspect is the O&M of the constructed WF. Three, simplified maintenance strategies are included in Vindby, including time-base and condition-based preventive as well as corrective maintenance options. The power production during operation depends on the chosen turbine type, number of turbines, and the weather; it is modelled using power curves. The energy demand is implemented such that it does not allow the full capacity to be met by offshore wind generation. Feedback is provided on the reduction in CO2 emission, also presented in number of households powered and equivalent of cars taken off the road. Other aspects of O&M included in Vindby are economics and costs, stakeholder satisfaction and optimization.

The game design of the prototype is the result of multiple iterations. The interaction between the player and the game is achieved by two means, text input and output in the Python console as well as feedback in a Graphical User Interface (GUI). The GUI is shown in Figure 7.1. On the left side, information about the selected cell is displayed. If the cell contains a WF, WF KPIs like LCOE and failure rate are also provided. In the center, the sea grid is shown. Blue cells are cells that have not been interacted with, light blue cells (17,24,54,57) are cells that have been researched, yellow cells (35) indicate WFs under construction, green cells (22,34,48) contain WFs that are running and red cells (27) indicate WFs which are stopped due to failure. On the right hand side, general game information is shown, such as the total available funds and installed capacity. Information about the

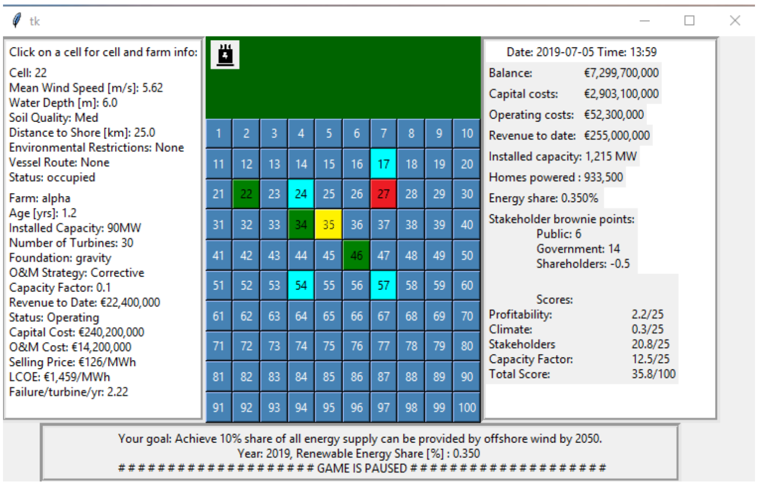

Figure 7.1: GUI of Vindby, including the sea grid (center), cell information (left), general game information (right) and information about the selected goal (bottom).

selected goal is shown at the bottom of the GUI.

7.4 Conclusions about outreach

The serious game presented in Paper A.10 can be used for training of engineers and researchers that need to gain insight into OWE, and as a dissemination tool to communicate the challenges of offshore wind to the general public. As a proof of concept, the small case study that was included in Paper A.10 has confirmed the serious game approach as a teaching method. This has been achieved by developing the game in a holistic way, integrating simplified OWF design and the design of a serious game. Nevertheless, the serious game Vindby is a simplification of reality, and the presented results should not be used in place of more complete engineering models. The main reason for the simplifications is to achieve playability, which would not be possible without some modifications to reality. The game Vindby comprises a playable and fully developed prototype. Since the development of a serious game for the wind industry actually presents an open-ended effort, as new technologies and models will be developed in the future, the game is however not complete and can be improved. One aspect that definitely needs improvement, preferably in cooperation with a game development team is the presentation of results and feedback through an improved GUI.

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Chapter 8

Conclusions and future work

8.1 Contributions

- The factors influential to maintenance scheduling have been identified in this thesis. This was done by conducting a review of the literature on the topic with a focus on decision support models. Chapter 2 of the thesis presents the collection of inputs to maintenance models in a single chapter. The underlying paper A.1 presents a comprehensive resource for inputs to maintenance modelling as well as the state of the art in modeling these factors.

- In addition to the literature review, some of the factors, namely the weather, weather forecast, repair duration, variation of the repair duration, component failures, vessel types, and electricity price have been investigated in Chapter 4, 5 and 6.

- In order to be able to include these factors in a decision support model, available modelling and optimization techniques were investigated in Paper A.1, and different modelling approaches have been applied throughout the thesis in Papers A.6, A.7, A.8, A.5, A.4, A.9 and A.10. The main approaches included Markov chain weather modeling, Monte Carlo simulations, statistical methods such as probability distribution fitting and drawing of distribution realizations, stochastic processes including the Langevin process and Markov decision process. Out of these modeling approaches, it is possible to support investigations of uncertainty. The stochastic processes have the advantage of being able to include the uncertainty in the model without relying on Monte Carlo methods.

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- In addition to identifying the influential factors and ways to model them, in Papers A.3 and A.2, summarized in chapter 3, indicators to monitor the important aspects of a WF asset have been presented. In collaboration with other PhD-candidates during a workshop, necessary properties for those indicators were defined in Paper A.3. Combined with the safety indicators, which are collected in a separate Paper A.2 and summarized in this thesis, the KPIs enable to monitor aspects of performance, reliability, maintenance, finances and safety. Currently, many different indicators are available in the field, and different companies and organisations use different metrics. The collection of indicators presented in the two research articles, and summarized in chapter 3 of the thesis, is therefor useful for both other researchers and the wind industry.

- In the investigations of the weather as an influential factor in 4, three different modelling techniques have been presented and evaluated. Additionally, in Paper A.5, the influence of the weather forecast was determined.

- The investigations of the repair duration as an input factor in 5 provide in depth knowledge about an input factor, that is often overlooked or omitted in maintenance models, possibly due to the lack of repair duration data. The analysis has shown the importance to account for variations in the repair time for WT components with a long mean time to repair, need for a small repair crew and those that can be repaired without need of a crane. This new knowledge has implications for both research and industrial application.

- As a means to increase the knowledge about offshore wind farms, a prototype of a serious game has been developed in Paper A.10. The game has the dual purpose of highlighting the main concepts of offshore wind to the general public as well as providing a learning tool for engineers starting a career in offshore wind energy. While the game still lacks validation for training purposes, the prototype shows the potential to help improve the player judgement of OWF design, operation and maintenance.

- One of the main challenges during the work on this thesis, which is also mentioned Paper A.1 as a general challenge in the research field of offshore wind, is the availability of data for the influential factors. Weather data is relatively easy to come by, and multiple public data sources exist. The fact that the weather is the influential factor included in most models, might even be due to the data being easily accessible and therefore conveniently included into the different modelling approaches. Information and data for failures, repair durations and spare part costs is only available on an aggregated level, possibly because of manufacturer rivalry. The WT manufacturers, who often cover the initial years of maintenance for the installed turbines, fear that providing data about the failure frequency and cost of repair might lead to a market disadvantage for them compared to their competitors. Worker salaries and vessel charter costs depend on many factors, like the season, type of vessel, oil price and naturally the country under investigation. Here it is challenging to find data that matches the specific conditions of a given case study, or based on the failure and repair data.

8.2 Conclusions

This thesis provides a summary of the factors influential to operations and maintenance planning for offshore wind farms. It provides indicators that can be used to measure different maintenance policies against each other and compare different wind farms, with a different location and/or different turbine types. Some factors, namely repair time and weather, have been investigated in detail and it was studied where taking into account uncertainty matters.

As an important input to maintenance modelling, different methods for weather modelling have been presented and discussed. Both of the methods that are frequently used in maintenance scheduling approaches are useful in different ways. ARMA models have the advantage of being flexible in use for both weather forecasting and time series generation. Markov chain models, while requiring the estimation of many more parameters, are straight forward to implement. They do not require extensive knowledge of the underlying data and are mostly based on probability of occurrence. However, it should be noted that assuming the Markov property for a given data set is a very strong assumption and should be validated before fitting a model.

The alternative weather model - the Langevin process - was shown to be a suitable alternative to ARMA and Markov chain models. Thanks to the structure of the process, fewer parameters need to be estimated from the data and therefore shorter time series of observations can be used compared to Markov chain models. Another advantage against Markov chain models is the handling of seasonality with multiple serial processes. The Langevin

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equations can directly be used to propagate the site specific weather conditions, without relying on time series simulation.

Investigations of the weather forecast have shown that allowing for a slightly reduced availability can significantly reduce the costs of maintenance.

The investigations of the repair times have shown that the variations in the repair time indeed influence the KPIs of OWFs. The three studies summarised in this thesis agree that the variations have the highest influence for those component failures with long repair times, which can be resolved using a CTV and a small maintenance crew. As all studies relied on assumed repair time distributions, investigations of the variations in actual repair time data should be carried out in the future.

The alternative approach to decision support modelling - MDP - has been shown to be a useful method for the investigated application. The case study confirmed the use of the method and additionally indicated an alternative maintenance strategy that might become more economical for future electricity prices.

The play-testing study with the serious game prototype has demonstrated the effectiveness of the game as a teaching tool and also revealed shortcomings in game development that should be improved in a future version of the game.

8.3 Recommendations for future work

- This thesis has shown the importance of variations in the repair times and uncertainties in the values used. As the availability of repair data is always limited, those researchers that are able to investigate operational data should in future studies investigate the nature of variations in the available data. It is assumed that this knowledge can be used to improve the models used to plan the scheduling of both preventive and corrective maintenance.

- Similar to the investigations with an alternate renewal process for exponential distributions, alternative distributions could be investigated. Most of these investigations will need to be conducted using numerical methods.

- The Markov Decision Process that has been presented in this thesis can be extended in many ways to include multiple turbines, different vessel types, shift lengths and work-time restrictions, and of course it can be extended to automate the optimization of the policy.

- To capture the correlation between wave heights and wind speed, a multi-variate Markov chain approach was presented by [67] - the Langevin approach presented in this thesis can be generalized as two-dimensional Langevin process in order to represent this correlation in a process with fewer parameters.
- It is recommended to investigate further the properties of the weather with regards to a possible underlying scale invariance. The time-series produced by the Langevin equations should theoretically not be able to model wind speeds at the scale that the approach was used at - however the properties of the simulated weather are so close that this cannot be seen from the application. An underlying invariance could explain this phenomenon and this should be investigated further and with data from other measurement resources.
- Combining together all the investigated ways to eliminate Monte Carlo simulations and building a comprehensive decision support tool based on closed form inputs is an interesting new approach. It is recommended to build this decision support model that does no longer rely on Monte Carlo methods.
- The serious game that has been presented as a teaching tool, can be extended in many ways and should be tested on a larger sample group in order to validate its usefulness for training purposes.

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Appendix A

Appended Papers

A.1 Paper 1

Decision Support Models for Operations and Maintenance for Offshore Wind Farms: A review.

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Review

Decision Support Models for Operations and Maintenance for Offshore Wind Farms: A Review

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Abstract: This paper reviews the state of the art in offshore wind farm operations and maintenance with a focus on decision support models for the scheduling of maintenance. Factors influential to maintenance planning are collected from the literature and their inclusion in state-of-the-art models is discussed. Methods for modeling and optimization are presented. The methods currently used and possible alternatives are discussed. The existing models are already able to aid the decision-making process. They can be improved by applying more advanced mathematical methods, including uncertainties in the input, regarding more of the influential factors, and by collecting, analyzing, and subsequently using more accurate data.

Keywords: maintenance scheduling; decision support; offshore wind; review; operation and maintenance; failure modeling; weather modeling; reliability data; vessel routing; maintenance cost

1. Introduction

The demand for energy from offshore wind parks is rising and the offshore wind industry is growing fast [1–3]. Currently, up to a third is the cost of energy can be attributed to maintenance cost [4]. In the last decade a rising number of researchers has been working on approaches to lower these costs. Condition monitoring can give a better overview of the turbine status and increase the detection rate of failures before they occur. Preventive maintenance can then stop these failure failures from happening, reducing unexpected downtime. Also, the strategy of how to handle unexpected failures and corrective maintenance has been the focus of research.

Many factors, such as probability of failures and weather conditions, influence the choice of maintenance strategy and including all of them when taking an informed decision can be challenging for human decision makers. A decision support system can be used to facilitate the choice. Decision support systems (DSS) arose shortly after the invention of modern computers and are now used across industries. Power [5] presents a brief history of the development of DSS from the 1960s to the early 2000s. Early definitions of DSS were broad and included any type of computerized system to aid human decision makers. Over time, different branches of decision support emerged. In Kessler [6], David L. Olsen summarized five types of DSS presented by Power [5]. These are communication-driven, data-driven, document-driven, knowledge-driven, and model-driven DSS. A communication-driven DSS supports the communication, when multiple people work together on a task. Data-driven DSS focus on data access and the use and manipulation of data. In document-driven DSS text manipulation is in focus, managing unstructured information. Knowledge-driven DSS present expertise in form of rules or procedures. This often overlaps with communication- and document-driven DSS. Model-driven DSS highlight statistical or operation research modeling. In the case of offshore wind farm operations and maintenance scheduling, model-driven decision support can be used.

In this review article, we present the current state of the art in operations and maintenance decision support research for offshore wind farms. In their review of operation and maintenance of wind power assets El-Thalji and Liyanage [7] observe that the main academic contributions in the field are on condition monitoring, diagnostics, and prognostics. During the literature research for this paper, the present authors have gotten the same impression of the field. We do not want to exclude condition monitoring from our analysis. However, the aim is to focus on maintenance scheduling in the present paper. Hofmann [8] has presented a review of decision support models for operation and maintenance planning in 2011. With this review we want to cover the development since 2011 and focus on the modeling details. In Section 2 we explore which factors are influential to the decision. The individual factors, how they are considered in recent literature and how the decision support tools model these factors are discussed in Sections 2.1–2.5. The maintenance strategy and different kinds of maintenance are discussed in Section 3. Different modeling techniques are investigated in Section 4, this includes methods currently used in decision support models for offshore wind farm maintenance scheduling. Section 5 reviews optimization techniques and discusses those techniques currently used in maintenance scheduling models for offshore wind farms. The availability of data and data used in the existing models and tools are discussed and presented in Section 6 before we discuss the results in Section 7 and conclude the paper in Section 8. Throughout the paper, references to the literature are ordered chronologically first and alphabetically within the year of publication.

2. Operation and Maintenance: Influential Factors

When scheduling maintenance for offshore wind farms, many different factors need to be considered. Many different researchers analyzed the influences on the maintenance and presented similar results. According to most publications, the factors influencing the planning and cost of maintenance are the occurrence of failures, availability of maintenance crew, spare parts and vessels, weather and external factors, the chosen maintenance strategy, and economical parameters such as the electricity price and subsidies. While laws and legal restrictions also influence the operation of offshore wind farms, they are only included in the models in form of working-hour restrictions and often not included at all. This is possibly due to the fact, that a wind farm maintenance provider or operator cannot wield influence on these factors. Table 1 summarizes the factors mentioned by the different authors.

Table 1. This is a table summarizing the factors influential to the offshore wind farm operation and maintenance scheduling.

Publication	Factors Mentioned
Henderson et al. [9]	accessibility, reliability
Nielsen and Sørensen [10]	weather, power production, damage, inspections, repairs, transport strategies, rate of interest on capital
Dinwoodie et al. [11]	failures of turbines, repair time, wave height, wind speed, weather windows, the number of turbines, vessel availability, spares provisions
Scheu et al. [12]	weather, component failures, vessel fleet size, vessel type, size of the maintenance crew, travel time, maintenance strategy
Besnard et al. [13]	location of maintenance accommodation, crew transfer vessels (type and number), use of helicopters, work shift organization, spare part stock management, technical support, crane ship availability (purchase or contracting), environmental conditions (dependent on time and season), economical parameters (electricity prices, vessel charter costs)
Dinwoodie et al. [14]	as Dinwoodie et al. [11] and costs
Halvorsen-Weare et al. [15]	investment costs, vessel costs (time charter, variable costs), failure probabilities, downtime costs, weather data

Table 1. *Cont.*

Publication	Factors Mentioned
Hofmann and Sperstad [16]	weather (including uncertainty), failure rates, electricity price, price for vessels (costs, fleet composition, types, quantity), workers (shift length, quantity), location of maintenance base, types of maintenance
Endrerud et al. [17]	component failures, weather conditions, vessels (availability, operational limits, costs), maintenance technicians, repair time, wind farm layout, cost of spare parts, logistics (warehousing and other costs)
Perveen et al. [18]	protection methodologies, the occurrence of cable faults and component failures, the repair strategy, wind speed forecasts and condition monitoring systems
Sperstad et al. [19]	as Hofmann and Sperstad [16]
Dalgic et al. [20]	climate parameters (wind speed, wave height), transportation systems (weather constraints, mobilization time, charter costs), turbine specific information (power curve, failure distribution), costs
Endrerud and Liyanage [21]	local weather, turbines, failures, vessels (operational limits, charter costs), costs of spare parts, electricity market price, maintenance crew
Sahnoun et al. [22]	turbines (rating and quantity), distance from shore, wind quality, water depth, accessibility, availability of workers, spare parts, boats and cranes, failure modes
Shafiee et al. [23]	failure rate of subsystems, delivery time of spare parts, availability of transport vessels, accessibility (weather dependence)
Gintautas and Sørensen [24]	vessel specific weather limits (wave height, wind speed), weather forecasts, operation failure
Raknes et al. [25]	transportation costs, downtime costs, penalty cost for postponed maintenance, technician transfer time, vessel properties (two types), weather conditions
Rinaldi et al. [26]	dynamics of the farm, repair time, spare part stock, interaction among components, accessibility (wave height, wind speed), turbines (rating and quantity), met ocean data, failure distributions, vessel mobilization time
Nguyen and Chou [27]	system reliability, cost effectiveness, weather condition, maintenance duration, production loss during maintenance, market electricity price, wind farm location

In the following subsections, we comment on the individual influencing factors presented in the literature. First, we investigate the modeling of degradation and failures. Next, we discuss the availability of maintenance supply, such as crew, vessels, and spare parts. Then, the routing of vessels and transportation are discussed. Subsequently, weather modeling, the uncertainty in weather and forecasts is presented. Finally, this is followed by economical parameters and cost estimation.

2.1. Degradation and Failure Modeling

The occurrence of a failure in a wind turbine in a wind farm gives rise to a necessary repair and forms the cause of any maintenance action. Since the occurrence of a failure directly causes maintenance actions and is therefore the reason for the connected costs, the existing analyses are concerned with the probability and frequency of failure occurrence. The main difference between different tools/models is the way the failures are presented. In some of the publications, historic operational data is used to estimate the failure behavior. In some cases, failures are assumed to occur after a certain amount of time, the occurrence of failures is therefore modeled in a deterministic way. The mean time between failure (MTBF) can be calculated from observed failures and is often used for this deterministic modeling. In other models, failures occur with a certain probability that is assessed based on collected data, so the failures are occurring randomly according to a defined probability distribution. To model from this probability distribution, samples are drawn from the distribution(s). Popular processes for failure distribution modeling are (homogeneous) Poisson processes (In a Poisson process, the probability of having a certain number n of (failure) occurrences $N(t)$ at time t is: $P(N(t) = n) = \frac{(\lambda t)^n}{n!} e^{-\lambda t}$), where the time intervals between failures are exponentially distributed, according to a given failure rate λ. In some models, the failure rate can be updated, leading to an inhomogeneous Poisson process, with a failure rate function $\lambda(t)$. Other distributions that are being used to sample the time between failures are the Weibull distribution (the Weibull distribution is a continuous probability distribution with density function $f(x) = \frac{k}{\lambda} \left(\frac{x}{\lambda}\right)^{k-1} e^{-(x/\lambda)^k}$), Gamma process (A Gamma process is a stochastic process, comprised of increments that are independently Gamma distributed, with density functions: $f(x) = \frac{\lambda^{\gamma t}}{\Gamma(\gamma t)} x^{\gamma t-1} e^{-\lambda x}$, where $\Gamma(\cdot)$ is the Gamma function.) and Bernoulli process (A Bernoulli process is a discrete stochastic process taking two different values and is comprised of a sequence of binary random variables). A summary of the different methods used to model degradation and failures in the literature is presented in Table 2.

Table 2. This table summarizes the methods used for degradation and failure modeling presented in the literature.

Publication	Failure Modeling	Degradation Modeling	Number of Components
Eecen et al. [28]	operational data		
Obdam et al. [29]		updated failure rates	
Nielsen and Sørensen [10]		damage growth function	
Dinwoodie et al. [11]	Markov chain, Poisson distributed failures	Weibull distributed failure rate	4
Douard et al. [30]	Poisson distributed failures	Weibull distributed failure rate	
Scheu et al. [12]	Poisson process		12
Dinwoodie et al. [14]	Weibull distributed failures		
Halvorsen-Weare et al. [15]			4
Hofmann and Sperstad [16]	Bernoulli process		3
Asgarpour and van de Pieterman [31]	component specific failure rate	updated based on data	
Endrerud et al. [17]	non-homogeneous Poisson process	Weibull distributed failure rate	19
Shafiee and Finkelstein [32]	Poisson process	Gamma process	bearings only
Sperstad et al. [19]	Bernoulli process		3
Dalgic et al. [20]	component specific failure rate		
Endrerud and Liyanage [21]	non-homogeneous Poisson process	Weibull distributed failure rate	19
Joschko et al. [33]	occurrence probability		including errors
Sahnoun et al. [22]	Poisson process	time-based and random	
Abdollahzadeh et al. [34]	Weibull distributions		4
Alaswad and Xiang [35]		discrete deterioration: Markov process continuous deterioration: Wiener process, Gamma process and Inverse Gaussian process	

Table 2. *Cont.*

Publication	Failure Modeling	Degradation Modeling	Number of Components
Asgarpour and Sørensen [36]	Poisson process	time-based degradation (electrical) discrete deterioration (mechanical) continuous deterioration (structural)	3
Pliego Marugán et al. [37]	Poisson process, periodic failures	constant failure rate, exponential increase, linear increase	4
Tibaldi et al. [38]		linear fatigue accumulation	
Rinaldi et al. [26]	Poisson process, Weibull distributed	adjusted failure rates (based on maintenance, fault category, environmental conditions)	
Scheu et al. [39]	9 different distributions		12
Welte et al. [40]		stochastic degradation process	
Nguyen and Chou [27]	time-based failure rate	Weibull distribution	6
Stock-Williams and Swamy [41]	operational data		
Wang et al. [42]		Weibull distributed lifetime	

2.2. Vessel, Personnel and Spare Part Logistics

To repair the defects and failures occurring in the offshore wind farm, there are three main requirements. The availability of maintenance workers that are trained to conduct the respective maintenance tasks is crucial. Many repairs need not only a repair team and tools, but also specific spare parts. The availability of those poses another restriction to performing the maintenance and should therefore be included in any maintenance model. To transport both workers and spare parts to the offshore location, transport vessels are required. Therefore, the availability of those presents another part of maintenance analysis and should be included in any model. Additional to the transport vessels, some repairs require jack-up barges or crane vessels. This includes gearbox replacements and blade repair. Most existing models include at least one of the factors.

Scheu et al. [12] consider in their decision support model two different vessel types, with specific weather restrictions. Additionally, the crew size varies for different turbine components and each vessel has a fixed crew capacity. Besnard et al. [13] present a model for an offshore wind farm. With this model, they optimize the number of maintenance technicians, length of shifts, location of accommodation and the choice of transfer vessels and helicopters. In the presented case study, an offshore accommodation with technicians available at any time was favored. For the optimal transport of the workers to the turbines, a crew transfer vessel with an improved access system was chosen. To find the optimal vessel fleet size and composition is the goal of Halvorsen-Weare et al. [15]. They present a mixed-integer program and compare 15 different instances. Hofmann and Sperstad [16] consider different combinations of vessel types, with different abilities and access restrictions, as well as different ownership models (purchasing the vessel, chartering the vessel). Spare parts are always considered available, with a fixed lead-time and cost. In the logistics module of Asgarpour and van de Pieterman [31] an equipment analysis, spare part analysis and repair class analysis is included. Endrerud et al. [17] include a deterministic waiting time for spare parts depending on the failure type. The number of technicians and vessels needed is also determined by the failure type. Only one type of technicians is considered. Three different vessel types can be chosen in the model, with different charter contracts. In Sperstad et al. [19] a deterministic optimization of the vessel fleet size and the decision whether to purchase or charter vessels is presented. They also consider different locations for the maintenance base. In their model, Dalgic et al. [20] consider four different transportation systems, a crew transfer vessel, a helicopter, an offshore access vessel and a jack-up vessel. Each system has a specific maximum number of workers it can carry as well as type specific access restrictions, travel times and mobilization costs. The shift length for the maintenance workers is 12 hours. Each worker can only be assigned to one turbine per shift. Endrerud and Liyanage [21] is based on Endrerud et al. [17] and the number of technicians and vessels needed as well as the wait time for spare parts is determined by the failure type. In Sahnoun et al. [22] the availability of vessels, spare parts and cranes is considered. The personnel are divided into electricians and technicians and the availability of spare parts in unlimited. A review of the organization of maintenance logistics was done by Shafiee [43]. He classifies the spare parts inventory management and the maintenance support organization (vessels, cranes, helicopters, personnel) as a tactical issue in offshore wind farm maintenance logistics. Gintautas and Sørensen [24] present constraints for both installation and O&M vessels given in the previous literature by Dinwoodie et al. [44], Besnard et al. [13], Nielsen and Sørensen [10], O'Connor et al. [45], Van Bussel and Bierbooms [46], O'Connor et al. [47], McMillan and Ault [48], Wu [49] and Ahn et al. [50]. Raknes et al. [25] consider two different vessel types—an accommodation vessel and a crew transfer vessel, in their analysis. The vessels vary in properties, such as capacity and weather conditions. Rinaldi et al. [26] consider the spares in stock and a procurement time as well as different types and numbers of vessels, both rented and purchased in their model. The model also allows for helicopters to be used.

2.3. Transportation and Vessel Routing

In addition to the availability of crew, spare parts and vessels, the transport of crew and parts to the offshore wind turbine must be organized. Therefore, a route must be established for the vessels to unload and pick-up crew and parts. Those tasks requiring a vessel or crane at the turbine need to be scheduled in the vessels route as well.

Van Bussel and Bierbooms [46] analyzed the transport of crew and small parts for the DOWEC reference wind farm [51]. They combine five different vessel types and four different maintenance categories. Their simulation shows that high availability can be achieved for a hard to access farm, by optimizing the access system and maintenance strategy. Three different transport options are considered by Nielsen and Sørensen [10]. The simplest option is to always access the wind turbines with a boat if a repair needs to be conducted. Option two is to conduct the repair as soon as possible, using a helicopter if access with a boat is restricted due to waves. The third option is to do a risk-based analysis to determine the transport alternative. Here the cheapest solution, including production losses, is calculated based on a weather forecast that is assumed to be perfect. Halvorsen-Weare et al. [52] investigate fleet composition and vessel routing for offshore oil and gas industries. Their optimization model provides weekly routes and schedules for the vessels. Since offshore wind turbine maintenance vessels differ from offshore supply vessels and since the needs for corrective maintenance and immediate access are hard to plan very far ahead, the model needs to be modified to solve vessel routing problems for offshore wind. Hofmann and Sperstad [16] do not model the vessel routing but consider a fixed travel time for each vessel type from the maintenance base to the wind farm instead. In Endrerud et al. [17] and Endrerud and Liyanage [21], vessels travel the shortest distance between their location and destination. A vessel specific speed is used to calculate the travel times. However, no optimization of the routing takes place. Sperstad et al. [19] compare different access restriction for the vessel routing. They use both single- and multi-criteria restrictions and show that a single value limit (significant wave height) is sufficient, as long as the value is estimated in a correct way. Dalgic et al. [20] consider three types of transportation, with a different routing plan each. For the crew transfer vessels and helicopters, the first mobilized transport system is routed such that the number of turbine visits is maximized, while minimizing the total number of vessels/helicopters used. The workers are dropped off at the turbines and later collected, such that the vessel/helicopter is free to travel within the wind farm during the shift. Tasks that can be completed within one shift are prioritized. The offshore access vessel visits the turbines sequentially and stays at the turbine while the maintenance is conducted, it is only limited by daylight and weather restrictions. Also, the jack-up vessel visits the turbines that need maintenance in sequence and is limited by weather restrictions. Halvorsen-Weare and Fagerholt [53] present two models for solving the offshore supply vessel routing and scheduling problem. As for the model in Halvorsen-Weare et al. [52], modifications are necessary to apply the models to offshore wind. Martini et al. [54] present an accessibility analysis for the North Sea. They investigate two different vessel types and present the access restrictions for them. Raknes et al. [25] present a vessel routing and maintenance scheduling model. They compare different vessel fleet compositions with a commercial mixed-integer programming solver and two rolling-horizon heuristics. In their model Rinaldi et al. [26] consider a mobilization and a response time for the vessels as well as operational limits for the vessels and restrictions for overnight work. Therefore, they also include a model to calculate the sunrise and sunset times for each day. Schrotenboer et al. [55] present a two-stage adaptive large neighborhood search to solve the technician allocation and routing problem. The optimization presented by Stock-Williams and Swamy [41] aims to find the optimal daily maintenance vessel routing and repair schedule.

2.4. Weather and External Factors

Rothkopf et al. [56] present a Markovian wave height model that uses tri-diagonal transition matrices. This model can be used in any Monte Carlo simulation for offshore simulations. Anastasiou and Tsekos [57] present a study on the persistence of different marine environmental parameters based on Markov theory. They assume that the process governing the distribution of the persistence of marine environmental conditions can be regarded as a stationary first order Markov process. The transition matrix for this Markov process can be established from recorded weather data. They use a discrete time Markov chain and compare the transition matrix of the original Markov process with a simplified two-by-two matrix with transition probabilities from below and above a certain threshold. According to their investigations, six to eight different states in the Markov model are sufficient to adequately model the marine environmental parameters. Finally, they also show that the Markov model has a better performance than the Kuwashima-Hogben model [58] in terms of persistence distribution. Monbet and Marteau [59] present a continuous-space discrete time Markov model of higher order to model significant wave height peak period and wind speed. The Markov model can be used to generate new sequences of the time series. Lange [60] investigated the uncertainty of wind speed forecasts and found that the statistical distribution of the prediction errors (deviation between predicted and measured wind speed) is Gaussian. Dinwoodie et al. [11] use autoregressive (AR) models to model both the wave height and wind speed. For the wind speed an AR model of order 2 is used and for the wave heights an AR model of order 20 is used. To use these AR models some transformations of the data must be conducted. For the wind speed, a fit of the monthly mean and diurnal variations must be removed. For the significant wave height, a fit of the monthly means is removed, and a Box-Cox transformation is applied. Douard et al. [30] use a hidden Markov model (HMM) to calculate the waiting time for each failure. This HMM calculates the waiting time based on meteorological site characteristics, seasonality is respected, the HMM is robust to model uncertainty and the variability in the meteorological site conditions is preserved. Scheu et al. [12] on the other hand use a discrete time Markov chain model to generate time series of the wave height. The wind speed is generated according to a correlation matrix. Dinwoodie et al. [14] use a multivariate autoregressive time series to model correlated wind speeds and wave heights. Feuchtwang and Infield [61] calculate the maintenance delays due to sea state with a closed form probabilistic model. In their model, they consider access restrictions and a Weibull distribution for the weather, fitted to represent the conditions of a given site. Hagen et al. [62] present a multivariate Markov model to generate sea state time series. The sea state is a combination of wind speed, wind direction, wave height, wave direction and wave period. They present two ways of capturing the seasonal variation within the sea state. The first method is to use monthly models assuming piece-wise stationarity. The second model uses a data transformation to deal with the seasonal variation. In their simulation model, Hofmann and Sperstad [16] use a Markov chain process to simulate weather time series. They assume a perfect weather forecast for the duration of the next shift. The met ocean module from Asgarpour and van de Pieterman [31] uses re-sampling of wind and wave data and provides wind shear model parameters as well as operational limits for each equipment type in addition to the time series for wind speed and significant wave height. Endrerud et al. [17] use significant wave height and wind speed at hub height in hourly resolution as input to their model. The only uncertainty is therefore the variation within the given data. For the simulation of the weather in the model Sperstad et al. [19] use the simulation model from Hofmann and Sperstad [16]. Dalgic et al. [20] also use a multivariate autoregressive model to generate synthetic weather. They use sea level wind speeds for the access restrictions and hub height wind speeds for the maintenance with a jack-up vessel and for production. For the wave climate, wave heights and wave periods are used. With this model, they maintain the persistence, seasonality and correlation between wind speed, wave height and wave period of the site-specific weather. Endrerud and Liyanage [21], such as Endrerud et al. [17] use the significant wave height and wind speed at hub height as input. Joschko et al. [33] in their simulation of offshore wind farm O&M processes use stochastic weather. The weather is generated inside the model according to a distribution that is taken from actual wind farm data. As an influence on the production and degradation wind speed, wave height, lightning and visibility are used Sahnoun et al. [22]. Abdollahzadeh et al. [34] take into account only the wind speeds at the location of the wind farm and model these according to a Weibull distribution. Ambühl et al. [63] model the uncertainty in the weather forecast by adding an error term to the weather forecast to calculate the actual weather, using the knowledge about normally distributed errors from Lange [60]. Gintautas and Sørensen [24] base their weather window predictions on weather forecasts and an acceptance criteria exceedance event formulation and present two case studies. The uncertainty in the weather conditions in this case stems directly from the uncertainty in the weather forecasts. They achieve a prediction of longer weather windows with their improved model. Hersvik and Endrerud [64] present a weather series generator using a piece-wise Markov chain process. In their model, there exists no transition probability matrix, but instead a piece of the original time series of random length is copied from a random place in the time series with the same transition between weather states. The model includes seasonality by looking at the current month for a transition first and only looks outside of the current month if the specific transition cannot be found there. The benefit of using piece-wise copies of the original time series is the high detail level in the generated time series that is lost, when transition probabilities between weather states are used. Martini et al. [54] presented a new approach to wind farm accessibility. In addition to previous accessibility studies, they also include spatial variability in wind speeds and wave heights. Their accessibility analysis is conducted for long-term accessibility and in high resolution. The model in Rinaldi et al. [26] uses time series as an input and requires a minimum weather window to conduct maintenance. A stochastic process for weather generation has been presented and investigated by Seyr and Muskulus [65]. The advantage of this method is that it can be used as an alternative to simulation-based generation models. Taylor and Jeon [66] present approaches of probabilistic forecasting of the wave height. The presented approaches are ARMA-GARCH models that might be applied to decision-making in the future as an alternative to other forecasting methods.

2.5. Economic Parameters and Cost Estimation

The goal of effective maintenance scheduling will be the maximizing of economic profit. Therefore, economical parameters such as electricity price or feed-in-tariff (FIT), cost of vessel hire, cost of spare parts and worker salaries are an important input to maintenance modeling. While electricity price or FIT are usually used to calculate the profits of a wind farm or electricity costs for other industries, when used in maintenance models, it is used to calculate the production loss from turbine downtime. Vessel hire, worker costs and cost of spare parts have a direct influence on the maintenance costs. Many models include fixed rates for the vessel hire, worker and spare part costs, while some of the existing models try to include variable vessel and worker costs.

Dinwoodie et al. [11] mention two ways to calculate the production loss. The basic method is to use the rated power of the turbine and multiply it by a capacity factor and length of downtime. A more accurate approach is to use a time series of the wind speed and determine the lost revenue from a power curve. In addition to the lost revenue, also costs due to vessel and staff hire, and component replacement must be considered. In Douard et al. [30] the cost estimation has both a deterministic and a probabilistic part. The deterministic part includes the capital cost, operational costs for fixed and preventive maintenance as well as the monitoring of the turbines. The probabilistic cost is corrective maintenance and condition-based maintenance which depend on the failure rates. Both deterministic costs and probabilistic costs include direct and indirect costs. The direct costs include the labor, transport, spare parts costs, and indirect costs being caused by the downtime (dependent on the maintenance duration) and the waiting time (dependent on the weather). Scheu et al. [12] focus in their decision support model on the production losses due to downtime. They are calculated by using a linearized power curve, the wind speed, and a FIT for the UK. Dinwoodie et al. [14] estimate cost distributions for different maintenance scenarios. They base the cost estimation on four different vessel charter scenarios, with different charter rates. Additionally, they include fixed mobilization costs and seasonality of the costs. The cost distribution is then derived via regression analysis. Hofmann and Sperstad [16] present the net present O&M costs including spare part and consumable costs, vessel costs, personnel costs as well as cost for using locations such as harbor and costs for transporting personnel to locations such as mother ships and offshore platforms. In addition to the net present O&M cost they also present the net present value of profit and the net present income based on electricity production. Asgarpour and van de Pieterman [31] present in their report the operation and maintenance cost estimator project by ECN. The cost estimator includes the operation and maintenance, logistics as well as met ocean modules. Endrerud et al. [17] include generic repair and replacement costs as well as vessel day rates, salary costs, warehousing costs, overhead costs, spare part costs, rent, taxes and insurance in their decision support model. They encourage the user to provide more accurate data to get a more accurate output, i.e., lost production and marine logistics cost, that is generated by the simulation. Dalgic et al. [20] in their analysis consider electricity price, fixed vessel cost, vessel charter costs, technician costs, fuel cost, cost of preventive maintenance, component repair cost and insurance cost. They use different costs for helicopters, crew transfer, offshore access and jack-up vessels and report the numbers used as input in their analysis. Endrerud and Liyanage [21] is based on Endrerud et al. [17] and the same costs are included. Sahnoun et al. [22] consider maintenance action costs, the energy cost, installation of monitoring systems. The costs depend on the failure type, the maintenance type the maintenance duration, weather conditions during the maintenance action and the cost of maintenance facilities as given from Nilsson and Bertling [67] as well as considering the production losses. Asgarpour and Sørensen [36] use the ECN O&M tool from Rademakers et al. [68] in their case study to estimate the total O&M costs. They consider all costs associated with inspection, monitoring, maintenance activities and revenue loss due to downtime and calculate the cost for each possible outcome in their decision tree. Shafiee et al. [23] consider in their cost model operation costs including rental payments, insurance, and transition charges (grid), as well as maintenance costs including both direct (transport of components, technicians, consumables, and spare parts) and indirect (port fees, weather forecast) maintenance costs. Rinaldi et al. [26] consider replacement costs for spare parts.

3. Maintenance Strategy

Shafiee [43] presents three different categories of issues in offshore wind farm maintenance planning. These are technical, strategic, and operational issues. The technical issues are covered by the failures. Operational issues are comprised of availability of vessels, crew, and spare parts, the weather and other external and economic factors. For the strategical issues, choosing the optimal maintenance strategy is the challenge wind farm operators are facing in their work. Therefore, any maintenance scheduling model should be able to incorporate and evaluate different maintenance strategies. Most models compare some fixed input scenarios or optimize certain aspects of the strategy, such as fleet size and grouping of repairs. All these approaches have the drawback that the operator or researcher using the model must already have an idea of how the maintenance can be improved and be familiar with the factors that influence the scheduling of maintenance. A maintenance model that can also optimize the maintenance strategy without input from the operator or a researcher, does not yet exist. However, since a well-developed model could be used by persons who are not familiar with the problems of offshore maintenance scheduling, the development of such a model is highly encouraged. Krokoszinski [69] wrote that an optimal O&M strategy should strive to maximize the total overall equipment effectiveness, which is the product of the planning factor and the overall equipment effectiveness. The overall equipment effectiveness is the factor between the valuable production time and available production time (equal to productivity). The total overall equipment effectiveness is the actually valuable production time with respect to the theoretical production time, so it includes e.g., downtime losses.

An overview over the different models and which kinds of maintenance they include is presented in Table 3. More details about the different kinds of maintenance are presented in the following subsections.

Table 3. This table summarizes the use of different types of maintenance in the literature.

Publication	Preventive Maintenance	Condition Monitoring	Condition-Based Maintenance	Corrective Maintenance
Van Bussel and Bierbooms [46]	✓			✓
Nilsson and Bertling [67]	✓ [1]	✓ [1]		
Nielsen and Sørensen [10]			✓	✓
Douard et al. [30]	✓	✓ [1]	✓	✓
Fu and Yuan [70]			✓	
Scheu et al. [12]				✓
Hofmann and Sperstad [16]	✓		✓	✓
Endrerud et al. [17]	✓			✓
Shafiee and Finkelstein [32]	✓			
Sperstad et al. [19]	✓		✓	✓
Yang et al. [71]		✓ [2]		
Endrerud and Liyanage [21]	✓			✓
Dalgic et al. [20]	✓			✓
Sahnoun et al. [22]	✓		✓	✓
Abdollahzadeh et al. [34]			✓	✓
Alaswad and Xiang [35]			✓ [2]	
Ambühl et al. [63]		✓		
Asgarpour and Sørensen [36]	✓			✓
Bach-Andersen et al. [72]		✓		
Helsen et al. [73]		✓		
Pliego Marugán et al. [37]	✓			✓
Pattison et al. [74]		✓	✓	
Shafiee et al. [23]	✓			✓
Raknes et al. [25]	✓			✓
Rinaldi et al. [26]				✓
Leite et al. [75]			✓	
Welte et al. [40]			✓	
Artigao et al. [76]		✓ [2]		
Nguyen and Chou [27]				✓
Wang et al. [42]	✓			✓

[1] Cost only. [2] Review.

3.1. Preventive Maintenance

Preventive maintenance is a kind of maintenance that is conducted pro-actively before the occurrence of a fault or failure. Without any prior knowledge of the timing of failures, preventive maintenance is planned to be conducted in a fixed time interval. Preventive maintenance can return a (degrading) component to an "as-good-as-new" state or lower the degradation by a fixed amount. Different models include preventive maintenance in different ways.

Van Bussel and Bierbooms [46] include regular preventive maintenance tasks in their model. Hofmann and Sperstad [16] consider time-based preventive maintenance in their model, defined by a fixed time interval, returning a components state back to its original value. Shafiee and Finkelstein [32] investigate different grouping strategies for age-based maintenance of wind turbine bearings. Endrerud et al. [17] and Endrerud and Liyanage [21] provide the possibility to include preventive maintenance as well as corrective maintenance tasks. The preventive task they mention are inspections, certification, and annual service. The preventive maintenance has no influence on the failure rate and occurrence of failures in their model. Dalgic et al. [20] present three different strategies, all involving preventive maintenance. In one strategy, workers are allocated to corrective and preventive maintenance tasks randomly. In the other two strategies, the corrective tasks are assigned first. In the third strategy, preventive maintenance is only conducted after corrective maintenance, with the time that is left in a worker's shift. They do not specifically state in which state a turbine is returned after preventive maintenance, it can be assumed to be "as good as new". Sahnoun et al. [22] consider systemic preventive maintenance on a time-based defined schedule. This is the most effective with regular degradation. Asgarpour and Sørensen [36] look at two different types of preventive maintenance, namely major and minor preventive maintenance. In Rinaldi et al. [26]'s model, preventive maintenance is considered and restores the component's reliability values to their initial states. In the model it is scheduled before any incident or failure. Wang et al. [42] include preventive maintenance at fixed time intervals in their analysis.

3.2. Condition Monitoring

Condition monitoring is a way to measure the state of a component, used to predict failures and schedule pro-active maintenance tasks. Different kind of condition monitoring exist, Artigao et al. [76] provide a review of the state of the art. Nilsson and Bertling [67] present the life cycle costs for two different case studies with a condition monitoring system. The case studies include the system data, maintenance contracts, scheduled maintenance, and the maintenance manuals. The data used comes from two offshore wind farms, the Olsvenne 2 and Kentish Flats. Fu and Yuan [70] also present a condition monitoring approach. They discuss the deployment and communication of sensor modes and finally conclude with an example. Yang et al. [71] present a review of condition monitoring. They present requirements for wind turbine condition monitoring systems, applicable techniques, commercial systems and signal processing techniques and issues. Finally, they investigate future development. Ambühl et al. [63] include an uncertainty of detection of damages during inspection and model this with a probability-of-detection curve. In their case, this is a one-dimensional threshold of detection. Bach-Andersen et al. [72] presented a purely data-driven predictive model for rotor bearing faults. The model is based on gearbox thermal sensors and provides robust prediction of faults, while being cheaper than vibration-based approaches. Helsen et al. [73] present an analysis of long-term monitoring. They present data storage issues, such as data acquisition, signal processing and data warehousing. They further present the data intelligence perspective and a case study. Condition monitoring is not included in the model form Rinaldi et al. [26] as they aim to reduce the reliance on monitoring.

3.3. Condition-Based Maintenance

Condition-based maintenance is a type of pro-active maintenance, conducted before an occurrence of a fault or failure that is based on the condition of the component. To conduct condition-based maintenance, condition monitoring or prediction of the condition of the components is necessary. There exist some recent publications reviewing condition-based maintenance techniques and condition-based maintenance optimization. Many publications focus only on condition-based maintenance, but some of the maintenance scheduling models also include condition-based maintenance. Hofmann and Sperstad [16] consider condition-based maintenance in their simulation. Sahnoun et al. [22] consider condition-based maintenance with information from the monitoring system being used together with a fault tree to diagnose the root causes of upcoming failures. Alaswad and Xiang [35] review existing condition-based maintenance optimization models. They conclude that most existing models focus on individual components. The optimization criterion is based on cost minimization, availability maximization and can also be multi-objective. Pattison et al. [74] propose a model where the maintenance schedule is based on reliability modeling. They start with a theoretical foundation of the reliability module and add dynamic degradation to it. This reliability/degradation module is updated with input from condition monitoring. The model then estimates the results under different maintenance actions. In this way the best maintenance strategy for the observed situation can be found. Leite et al. [75] summarize and review different condition-based maintenance techniques and state further needs for condition-based maintenance—especially the need for more "run to failure" data. Welte et al. [40] present two options to include condition-based maintenance into an existing maintenance decision support tool.

3.4. Corrective Maintenance

All maintenance that does not fall under any of the above-mentioned categories can be called corrective maintenance. Corrective maintenance is defined by the European Committee for Standardization [77] as "maintenance carried out after fault recognition and intended to put an item into a state in which it can perform a required function". Maintenance actions that are performed to correct a faulty or defect components still account for most maintenance actions in offshore wind farms. Since they cause unplannable downtime to a wind turbine or parts of the wind farm if cables or converters are affected, they should be conducted as efficiently as possible. To ensure fast replacements and repairs of components—restoring them to an operational state—DSS are beneficial.

Scheu et al. [12] presented a model that includes exclusively corrective maintenance. Hofmann and Sperstad [16] consider corrective maintenance in their model. It is given priority over preventive and condition-based maintenance. In the model and decision support tool presented by Endrerud et al. [17] and Endrerud and Liyanage [21], corrective maintenance is considered to be well as preventive maintenance. Dalgic et al. [20] also include corrective maintenance together with preventive maintenance in their model. Three different strategies of allocating workers to the maintenance tasks are investigated in their work. Sahnoun et al. [22] assume that corrective maintenance brings components back to a state "as good as new" and corrective maintenance is only conducted after a break down at twice the cost of preventive maintenance. Asgarpour and Sørensen [36] look at two different types of corrective maintenance, namely major and minor corrective maintenance. Corrective maintenance restores components to an as-good-as-new state in Rinaldi et al. [26] and restores the reliability values to their initial states. Nguyen and Chou [27] consider different grouping strategies for corrective maintenance.

4. Modeling Techniques

4.1. Properties of O&M Models

During the O&M phase, the OWF is influenced by different factors such as weather, turbine and component failures, available resources and maintenance personnel and the electricity price as has been discussed in Section 2. An O&M model should be able to capture all these factors and their influence in a realistic way. Realistic here, means that the model should be able to capture uncertainties in the information about the wind speed and wave height, the occurrence of failures, electricity prices, repair times, personnel, spare parts, and vessel-hiring costs. However, the model should enable even inexperienced users to gain valuable information. Therefore, it is necessary that the model output can be calculated within a short period of computing time and that the output is in a format that can easily be analyzed and displayed. If the model that is meant to support a decision takes longer to provide this support than it takes human decision makers to analyze the raw data based on their experience, the decision support tool becomes superfluous. Additionally, a good model should be flexible to changes in the input variables, being able to describe different OWF locations and layouts as well as different turbine types and scheduling approaches. More general, the O&M model should enable the user to estimate the maintenance costs and predict future development. It should provide researchers and maintenance planners in the industry with a tool to investigate different control mechanisms such as changes in the strategy for scheduling the corrective maintenance and investment planning. In addition to how a model can cope with uncertainties and variations in the input, the accuracy and form of output also need to be considered. Models that give estimations of mean costs and no information about the variation in the costs, have the disadvantage that the range of possible outcomes is not known. If the output includes a distribution of costs or gives confidence intervals for the predicted values, the results represent the actual cost situation in a more accurate way. Depending on the use case of the model, the mean costs can be sufficient information. For other applications, the mean costs might not be the adequate solution and the distribution of the costs is the desired output. Similar considerations can be made for other outputs, such as availability.

4.2. Types of Models

4.2.1. Discrete Event Simulation

Discrete event simulation (DES) models a system as a discrete sequence of events and is explained in Nance [78]. The simulation jumps from one event to the next and leaves out the time in between those state changes. The model is inherently stochastic and depends on basic random number generation. DES can be understood as a discrete form of a dynamic stochastic model. DES has very low computational requirements since only events are simulated and not the time in between. An example of a discrete event model is illustrated in Figure 1, showing the events happening on ground between airplane landing and take-off. In the framework of maintenance scheduling, events can be the failure or repair of turbines that change the status from "running" to "stopped" and back, respectively. DES provides a very basic framework for modeling maintenance. DES is very simple and can be implemented in most programming languages—even by inexperienced programmers and researchers. However, DES does not have the means to include different scheduling methods and complex interaction of input variables, such as wind speeds and downtime. Therefore, DES has a limited use for the wind industry and research in maintenance scheduling of offshore wind farms. Due to its simplicity it can act as a "stepping-stone" for explaining the problem of maintenance scheduling to untrained personnel or students. However, to develop a decision support tool beneficial for operators or maintenance providers, one should consider other—more complex– types of models.

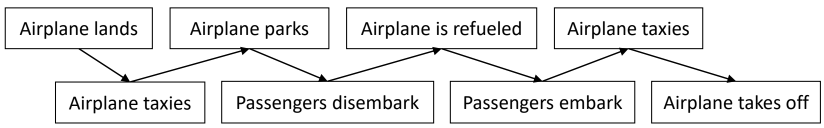

Figure 1. A simplified illustration of a discrete event model, showing possible events taking place at an airport between the arrival and departure of an airplane.

4.2.2. Markov Models

Discrete Time Markov chains (DTMCs) are stochastic processes fulfilling the Markov property as explained by e.g., Kulkarni [79]. Stochastic processes consist of states and the probabilities to get from one state to another, called the transition probability. The Markov property assures that the next state of the chain only depends on the current state and the process is thus memoryless. DTMCs can be displayed as a state diagram for simple chains, displaying the different states the model can be in and the transition probabilities, an example is shown in Figure 2. A form that can be implemented and used in simulation software is the use of a transition matrix, including all the transition probabilities from each state to another, after sorting the states. DTMCs are already used in some of the existing models to model e.g., the significant wave height over time. A model combining DES with the DTMC state change mechanism is the most used modeling technique today. This provides simple state changes with transition probabilities and jumps from event to event, so times with no state changes do not have to be simulated. This again saves computational time and effort. The main problem with discrete models is that the turbine itself operates continuously. It experiences continuous loads from wind and wave that cause the failure events. In addition, the power output changes with the wind speed and is thus not constant between state changes. Depending on the wind speed and market price for electricity, the downtime losses are also continuous. Therefore, using a discrete model will always be a simplification of what is happening in reality. For use in the wind industry, discrete models can be a resource effective solution for modeling maintenance. However, they should be benchmarked with models that are more complex to provide confidence in the simplification.

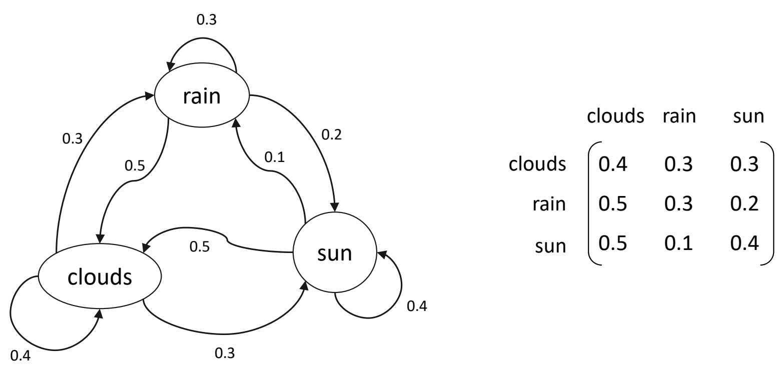

Figure 2. An example of a Markov chain, displayed as both a state diagram (**left**) and a matrix with transition probabilities (**right**).

Continuous Time Markov Chains (CTMCs) are analogue to the DTMC, continuous stochastic processes fulfilling the Markov property. The main difference to the DTMCs is that instead of the transition probabilities, CTMCs use transition rates – the derivatives with respect to time of the transition probabilities between different states. While DTMCs can only model time steps of a fixed size, CTMCs offer the possibility to also describe phenomena that benefit from a continuous representation, such as the production, loads and weather. Additionally, CTMCs might be described with fewer parameters than DTMCs. While the implementation of a DTMC is very straight forward and much like a DES, CTMCs require more advanced methods. An example of a discrete Markov process is a random walk with an integer step-size, its scaling limit in dimension 1 (step-size converging to zero) is the continuous process called Wiener process, describing Brownian motion.

4.2.3. Differential Equations

Ordinary differential equations (ODEs) are equations, where the relationship $F(t, x, x', \ldots)$ between a variable t, an unknown function $f(\cdot)$ of this variable $x = f(t)$ and the derivatives of this unknown function $(x', x'', \ldots)$ is known. Often, this independent variable t is time. This means that all variables in the function $F(\cdot)$ are dependent on time. When more than one unknown functions of the same variable exist, a system of ODEs can be used. Depending on the nature of the relationship $F(\cdot)$, different mathematical approaches to finding a solution exist, providing exact solutions for integrable functions or numerical results using e.g., the Euler or Runge-Kutta method. Software that can be used for solving ODEs includes MATLAB and Maple.

In contrast to the ODEs, partial differential equations (PDEs) can have two or more independent variables. In addition to the time, this can be e.g., distance from a certain point. Examples for time-independent variables in wind farm maintenance modeling are the quality of repair or quality of a weather forecast. PDEs could be used for maintenance modeling; however, solving PDEs is not as straight forward as solving ODEs and the benefits most likely do not outweigh the complications in solving.

Stochastic differential equations (SDEs) are differential equations, where one or more terms are stochastic processes. The SDEs can be written in different forms. One of the most commonly used forms in physics are Langevin equations. These consist of ODEs using a deterministic function and an additional random term. The random term can take different forms, most commonly (Gaussian) white noise. Other forms of presenting SDEs include the Smoluchovski and Fokker-Planck equations, based on PDEs and the Itô equation, similar to the Langevin equation in differential notation. SDEs can be numerically solved by using e.g., the Euler-Maruyama method, the generalized Runge-Kutta method or Monte Carlo simulation. In the given problem setup of maintenance scheduling, SDEs can be a good way to incorporate the uncertainties in the variables. Existing models often use the mean for different input, such as the mean annual failure rate, mean times to repair or mean wind speed during downtime. With SDEs, these means can be used for the deterministic function and uncertainties in the observations can additionally be modeled by the random term. One of the drawbacks is the solving of the equations. Numerical methods to solve the equations are limited and often suffer from poor numerical convergence. Therefore, the main challenge when using SDEs for modeling the scheduling of maintenance will be to investigate the existence of solutions to the equations and the (numerical) calculation of these. Since the SDEs will depend largely on the input parameters, they cannot easily be used for different wind farm layouts and site, without changing the equation structure. This is another drawback, since a maintenance model should be able to capture the properties of different wind farms without the hassle of fitting a new set of equations to each case.

4.3. Conclusions about Modeling

A useful O&M model needs to be able to deal with several different input variables and potentially large data sets. Of the investigated candidates, all can capture the influencing factors in varying degrees of accuracy and with varying complexity. Those models that can use stochastic input are also able to provide stochastic distributions as output. For simple models, not capturing the uncertainties, DES and DTMCs can be combined to model the variations in the weather while still using discrete events as basis for the scheduling. This would, however, only cover uncertainties in the weather in a very basic way, e.g., through the probabilities of changes from one weather state to another in the Markov chain. Using continuous Markov models instead of discrete models provides the advantage of a better time-resolution, which can be beneficial to represent weather windows or repair durations. However, a validated discretization can capture the main properties. When researchers aim for more complexity and are not restricted by computational time, models that match the complexity of the input data are recommended. This means the most complex model that can be equipped with reliable data should be used. When no or only simple data sets are available, the complexity of the model should be adjusted accordingly. ODEs are a well-documented mathematical field. Once the model is described by ordinary differential equation, solving can be done by using one of many software options. However, since ODEs can only depend on one variable, this might be limiting in some cases. To avoid the dependence on one single variable, PDEs can be used. However, solving these is not as straight forward as solving ODEs. The most general way of modeling the scheduling of maintenance with differential equations are SDEs. These can also incorporate the uncertainties in the inputs, by including a random term. However, the existence and convergence of solutions is not guaranteed. Therefore, SDEs are not yet suitable for the use in the industry, before researchers have validated specific equations and investigated the necessary requirements for the existence of solutions.

4.4. Modeling in the Literature

As summarized in Table 4, many of the existing approaches use Monte Carlo simulations, combined with other modeling approaches. Many of the earlier models use DESs and Markov chain models. Other modeling approaches used are autogressive models and different kinds of stochastic processes.

Table 4. This table summarizes the kinds of models presented in the literature.

Publication	Monte Carlo	Discrete Events	Markov	Others
Van Bussel and Bierbooms [46]	✓	✗	✗	✗
Pérez et al. [80]	✓	✓	✗	✗
Pérez et al. [80]	✓	✓	✗	✗
Byon et al. [81]	✓	✓	✗	✗
Pérez et al. [82]	✓	✓	✗	✗
Douard et al. [30]	✓	✓	✓	✗
Scheu et al. [12]	✓	✓	✓	✗
Dinwoodie et al. [14]	✓	✓ [1]	✗	Weibull distribution, autoregressive model [2]
Hofmann and Sperstad [16]	✓	✓	✓	binomial process
Leigh and Dunnett [83]	✗	✗	✗	Petri nets [3]
Endrerud et al. [17]	✓	✓	✗	Poisson process, agent-based method
Dalgic et al. [20]	✓	✗	✗	multivariate autoregressive model [2]
Endrerud and Liyanage [21]	✓	✓	✗	Poisson process, agent-based method
Joschko et al. [33]	✓	✗	✗	Business Process Model Notation [4]
Sahnoun et al. [22]	✓	✗	✗	multi-agent system [5]
Gintautas and Sørensen [24]	✗	✗	✗	stochastic model
Raknes et al. [25]	✗	✗	✗	mixed-integer solver, rolling-horizon heuristic
Rinaldi et al. [26]	✓	✗	✗	✗
Stock-Williams and Swamy [41]	✗	✗	✗	genetic algorithm

[1] Dinwoodie et al. [14] use a Bayesian belief network, which is an event model, displayed as an acyclical graph, combined with tables of condition probability. Charniak [84] introduces the concept. [2] An autoregressive model is a special case of the more general ARIMA model for time series, explained in e.g., Cryer and Chan [85]. [3] A Petri net is a discrete event dynamic system in graphical notation, see Murata [86] for an introductory review. For limited states it can be converted to a direct graph [87]. [4] Business process model notation is a type of graphical modeling notation. Ko et al. [88] provide a literature review and classification of business process modeling, while Muehlen and Recker [89] review the notation. [5] In multi-agent systems multiple agents act and react upon their environment and other agents. Lee and Kim [90] present a review of multi-agent systems in manufacturing and supply chain management.

5. Optimization

Optimization is the mathematical concept of finding the optimal solution to a (utility) function, given certain constraints to the solution. In the case of maintenance scheduling, the most obvious goal is to minimize the costs. Typical constraints are the availability of vessels, technicians and spare parts, environmental constraints, such as wave height and wind speeds and legal constraints, such as working hours, vessel speeds or limitations to routing. In mathematical optimization, one can distinguish between single- objective optimization and multi-objective optimization. The latter is the case when there is not one single goal for the optimization, but multiple. In the case of the offshore wind farm maintenance, this can mean to not only minimize costs, but at the same time maximize availability of the wind farm. This seems to be equivalent at the first glance, since downtime leads to production losses. However, maximizing availability will lead to a higher number of corrective maintenance actions that cannot be grouped together. This in turn influences the cost of maintenance. Legal restrictions and public opinion can be reasons for the wind farm operator to maximize availability, while still trying to minimize costs. In the following, we give an overview over different mathematical optimization algorithms and methods. The overview includes existing optimization techniques, with a focus on those that are implemented in the state-of-the-art maintenance models. For a detailed introduction to optimization, we want to refer to literature in the field, such as Diwekar [91]. Many introductory books on optimization focus on the type of problem (model) for which an optimal solution is found. We structure this section according to the type of optimization method.

5.1. Methods for Optimization

5.1.1. Algorithms

An algorithm can be figuratively described as a recipe that one can follow to reach an optimal solution to a given problem. The most famous example of optimization algorithms is most likely the Simplex algorithm, developed by George Dantzig. The Simplex algorithm was developed to be used in linear programming, but has since been extended to solve e.g., dual problems and network flow problems. A famous example from network optimization is the Kruskal algorithm, solving for a minimum spanning tree in an undirected graph. For unconstrained non-linear optimization problems, there exist the "steepest descent method" and Newton method for finding the optimum. For constrained non-linear problems, the Frank-Wolfe method, Penalty function method or Barrier function method can be applied. Integer programming models, such as the famous traveling salesman problem, can be solved by enumeration methods (only computational feasible for a small set of feasible solutions), relaxation and decomposition methods which are based on e.g., the Simplex method for linear programming. Additionally, branch and bound methods, originally developed by Land and Doig [92] can be applied. However, for integer programming models, heuristics are often used instead of algorithms, since they are less computational expensive and therefore time saving.

5.1.2. Heuristics

When using a heuristic method, as opposed to an algorithm, the convergence to the global optimum is not guaranteed. In general, those methods reach a solution faster and can also be used for more complex problems. One can distinguish between different types of heuristics. Constructive methods are methods in which the solution is constructed stepwise. For integer programming problems, one can start with free variables and fix a new variable in each step. Greedy algorithms are such an example of constructive heuristics. For the traveling salesman problem, heuristics such as the nearest neighbor algorithm or nearest addition algorithm have been shown to converge to the optimal solution. However, this does not hold in general. For vehicle routing problems, a heuristic such as presented by Clarke and Wright [93] can be used. However, it is not certain that it will produce a feasible solution. Local search heuristics improve the solution in each iteration by searching the neighborhood of the previous solution for a better one. Here it is possible to end up trapped in a local optimum. To improve the performance of such a local search heuristic, one can use different starting points to find several local optima. Then, the best one can be chosen as the global solution. Metaheuristics can aid in generating the starting point systematically. Examples for metaheuristics are the tabu search developed by Glover [94], where a memory is added to the local search. Simulated annealing, developed by Kirkpatrick et al. [95] generalizes the concept by choosing a random neighbor. Approximation algorithms, as presented in by Christofides [96] for the traveling salesman problem, can provide a bound for the optimal solution.

5.1.3. Stochastic Programming

Stochastic programming is not an optimization method, but rather a form of optimization problem. In stochastic programming, as opposed to deterministic programming, uncertainties can be incorporated in the analysis. One way to solve these kinds of problems is to use decision trees, where each possible event is modeling with its own branch, weighted with its probability of occurrence. Birge and Louveaux [97] present an introduction to the topic, including different solution methods and approximation methods. Stochastic programming can be relevant for offshore wind farm modeling, because of all the uncertainties involved in the planning of the maintenance tasks.

5.1.4. Dynamic Programming

Dynamic programming is also not a method itself, but rather a form of solving different optimization problems. We want to describe and discuss it here, because of its possible relevance to wind farm modeling. In dynamic programming, different stages in the optimization are modeled, where each stage can be interpreted as a time step. Dynamic programming allows to optimize both deterministic and stochastic programs. The two main fields of dynamic programming are "Markov decision processes", modeling discrete states and decisions, and "control theory", concerned with continuous states and decisions. For further reading about dynamic programming, we suggest Puterman [98] for Markov Decision Processes and Powell [99] for an emphasis on modeling and solving of larger problems. Since in an offshore wind farm the aim is to find the optimal solution over a long period of time (up to 25 years), it is beneficial to be able to update the inputs to the optimization over time, as more and more information about the system will be gathered. This can be achieved when using dynamic programming. As uncertainty should also be included, we believe tools from dynamic programming can be used to optimize the strategy for the maintenance of an offshore wind farm.

5.2. Conclusions about Optimization Methods

The discussion of the different optimization methods shows that for the case of optimizing the maintenance strategy of an offshore wind farm, different methods might be used. Stochastic programming shows the advantage of being able to represent the uncertainty in the inputs to the optimization. To solve these stochastic programs, the existing models use a Markov decision formulation with discrete time steps or discrete event steps. However, as discussed above, the existing models do only include uncertainties in very few of the influencing factors to the optimization. The present authors have shown the importance of including the uncertainty for additional parameters [100–102]. Therefore, we believe that approximate dynamic programming will be beneficial to solving the larger (stochastic) optimization problems, when the uncertainties are included for all influencing factors.

5.3. Optimization in the Literature

Most existing models provide multiple outputs, such as wind farm availability, production losses due to downtime, the number of failures, number of maintenance actions or costs of spare parts. However, an optimal strategy must be found in most cases by comparing the outputs for different strategies and manually selecting the best option. Some publications do present optimization methods. Sahnoun et al. [22] use a multi-criteria decision algorithm. Abdollahzadeh et al. [34] use multi-objective particle swarm optimization to determine the optimal reliability threshold for their preventive maintenance strategy. Pattison et al. [74] use for the optimization of the maintenance scheduling in their reliability centered maintenance model a multi-objective and multi-variable optimization. Hou et al. [103] use a particle swarm optimization—minimum spanning tree algorithm in their optimization of the cable layout in a given offshore wind farm.

6. Data Sources and Availability of Data

To fit and validate wind farm models, data for the input are needed. The closer the data is to the actual site conditions, the closer will a calculated optimum be to the actual optimal solution. Therefore, the availability of data directly influences how much decision support a model can provide. Unfortunately, not all types of data are easily available to public research. In the following we present data sources and which data different models are based on.

6.1. Data in the Literature

Feng et al. [4] provide data from nine different offshore wind farms in the UK, with the turbine manufacturer and type, rating, water depth, distance from shore as well as the operator. For production and turbine specific data, Sahnoun et al. [22] reference data from Kooijman et al. [51]. In their case study, Asgarpour and Sørensen [36] use the reference wind farm from the NORCOWE project. This is a reference wind farm located in the North Sea, 80km from the Danish coast. The reference wind farm consists of 80 DTU-10MW reference turbines and the water depth varies between 20 and 25 m. Another reference turbine is the one provided by Jonkman et al. [104]. This turbine has been used by, among others, Seyr and Muskulus [101].

6.1.1. Weather

Weather data is relatively easy to come by, as there are several meteorological measurement and re-analysis campaigns that provide data to the public. One of the data sources is the European Centre for Medium-Range Weather Forecasts (ECMWF) [105], who provide real-time and re-analysis data for, among others, ocean waves and wind speeds. The data sets vary in length and resolution, depending on the kind of data (ERA-interim re-analysis data for ocean waves is e.g., available from 1979, with a spatial resolution of 80 km). The three measurement campaigns FINO 1,2,3 from the "Bundesministerium für Wirtschaft und Energie" and "Projektträger Jülich" provided online from the Bundesamt für Seeschifffahrt und Hydrographie (BSH) [106] supply measurements of wave heights and wind speed in the offshore environment among their data. The records vary in lengths, with FINO 1 measuring data since 2003 and providing wind speed measurements in 10-min aggregated means. Feng et al. [4] provide monthly wind speed data for a UK offshore wind farm and annual average wind speed for four UK offshore wind farms. Climate data from an operating offshore wind farm NoordzeeWind is available for three years [107–109]. The WaveNet database from the Centre for Environment, Fisheries and Aquaculture Science (CEFAS) [110] provides real-time wave data from a network of buoys. The British Oceanographic Data Centre (BODC) [111] provide instrumentally recorded ocean current, tide, and wave data. Another source of weather data is the Norwegian Meteorological Institute [112], providing wind speed and direction as well as temperature and precipitation, with varying time-resolution dependent on the type and location of the measurement. Tolman [113] presented Wavewatch III, a wave model that can provide wave spectra at a selected location. Some publications use data from unpublished sources, such as from operating wind farms, airports, and an oil platform. Which weather data is used in which publication can be seen in Table 5.

Table 5. This table summarizes which weather data has been used in the different models.

Publication	ECMWF [105]	FINO [106]	Others
Dinwoodie et al. [11]		✓	NoordzeeWind [107–109] Centre for Environment, Fisheries and Aquaculture Science (CEFAS) [110] British Oceanographic Data Centre (BODC) [111]
Scheu et al. [12]	✓		
Dinwoodie et al. [14]		✓	
Feuchtwang and Infield [61]			Barrow and Scroby Sands wind farms
Halvorsen-Weare et al. [15]			EKLIMA [112]
Hofmann and Sperstad [16]			Offshore oil platform
Endrerud and Liyanage [21]		✓	
Dalgic et al. [20]		✓	
Sahnoun et al. [22]			Le Havre airport (wind speed) Rayleigh distribution [114] (wave height) Uniform distribution (lightning)
Asgarpour and Sørensen [36]		✓	
Seyr and Muskulus [101]	✓		
Rinaldi et al. [26]			Wavewatch III [113]
Seyr and Muskulus [65]	✓	✓	
Taylor and Jeon [66]		✓	

6.1.2. Failures

Data for failures are especially hard to find, since most manufacturers do not want to make their numbers public and because operators often do not have the complete failure history of their turbines. For onshore wind farms, failure data is easier to find than for offshore wind farms. The problem with using the failure rates of onshore turbines, when modeling offshore wind farms, is that offshore turbines often are of different types than onshore turbines and harsher weather conditions offshore lead to increased degradation and different failure causes than onshore. Data from onshore wind farms can be found in [114–120]. Tavner et al. [115] provide data from onshore wind farms on failure rate and sub-assembly reliability. They also provide a taxonomy for turbine sub-assemblies. A homogeneous Poisson process model is used to calculate the probability of failures from the MTBFs. They use data collected over 10 years in Germany and Denmark and assume that the failures are i.i.d. exponentially distributed. Sub-assembly failure rates and MTBF are provided for 12 sub-assemblies. Arabian-Hoseynabadi et al. [116] present a failure modes and effect analysis for onshore wind turbines. They present data from a real 2MW turbine (V80). 107 turbine parts, 16 failure modes and 25 root causes and present the top 10 for each category. Wilkinson et al. [117] provide a turbine taxonomy and reliability database listing fault events, failure rates, downtime, wind farm figuration and additional turbine information. They present the normalized failure rates for subsystems and assemblies of multiple manufacturers as well as the normalized hours lost due to the faults. Mean annual failure rates are available from Faulstich et al. [118] for different turbine subsystems. The annual failure rates and downtimes per failure have been calculated based on the data from 1500 wind turbines that were monitored between 1989 and 2006. Burton et al. [114] report the MTBFs for onshore turbines. Lin et al. [119] present common failures and failure frequencies as well as annual availability numbers for Chinese onshore wind farms. Reder et al. [120] in their paper give failure rates and downtimes for 4300 onshore turbines in the Mediterranean region.

Data from offshore wind farms is reported by [4,107–109,121,122]. Stiesdal and Madsen [121] provide a formula to calculate failure rates and present example failure rates, for offshore wind turbines. Data from Egmond aan Zee wind farm collected by NoordzeeWind has been reported for three consecutive years in [107–109]. Feng et al. [4] report operational performance such as availability and energy yield for four different UK offshore wind farms. Carroll et al. [122] present failure rates for

19 turbine components and four types of repairs/replacements. They also provide repair times, repair costs and number of technicians required for these same components and types. A summary of the different data sources and which data set is used in which model is presented in Table 6.

Table 6. This table summarizes which failure data has been used in the different models. The data sources are Tavner [123], Wilkinson et al. [117], Faulstich et al. [118], Burton et al. [114], Stiesdal and Madsen [121], NoordzeeWind [107–109], Feng et al. [4] and Carroll et al. [122].

Publication	[123]	[117]	[118]	[114]	[121]	[107–109]	[4]	[122]	No Info
Dinwoodie et al. [11]						✓	✓		
Scheu et al. [12]			✓						
Dinwoodie et al. [14]					✓				
Hofmann and Sperstad [16]									✓
Endrerud et al. [17]	✓		✓						
Dalgic et al. [20]									✓
Endrerud and Liyanage [21]			✓						
Sahnoun et al. [22]				✓					
Pliego Marugán et al. [37]		✓							
Seyr and Muskulus [101]								✓	
Rinaldi et al. [26]								✓	

6.1.3. Costs

Also, data for costs of spare parts, technician salaries and vessel charter rates are not very easy to come by. The O&M costs for four UK offshore wind farms are reported in Feng et al. [4]. They also provide a comparison of the cost of energy for four different electricity generation technologies, namely coal gas, onshore wind, and offshore wind. Hofmann and Sperstad [16] do not present costs in their study, because they do not have any cost input data. Endrerud et al. [17] and Endrerud and Liyanage [21] use spare parts cost from Malcolm and Hansen [124]. Dalgic et al. [20] use vessel charter costs from Det Norske Veritas (DNV) [125] and Dalgic et al. [126]. They do not specify the source of the other cost data, but provide the numbers used in their case study. Ambühl et al. [63] mention the operational costs of a CTV from Besnard et al. [13] and assume that the transportation cost by helicopter is twice that of a vessel as suggested by van Bussel and Schöntag [127]. Shafiee et al. [23] present estimates for the annual OPEX in their life cycle cost analysis.

6.1.4. Vessel Information

Van Bussel and Bierbooms [46] present wind speed and wave height restrictions for five different access vessels. Out of these, one is fictitious and another one is based on optimistic assumptions. It is likely that the restrictions for vessels have been improved in the last 14 years. However, due to the lack of publicly available the values presented by Van Bussel and Bierbooms [46] are still widely used in research. Douard et al. [30] use wind speed and wave height limits. Feuchtwang and Infield [61] consider a threshold wave height for the access of 1.5m. Hofmann and Sperstad [16] do not provide any information about the access restrictions for the vessels. Sperstad et al. [19] present different methods of estimating the wave height restrictions for different vessel types. They show that using a single significant wave height limit has a similar outcome as using multiple access restrictions, but it depends on how this single value is estimated. Additionally, they also present some vessel data, such as capacity and size. Dalgic et al. [20] use information on the properties of different vessel types from O'Connor et al. [45], Tavner [123], Al-Salem et al. [128], Dai et al. [129] and Walker et al. [130]. Endrerud and Liyanage [21] present similar numbers as Sperstad et al. [19]. However, they do not say where they get these values from. Access restrictions reported by Sahnoun et al. [22] are 8 m/s wind speed and 1.5 m significant wave height. A source for these values is not provided. Ambühl et al. [63] use the access restrictions of 1.5 m significant wave height for boat access from Rademakers et al. [68] and wind speed of 20 m/s for helicopter access from Nielsen and Sørensen [10]. Rinaldi et al. [26]

provide the maximum wave height and wind speed values for one existing vessel and one vessel under planning in their study.

7. Discussion

7.1. Factors to Consider

In the literature the factors influencing the planning and cost of maintenance are identified as (a) the component degradation and occurrence of failures, (b) availability of maintenance crew, spare parts and vessels, (c) transportation and vessel routing, (d) the weather, (e) economic parameters such as the electricity price, and (f) the maintenance strategy.

(a) failure modeling, (i) different stochastic processes with failure rates are used by [11,12,14,16,17,19–22,26,30,32–34,37,39]; (ii) damage accumulation or time dependent failure rates are included in [10,17,21,22,26,30–32,35–38,40]
(b) The availability of crew, parts and vessels is (i) considered as a (limited) resource, sometimes dependent on the failure type, by [12,13,16,17,20–22,25,26,31]; (ii) while [15,19] optimize in their analyses for the number of vessels.
(c) Vessel routing and transportation has been studied by [10,25,41,46,52,53].
(d) The weather is used as an input to the decision support models by [11,12,14,16,17,19–22,24,26,30,33,34,41,63,101];
weather generation in the models is based on (i) Markov models by [12,16,19,30,56,57,59,62,64]; (ii) autoregressive by [11,14,20,66]; (iii) re-sampling by [31]; (iv) probability distributions by [33,34,61]; and (v) a Langevin process by [65].
(e) For cost calculations (i) production losses due to downtime (indirect costs) are considered by [11,12,20,22,30,36]; (ii) maintenance costs in form of vessel hire, spare parts or worker salary (direct costs) are considered by [11,14,16,17,20–23,26,30,31,36,67].
(f) The types of maintenance are discussed in the following Section 7.2.

7.2. Types of Maintenance

The different types of maintenance discussed in the review are (a) preventive maintenance, (b) condition monitoring, (c) condition-based maintenance and (d) corrective maintenance.

(a) Preventive maintenance is conducted preventively on a fixed schedule to prevent failures from happening. It is included in the models and analyses by [16,17,20–22,26,32,36,46].
(b) Condition monitoring can be used to monitor the performance of a wind turbine or component and can aid in predicting failures before they occur. Condition monitoring is studied by [63,67,70–73].
(c) Condition-based maintenance is similar to preventive maintenance conducted to prevent failures. It is, however, based on the condition of the system instead of a fixed schedule. Condition-based maintenance is (i) considered in the models by [16,22,40]; and has been (ii) reviewed by [35,75].
(d) Corrective maintenance must be carried out after a fault to return the component to a state in which it can perform its required function. Corrective maintenance is included in the models by [12,16,17,20–22,26,36].

7.3. Modeling

The existing decision support tools and models are based on DES, Markov models and autoregressive models. Alternatives to these models are other stochastic processes, or differential equations. Since solutions to differential equations are not always guaranteed, one needs to be careful with using these. For simulation-based models, DES and Markov models will therefore likely stay popular choices—also for offshore wind farm maintenance scheduling.
The existing models can capture most influencing factors; however, handling of uncertainty in the inputs is still an area that can be improved upon. Different wind farm layouts and locations can be included in the existing models, albeit being complex in implementation. The existing models lack an

accessible way to handle uncertainties in the input and provide information about the variability in the output. Currently, mean values are reported and sensitivity analyses must be done by manually varying the inputs.

7.4. Optimization

Many different optimization tools exist, with stochastic and dynamic programming being able to include uncertainty and therefore potentially useful for decision support for wind farm maintenance planning. In the existing tools, no optimization is included and must be performed on a case basis by manually varying the input to compare different strategies. Optimization models have been presented by Abdollahzadeh et al. [34] to determine the reliability threshold for preventive maintenance, Pattison et al. [74] for maintenance scheduling decisions and Hou et al. [103] for optimal cable layout.

7.5. Data

The sources of data that have been referenced and used in the existing models are

(a) for reference turbines: [51,104,131], and [132] for a reference wind farm;
(b) for the weather: [105,106], NoordzeeWind [107–109], [110–112];
(c) for failures: [114,116,117,119,120,123] for onshore data and [4,107–109,118,122] for offshore wind turbine failure data;
(d) for cost information: [4,13,23,124–126];
(e) for information about vessels: [10,22,26,41,45,46,68,123,128–130] seem to generally agree on a wave height limit of 1.5 m for boat access.

7.6. Usefulness of Models

The existing models used for decision support for offshore wind farm maintenance scheduling can be used by decision makers to gain more information before taking a decision. Most models can include different influential factors in the analysis. However, to optimize the maintenance strategy, the decision maker needs to manually vary the inputs to compare different strategies. None of the tools can provide a strategy-suggestion based on the inputs. The value of information for different input variables also must be calculated manually by conducting sensitivity studies and varying the inputs.

7.7. Trends and Future Work

Multiple authors mention collection of reliability data and improvement to reliability modeling as work needed in the future. It is mentioned that this can be achieved by including condition monitoring and condition-based maintenance in future models. As mentioned also by El-Thalji and Liyanage [7], there have been numerous academic contributions in the field of condition monitoring, diagnostics, and prognostics. Some possibilities for novel failure prediction methods are those presented by Artigao et al. [133], Gonzalez et al. [134], Tautz-Weinert and Watson [135]. Other sectors for improvement that have been mentioned are improved weather modeling—including more weather parameters, improved optimization methods and the treatment of uncertainty. The suggested method for future modeling is stochastic models.

8. Conclusions

In this review article, an overview over the current state of the art in operations and maintenance scheduling has been presented. The influential factors have been identified. Degradation and failure modeling; vessel, personnel, and spare part logistics; transportation and vessel routing; weather modeling; and cost estimation have been investigated in further detail. The types of maintenance have been presented and different maintenance strategies discussed. An overview over which maintenance strategies are included in which models has also been included. Modeling techniques and optimization methods have been presented and their use in current literature discussed. It was further discussed how the existing tools can aid with decision support. Finally, the importance and availability of necessary and useful data was discussed. The analysis and discussion have shown that existing models are not yet able to deal with uncertainties in all input factors. The weather input is well researched, also because of its relevance to fields other than offshore wind. Information about vessels and vessel routing is known and experience from other offshore industries can be used. In degradation and failure modeling, several approaches have been pursued; however, they show a dependence on data collection. Other factors, such as the duration of repairs, travel times, sensitivity of alarm systems or interaction between turbines or components are not as well integrated in state-of-the-art models. The mathematical techniques used at the moment are mostly simulation-based and optimization has to be done 'by hand'. The discussion of methods has shown that concepts exist that are able to improve the modeling by using more complex methods to include uncertainty in the inputs or to avoid Monte Carlo simulation. Techniques to include an automated optimization have also been discussed which can increase the usefulness of models to decision support.

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A.2 Paper 2

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Safety Indicators for the Marine Operations in the Installation and Operating Phase of an Offshore Wind Farm

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Abstract

As a measure of performance, safety indicators are already used for many types of operations, such as in the offshore oil and gas industry. The indicators are used by operators to enhance the safety and performance of the individual plants or vessels and total productivity of the system.
This paper reviews existing safety analyses of the offshore wind industry, the onshore wind industry and offshore oil and gas industries. An offshore wind farm is divided into subsystems and operational phases. Safety indicators are developed for the phases and subsystems by reviewing existing safety indicators from related industries and adapting them to the offshore wind industry. The indicators for the individual subsystems and phases are then combined to provide safety indicators for the whole wind farm over the lifetime. Finally, the indicators are matched against incident data from the offshore wind industry and an outlook for further research and indicator validation is given.

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Keywords: Safety Indicators, Marine Operations, Offshore, Wind Energy, Maintenance, Performance

1. Introduction

Safety indicators as a measure of performance are already in place for many types of operations. Øien et al. present the theoretical background of safety indicators in [1] and their application in [2]. Safety indicators are widely used in the offshore oil and gas industry as presented e.g. by Skogdalen et al. [3] and Utne et al. [4]. Safety indicators are used to enhance the safety and performance of the individual plants and total productivity of the system. This can be achieved through proactive work preventing losses that becomes possible thanks to the indicators as stated by Pasman et al. in [5]. The indicators are also used in political discussions to have a common framework when discussing worker safety with unions. According to [6], indicators should be "complete, consistent, effective, traceable, minimal, continually improving and unbiased". When looking at safety indicators the question is not about the probability of an accident, but whether it can happen at all. Until now, indicators are used in the offshore oil and gas industry, however

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no such indicators exist for the offshore wind industry (OWI). According to Hopkins [7], safety indicators are only worth developing if they can drive improvement. A large amount of the energy costs is caused by downtime and maintenance as described by Feng et al. [8] and Scheu et al. [9]. When enhancing the performance of an OWF, it is important not to compromise safety of the maintenance personnel. Therefore safety indicators can in fact help drive the improvement of the performance of an offshore wind farm and are hence worth developing.
In this paper, we define a safety indicator as a measurable representation of a risk influencing factor [1], where the risk influencing factor is defined as an aspect of a system or an activity that affects the risk level of this system or activity, as defined by Øien [10]. The aim of this paper is to identify safety indicators for the offshore wind industry and establish a common framework for the installation and operational phase of an offshore wind park. This is done by taking a holistic approach and considering an offshore wind farm (OWF) from the beginning of installation until the decommissioning. The wind farm is divided into subsystems, according to the phase (installation, operation), technical subsystems (substations, vessels, turbines and turbine subsystems) and operations (transport of material and workers, turbine access, execution of maintenance actions). Existing analysis of the individual subsystems is reviewed, taking into account analysis from other offshore industries and onshore wind energy. Based on this review, safety indicators are developed for all the subsystems. The indicators are combined to provide safety indicators for the whole wind farm. The indicators are validated with incident data and presented in the conclusions of the paper.
The paper is structured as follows. Section 2 gives an overview over the methodology used. The OWF with all the subsystems is presented in Section 3. Section 4 reviews the existing analysis and presents the safety indicators for the different subsystems. The indicators are related to reported incident data in section 5. Finally in section 6, the paper concludes with a presentation of the developed safety indicators and gives ideas for further research.

2. Methodology

In this paper, an OWF is analysed by dividing it into different phases and subsystems. This is done by reviewing existing literature on OWFs and adapting the subsystems. Subsystems of offshore wind turbines are presented e.g. by Arabian-Hoseynabadi et al. [11] and Faulstich et al. [12].
This paper further presents a review of existing analysis in the field of health and safety in relation with the OWI. Since few publications exists specifically on the OWI, analysis from related fields namely the offshore oil and gas industry and onshore wind industry are reviewed to cover additional perspectives on the topic.
The SINTEF report on health and safety by Tveiten et al. [13], investigates among others hazards and accident scenarios for OWFs. The report on Worker Health and Safety by the Transportation Research Board [14] also investigates hazards of working on an OWF. Two reports by the G9 Offshore wind health and safety association [15,16] give an overview of incidents and accidents on OWF and provide a breakdown of the accidents according to incident areas and work processes.
Aneziris et al. [17] investigate hazards for onshore wind farms, reviewing also the database of the Caithness Windfarm Information Forum [18]. This database is regularly updated, the authors used the first 1142 reported accidents, accessing the database in 2012. Arabian-Hoseynabadi et al. [11] present annual failure rates and risk priority numbers (RPN) for the individual subsystems. Faulstich et al. [12] also give annual failure rates and consider downtime per failure for the subsystems discussed in their paper. We present the failure rates from both papers and give a comparison and discussion of the values.
For the analysis of offshore structures in the offshore oil and gas industry, we chose a paper by Skogdalen et al. [3] focusing on safety indicators for deep water drilling blowouts and a paper by Utne et al. [4] on shutdown preparedness. To cover the external factors that influence the performance and safety of an OWF, we review the work of Dai et al. [19] on the risk of collision between vessels and offshore wind turbines. Dai et al. also identify risk reducing measures which we present and discuss as well.

3. Description of the wind farm and its subsystems

When considering an OWF, the main stakeholder involved is the WF operator. The operator of a wind farm (WF) is interested in maximizing the performance of the WF in order to maximize the profits. Both downtime and

Table 1. Turbine subsystems in the two papers and their equivalences

Faulstich et al.	Arabian-Hoseynabadi et al.
generator	generator
gearbox	gearbox
mechanical break	mechanical break
yaw system	yaw system
hydraulic system	hydraulics
rotor hub	rotor and blade assembly
rotor blades	
electronic control	electrical control
electrical system	grid and electrical system
drive train	main shaft
support and housing	tower, foundation and nacelle
sensors	
	pitch control system

maintenance are expensive, so improving the performance is vital to maximizing profits. The main performance requirement for the OWF is power production. The production of power depends on the availability and operation of the WF subsystems like the turbine itself, substations and power cables. To monitor the performance, key performance indicators like the energy-based availability can be used. We do not investigate the monitoring of performance in this work. Rather we want to focus on safety indicators that enable the operator and other stakeholders (worker unions, maintenance providers) to monitor the system and worker safety, while maximizing profits with the help of key performance indicators. The analysis of the main stakeholder and subsystems corresponds to the first steps in a system engineering process [20] and our analysis could be further extended using this approach. Since we want to see the OWF through all the phases of operation, we begin with identifying the operational phases we want to investigate. Aneziris et al. describe three different operational phases in their paper [17]. These are “installation”, “commission” and “maintenance/operations”. In the SINTEF report [13], Tveiten et al. chose “installation and commissioning”, “operations”, and “maintenance” as their operational phases. To compare input from both papers, we combine the categories “installation” and “commissioning” into one phase and choose “maintenance and operations” as second phase.

The next part of our analysis will be the individual turbines as parts of the whole OWF. In their paper, Arabian-Hoseynabadi et al. [11] focus on one individual turbine and identify eleven turbine subsystems, listed in Table 1. The authors further investigate these subsystems and divide them until they reach a total of 107 parts in a wind turbine. However, the individual parts are not reported and can hence not be used here. Still, considering the eleven subsystems is already enough, when combined with the two different operational phases and additional subsystems outside the turbine. Faulstich et al. [12] identify twelve turbine subsystems as presented in Table 1. They do not divide the system into more parts and look at failure rates for these turbine subsystems. Combining the two turbine subsystems “rotor hub” and “rotor blades” discussed by Faulstich et al. makes it possible to compare the failure rates to those presented by Arabian-Hoseynabadi et al.

For the analysis of the support structure of the wind turbine, we only consider general reviews of the oil and gas industry and do not consider OWF specific structures apart from the tower mentioned above. Since offshore structures in the oil and gas industry are usually larger and have different properties than turbine structures, these analyses will not match the OWI exactly and review of different OWI specific support structures, such as monopiles, jackets and floaters should be considered for further work. Subsystems of the OWF outside the turbine include vessels, access systems, substations, cables and organizational structures. In this paper, we focus on the collisions between vessels and wind turbines, as considered by Dai et al. [19].

4. Safety indicators

In this section we present the safety indicators as described in existing literature. First we discuss hazards during the life time of an OWF, separately for each operational phase. These hazards can be translated into safety indicators by e.g. monitoring the number of incidents due to the hazards. Next, possible failures for a single turbine and its subsystems and indicators from related industries are reviewed. The failures in a turbine can be related to safety indicators, since a higher failure probability will lead to more frequent repair, which in turn enhances the likelihood of other risk factors. Finally, indicators for the risk of collision with a vessel are presented.

4.1. Hazards according to phases

The hazards according to operational phases, identified by Tveiten et al. [13] and Aneziris et al. [17] are presented for the installation and commissioning phase in Table 2. In both phases Tveiten et al. focus mainly on properties of the system, such as slippery surfaces, dangerous substances and failures in the organizational structure. Aneziris et al. however, focus their hazards on the work tasks that are carried out, like mechanical or electrical work. This difference in approach makes it difficult to compare the results. However, some hazards are being identified in both publications and named differently. Both lists recognize the danger due to the height of the turbine. This can be measured by a safety indicator measuring the number of incidents due to the identified hazards. These are “falling structure/load/object”, “kinetic energy” and “potential energy” in Tveiten et al. and “contact with falling, hanging or moving objects” by Aneziris et al. The hazards concerned with marine and helicopter operations can be referenced to the hazards concerned with moving vehicles by Aneziris et al. Safety indicators can measure again the number of occurring incidents due to these hazards. External factors such as weather, are only considered by Tveiten et al. and not included in the analysis by Aneziris et al. In general the analysis by Aneziris et al. is narrower than the analysis by Tveiten et al. However, having many different indicators about dangerous working environment or distinguishing between different classes of dangerous substances as in the analysis by Tveiten at al. is not practical to monitor. A solution to this would be to group the hazards by dangerous substances together and not report the details. This leads to one safety indicator presenting the number of incidents due to contact with (hazardous) substances. The same could be done for external factors, like wind speed and direction, wave height and persistence or possibility of earthquakes. It is possible to define certain thresholds for these factors, as done by Scheu et al. [9] for wave height and wind speeds, and then only report violations of the thresholds as part of the safety analysis.

4.2. Failures in a single turbine

Reviewing the analysis of Faulstich et al. [12] and Arabian-Hoseynabadi et al. [11], we analyze a single turbine as part of an OWF. As described, the authors consider different subsystems for a turbine. They evaluate different data on the annual failure rates of turbines and conclude that the subsystems with the highest failure rates are “electrical systems”, “electronic control” and “rotor and blade assembly”. While both papers agree on the three subsystems with the highest failure rates, analysis differs for the subsystems with lower failure rates. Since high failure rates result in more frequent maintenance and repair actions, high failure rates increase the risk of accidents for the maintenance personnel. In a safety analysis, the stakeholder aims to monitor and consequently improve the workers safety. Since an improvement in the failure rates will lead to fewer repair actions and therefore increase the workers’ safety, we suggest monitoring the failure rates as part of a safety analysis. An improvement in the turbine is most likely in the subsystems with the highest failure rates, so for a first safety analysis considering those three subsystems will be sufficient. In further development of the safety indicators, new analyses and comparison between the existing data should be considered to specify failure rates for all turbine subsystems and further validate the already existing failure rates.

4.3. Safety indicators from oil and gas industry

Skogdalen et al. [3] develop safety indicators for offshore oil and gas drilling. The indicators are summarized in Figure 3 in their paper. The indicators for operational aspects, schedule and costs can be used for the OWI just as they are for the oil and gas industries. The drilling phase in oil and gas industry can be compared with the installation phase of the WF. When looking at the “well incidents” the indicators can no longer be used and have to be adapted to the specific incidents that can occur in the OWI as presented in the G9 reports [15,16]. The indicators for the “operator well response” can again be used for the OWI, by simply changing “well incident” to “turbine incident” and “well response action” to “incident response action”. The indicators concerned with the technical condition of the safety critical equipment need to be adjusted to the wind farm as well. Utne et al. [4] develop twelve indicators for shutdown preparedness in oil and gas industry. Shutdown preparedness means to schedule maintenance tasks ahead of time to fulfill them during unexpected or planned shutdown of the system. This relates to the OWI such that the maintenance has to be planned ahead and performed during weather windows that allow access to the OWF. Utne et al. consider five qualitative indicators. The number of work orders (WO) with a low man hour estimate is an indicator for poorly planned WOs. The same holds for the number of WOs missing location codes or short descriptions. The indicator measuring if the needed material and spare parts are in stock also judges how well a WO is prepared. Assessing the work scope is necessary to decide whether a maintenance job needs a shutdown to be performed. This indicator will not be useful in the OWI, since weather windows are used instead of shutdowns and maintenance is not possible without accessing the turbine. The indicators concerned with volume as presented in Table 1 in their paper can again be used in the OWI. The two indicators on utilization can also be used in the OWI. They can help to see how well the weather windows are used to perform maintenance tasks and how this impacts the future turnaround.

4.4. Collisions between vessels and turbines

Dai et al. investigate the risk of collisions between vessels and offshore wind turbines [19]. They consider four different vessel types and seven different collision scenarios in their analysis. The overall conclusion of the paper is that collisions may cause structural damage to the turbines. Therefore it is important to include the risk of collisions in any safety analysis and we take a closer look on the risk mitigating aspects presented by Dai et al. They can be monitored and the violation of rules, crossing of thresholds or lack of monitoring can be used as safety indicators. Dai et al. group their risk mitigating aspects into six groups. Considerations about the energy that can be absorbed during a collision without damaging the structure are usually made during the design phase. Depending on the location of the turbine these energies can be very low (only maintenance vessels are expected to interact) or very high (risk of being hit by oil tankers). The presence or absence of a specific boat landing structure can also be monitored as a safety indicator. If a structure is present, the damage to the turbine while landing a maintenance vessel is lower. “Vessel capability” and “crew competence” are important for mitigating risk and ensuring safe operations according to Dai et al. The capability of the crew can be measured by hours of experience or training hours. Reliability of the navigation, propulsion and control system should be high. The safety indicators should reflect the risk of a possible failure. As already stated above, the environmental conditions like sea state and wind speed need to be monitored and threshold levels established. The number of their violations can give an additional safety indicator. In the organizational part of the system, procedures and maintenance strategies are developed as well as contingency plans. Follow up analysis is conducted based on the incidents reported. For monitoring this, multiple indicators can be monitored. Procedures can be used to set the course of the vessel not directly against the turbine structure but slightly off, to avoid collision or to establish safety zones around OWFs to prevent external vessels from crashing. The violation of these procedures can be measured, either in absolute numbers of vessels entering the safety zone or in terms of the number of turbine accesses per passing vessel. Even though all these indicators have the goal to prevent collisions, Dai et al. suggest that emergency procedures should be established in order to ensure safety. The existence or the lack of such emergency procedures and evacuation facilities should also be monitored by safety indicators. Since the concept of safety indicators depends heavily on the reporting of incidents and accidents it is necessary to establish a suitable reporting system for the OWF. The compliance with the system can again be measured by indicators, when reporting the lack of incidents is requested. Dai et al. focus on turbines with monopile structures, additional analysis of collisions between vessels and other structure types like jackets or floating turbines should be considered in future work.

5. Indicators and incident data

This section reviews the incident data reports from the G9 Offshore wind health and safety association [15,16] and matches them to the indicators and hazards discussed before. In 2013 a total of 616 incidents was reported. This number rose in 2014 to 994 reported incidents. However, the lost time injuries frequency, comprised of the percentage of fatalities and lost work days in the total number of reported incidents, decreased by 34%. Therefore the authors suggest that the reporting system has improved leading to a higher number of reported incidents. This higher number

Table 2. Hazards during installation and commissioning

Type of hazard	Tveiten et al.	Aneziris et al.
Uncontrolled movement of object	Falling structure/load/object Kinetic energy Potential energy	Contact with falling objects from crane or load Contact with falling objects from other Contact with hanging or swinging objects Contact with flying object machine or tool Contact with moving parts of a machine
Transportation	Marine operations (ship collision, man overboard) Helicopter operations	Struck by moving vehicle In or on moving vehicle with loss of control
Miscellaneous	Vibration (during testing)	
Electrical dangers	Short circuit Overcharge Electrostatic phenomena (shock, spark)	Contact with electricity - tool Contact with electricity - electrical work Contact with electricity
Exposure to dangerous work environment	Fire and/or explosion Radiation Noise	Fire - working near flammables or combustibles
Indirect effects on worker health	Physiological effects due to heavy lifting, repeated movements, uncomfortable positions Psychological effects	
Uncontrolled movement of person	Work at height Slippery surfaces Base/ground failure	Fall from height - fixed ladder Fall from height - other situation Fall on same level
Exposure to dangerous material	Flammable materials Poisonous materials Harmful material Oxidizing/corrosive material Battery acid	Fire - working near flammables or combustibles
Organizational malfunctions	Insufficient/missing safety equipment Incorrect use of machinery/tools Lack of relevant expertise Several actors/companies involved in same operation Time pressure	Trapped between Contact with hand held tool by self
External factors	Wind Waves and currents Lightening Earthquake Sabotage Terrorism	

however does not automatically imply a decrease in worker safety. Following the same structure as for the indicators, we first analyze the general incidents before looking at the turbine specific incidents.

In 2013, 26% of recorded incidents were due to lifting operations including 9 incidents that lead to lost work days. In 2014 this number decreased to 14% of the total incidents, including three lost work day incidents. Lifting operations were not considered as an individual hazard in any of the reviewed analyses. The closest presented hazards were those concerned with "work at height" and "falling structure/load/object" in Tveiten et al. [13] and "contact with falling objects from crane or load/from other" and "contact with hanging or swinging objects" by Aneziris et al. [17]. In both incident data reports, incidents that occurred while working at height are listed. For 2013 a total of 45 incidents have been reported and for 2014 the number of reported incidents is 77. Working at heights contributes hence to just over 7% of the reported incidents in both years. Monitoring this risk with an individual indicator thus seems practical. Incidents due to dropping objects are listed separately in the 2014 incident data report, with a total of 93 incidents due to dropped objects, of which none cause lost work days. However, the largest part of those dropped object incidents occurred during lifting operations or working at heights. This supports the intuition, that during lifting parts or working at heights is the time when dropping occurs most frequently. Having indicators in place for those cases, as suggested by the literature, is considered to be reasonable by us. Distinguishing between different sources of falling objects as suggested by Aneziris et al., however, seems to be unnecessary. A distinction between work processes during which the dropping occurs, as done in the 2014 incident data report seems more desirable. Marine operations, with 131 reported incidents in 2013 and 237 in 2014 are accounting for more than 20% of all reported incidents in both years. This includes maritime operations, transfer by vessels, vessel mobilization and vessel operations. Out of these 106 and 167 incidents occurred on vessels, causing 7 lost work days in 2013 and 12 in 2014. In other words 10% of the lost work days in 2013 were caused on vessels during marine operations. This percentage rose in 2014 to over 25%. Monitoring the health and safety of workers on vessels during marine operations therefore seems to be an integral part of any safety analysis.

For the incidents related to specific turbine subsystems, the nacelle region accounts for 40 reported incident in 2013 and 83 in 2014. These are 6% of the reported incidents in 2013 and 8% in 2014. The nacelle region hosts most of the subsystems of a wind turbine other than the rotor. Therefore work on any of the subsystems could lead to an incident in the nacelle region. In 2013 four work days were lost in the nacelle region, one of them caused by manual handling, one by operating plant and machinery and two work days by "other" work. In 2014, four work days were lost, of which three were lost due to manual handling and one due to operating plant and machinery in the nacelle. This analysis does not give information on the subsystem that was involved in the incident. Knowing during which activity the incident occurred, gives information on how to prevent it. In other words, knowing the activity that causes incidents give an operator the chance to train workers for these situations to prevent incidents from happening. In the hub and blade area 24 incidents were reported in 2013 and 20 in 2014. These account for 4% and 2% of the reports. In both years, one work day was lost in the hub and blade area. Even though these number are not high, we suggest to survey the hub and blade assembly as an individual subsystem, due to its unique function within the turbine and the resultant unique work tasks.

The incident data report from 2013 mentions a total of 15 incidents with chemicals and hazardous substances, comprising under 3% of all incidents. In 2014 this number went down to 10 incidents (1%). This supports the previously mentioned idea to monitor several hazard categories mentioned by Tveiten et al. with one common safety indicator. These are "flammable materials", "poisonous materials", "harmful material", "oxidizing material", "corrosive material", "carcinogenic material", "material harmful to genes" and "battery acid". A suggested name for the new indicator is "contact with hazardous substances".

Categories for organizational problems or collisions are not included in the G9 incident data reports. Hence the indicators for these cannot be validated. System safety theory advises to include human error in the analysis. Therefore the authors suggest to keep the indicators for organizational failures in place. No collisions happened during the incident data recording interval and therefore no such incidents are recorded. Since a collision of a ship and a turbine has extensive consequences, monitoring the risk and possibility of such a collision seems sensible.

Two incident areas are mentioned in the data reports, where no indicators were considered in our previous analysis. The transition piece area accounts for 32 and 53 reported yearly incidents in 2013 and 2014 respectively. These are just over 5% of incidents, accounting for 2 lost work days in both years. Since this is the area where maintenance personal accesses the turbine and vessels could collide with the structure, detailed monitoring of the type of work

Table 3. List of Proposed Safety Indicators

Category	Subcategory	Indicator (*Description*)	Measure
Organizational	*For organizational safety indicators, please see Utne et al. [4], Table 1, indicators Q1, Q2, Q3, Q4, U1, U2, U3, U4, U5, V1, V2 and Skogdalen et al. [3], Figure 3, indicators for "schedule and costs", "operational aspects" and "Operator well response". For the indicators concerned with the well response, note that "Time from first indication of well incident to first response" is substituted by "Time from first indication of subsystem failure to first response" and "Evaluation of well response action" is replaced by "Evaluation of repair action/failure response action".*		
Technical failure	All turbine subsystems	Annual failure rates for turbine subsystems (*The mean number of failures per year for each turbine subsystem gives a probability of failure*).	Probability
Work Environment and Training	Lifting	The number of incidents during lifting operations (*This indicator is measured as a percentage of the total number of lifting operations performed. Incidents caused by falling objects are monitored separately and are therefore excluded.*)	Percentage
	Work at heights	The number of incidents during work at heights. (*The indicator is measured as a percentage of the total number of work actions performed at heights. Incidents due to falling objects are excluded and monitored by a separate indicator.*)	Percentage
	Falling objects	The number of incidents due to the falling of an object during any operation in the WF (*measured as a percentage of the total work actions performed*).	Percentage
	Hub and Blade	Number of incidents occurring in the Hub and Blade area of the rotor of a turbine during work actions. (*The number is given as a percentage of the total work actions in the hub and blade area and give the percentage of work at the rotor that results in incidents.*)	Percentage
	Nacelle electrical	Number of incidents caused by electrical work in the nacelle (*measured as a percentage of all electrical work actions undertaken*).	Percentage
	Nacelle mechanical	Number of incidents caused by mechanical work in the nacelle (*measured as a percentage of all mechanical work actions undertaken*).	Percentage
	Contact with Substances	Number of incidents where a worker was exposed to a hazardous substance (*measured as a percentage of total number of work actions performed in a place with possible exposure*).	Percentage
	Substation	Number of incidents occurring in the substation (*measured as percentage of the total number of work actions performed in the substation*).	Percentage
Transport and Traffic	Helicopter incidents	Number of incidents happening during transportation with a helicopter. (*This includes material and worker transportation to and from the wind farm. Given as a percentage of total transportation actions with helicopters.*)	Percentage
	Vessel incidents	Number of incidents happening during transportation with a vessel. (*This includes worker and material transportation both to and from the wind farm and is given as a percentage of total (vessel) transportation actions.*)	Percentage
	Transition piece incidents	Number of incidents during turbine access in the transition piece area (*given as a percentage of total turbines accesses in the TP area*).	Percentage
	Collisions internal	Number of vessel accesses complying with the safety procedure. (*Measures the risk of vessels, part of the WF, colliding with the turbine structure or substation by measuring the number of vessel accesses complying with a procedure, like setting the vessel course not directly at the turbine, as percentage of the total accesses to the WF.*)	Percentage
	Collisions external	Number of safety zone violations. (*The number of wind farm accesses per violation of the safety zone measures the risk of an external vessel colliding with the turbine structure or substation.*)	Percentage
	Boat landing structure	Presence of a boat landing structure. (*A landing structure improves the energy absorbed by the structure.*)	Binary
External Factors	Wind	Number of vessel/helicopter operation in violation of wind speed thresholds (*as a percentage of total number of operations*).	Percentage
	Wave	Number of vessel operations in violation of wave height restrictions (*as a percentage of total number of vessel operations*).	Percentage
	Seismic risk	Peak ground acceleration factor. (*This is a factor of standard gravity g providing information about the risk of earthquakes. It can be obtained from seismic hazard maps.*)	Factor

carried out when an incident happens is suggested. Substations, both onshore and offshore, including high voltage areas and cable work caused 18 and 25 incidents, respectively. This is approximately 3% of the total reported incidents each year. In 2013 substation work and cable areas accounted for one lost work day. In 2014 no work day was lost in the substation area. The number of incidents is not exceptionally high in the substation area. However, due to the unique function and properties of it, having an indicator in place for the substations is recommended. Further, due to its unique properties, monitoring of this indicator is relatively easy.

6. Conclusion and Further Research

In this paper, we presented a review of existing literature on system and worker safety specific to the field of offshore and onshore wind industry including some related analyses from the offshore oil and gas industries. The analysis includes both the installation and operational phase of the OWF as well as individual turbines, turbine subsystems and the interaction with vessels. Finally, the incident data reported by G9 [15,16] was connected to the hazards described in other publications like Tveiten et al. [13] and Aneziris at al. [17]. Most of the indicators were found to be relevant, when compared to reported incident data. However, grouping together different indicators concerned with hazardous substances can facilitate the recording process and will most likely enhance the utility of the indicators. Additional indicators for the access to the turbine and substations are recommended as well as indicators monitoring the organizational structure and reporting system. The full list of the proposed safety indicators for the wind farm can be found in Table 3. The table includes the categories and names of indicators, a short description and a suggestion for measuring. For future research, additional review of other structures than monopiles is highly recommended. In a next step, face validation by industrial partners namely WF operators should be considered. Finally, the safety indicators have to be used in operations, data needs to be collected and the indicators need to be revised based on the collected data. A continuous loop of adjusting the indicators based on available incident data will help improve the indicators and can eventually lead to an improvement of the worker health and safety in an offshore wind farm.

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A.3 Paper 3

Key performance indicators for wind farm operation and maintenance.

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Key Performance Indicators for Wind Farm Operation and Maintenance

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Abstract

Key performance indicators (KPI) are tools for measuring the progress of a business towards its goals. Although wind energy is now a mature technology, there is a lack of well-defined best practices to asses the performance of a wind farm (WF) during the operation and maintenance (O&M) phase; processes and tools of asset management, such as KPIs, are not yet well-established. This paper presents a review of the major existing indicators used in the O&M of wind farms (WFs), as such information is not available in the literature so far. The different stakeholders involved in the O&M phase are identified and analysed together with their interests, grouped into five categories. A suggestion is made for the properties that KPIs should exhibit. For each category, major indicators that are currently in use are reviewed, discussed and verified against the properties defined. Finally, we propose a list of suitable KPIs that will allow stakeholders to have a better knowledge of an operating asset and make informed decisions. It is concluded that more detailed studies of specific KPIs and the issues of their implementation are probably needed.

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Keywords: Wind Energy, Performance, Operation and Maintenance, Key Performance Indicator, Review

1. Introduction

Wind energy has become a mature and cost-competitive source of electricity in Europe [1]. Although new offshore wind projects still show remarkable growth rates [2], changes in regulations amplify the interest in optimising the performance of existing installations. Consequently, in the last years much effort is put into improving operation and maintenance (O&M).

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A key perfomance indicator (KPI) is “a metric, measuring how well an organisation or an individual performs an operational, tactical or strategic activity that is critical for the current and future success of the organisation“ [3]. Using key performance indicators (KPIs) allows stakeholders to measure the progress towards a stated goal. Many industries use KPIs, like the nuclear industry [4], the financial sector [5] and health care [6]. During the O&M phase of a wind farm (WF), KPIs can influence the decision-making process by providing the stakeholders with valuable information assessing the status of the operational asset. Indeed they reflect changes in the O&M strategy.
Although many indicators have been defined, there is still no consensus within the wind industry and no agreement on the calculation or even the definition of KPIs during the O&M phase of a WF yet. The literature on this topic is limited; A study from 2011 only investigated four KPIs for the wind industry initiative [7]. The existing European standards for maintenance [8,9] provide a guideline for terminology and 71 maintenance indicators. We present a complimentary study, focused on the wind industry, by filtering the existing ones. Additionally, this review covers operational and financial indicators.
The Advanced Wind Energy System Operation and Maintenance Expertise (AWESOME) project organized a joint industry workshop (JIW), gathering both industrial and academic partners. The present authors addressed the need for KPIs for the O&M phase of a WF that was stated by the partners during the JIW. This paper presents a condensed and updated version of the results of the report [10] and intends to shed light on the definition of KPI properties, classification of KPIs and assessment of their value to wind farm O&M activities.
This paper is organized as follows. Section 2 describes the methodology of the workshop and of the paper. In Section 3, the different stakeholders are identified and analysed together with their interests resulting in five different categories; major indicators are reviewed and discussed. A proposed list of KPIs is given in Section 4; their properties and suitability are discussed. The study is concluded in Section 5 with further research suggestions.

2. Methodology

Based on the goal of defining KPIs for the O&M phase of a WF we conducted the analysis of the KPIs in five main steps. We used the well-established brainstorming technique [11] that is also applied in other fields [12], since it was suitable for the format of the JIW. First, we addressed the definition of the term KPI. In the context of the O&M phase of a WF, KPIs have to support informed decisions and reduce uncertainty by managing risks. Defining KPIs helps the stakeholders to address different concepts of the WF project by using the same metrics, leading to a common understanding of the important aspects and the success of a WF project. KPIs should answer the question: Which information should be monitored by the different stakeholders during the O&M phase of a WF?
Having defined the purpose of the KPIs, we identified the different stakeholders involved in the O&M phase of a wind power project. Once the stakeholders were identified, we discussed, collected and assembled their needs. Some of them are overlapping, so the main requirements were grouped into five categories. This has been addressed in Section 3.1. Next, we investigated the main properties that KPIs should fulfil, leading to a set of recommended properties that is presented in Section 3.2. For each defined category we conducted a review of the state-of-art, followed by a discussion, in Section 3.3. Our study initiated from the BS EN 15341:2007 [8] standards which offer maintenance related KPIs. These standards deal with all industrial and supporting facilities, introducing 71 KPIs, while they focus only on the maintenance. Finally, we present a comprehensive set of KPIs for the O&M industry that fulfil all the properties we previously defined.

3. Results

3.1. Stakeholders and their requirements

Various stakeholders are involved in the O&M phase of a wind power project. Their strategic decisions rely on the information they have about the current status of the operating asset, referring to different aspects, i.e. regulatory, economical, technical and safety aspects. The different stakeholders are identified and presented here, together with their main needs for information.
Wind Farm Operator
The WF operators’ main interest is to maximise the revenue of the WF and hence the energy production throughout

the lifetime of the project. The operator needs information about the energy production, the efficiency of the WF, the production losses and might also request information about future expectations of energy production and remaining lifetime, as well as the current value of the asset, profits, costs and debt.

The Investor

Investors and banks can partially or completely own the WF. They are mainly interested in the economic and financial aspects of the wind power project development, including information about production, efficiency, future expectations, costs, debt, profits and current value of the asset.

The Maintenance Service Provider

Maintenance services are commonly outsourced to a maintenance service provider (MSP), who is often the original equipment manufacturer (OEM). The most important aspect of a standard O&M contract is the wind turbine availability warranty. This warranty states a certain percentage of time that the WFs operation shall not be affected by maintenance actions from the MSP. Otherwise, the MSP shall pay the WF operator compensations. The main interest of the MSP lies in reducing the time and cost of the maintenance operations through a good understanding of the health status together with the failure history and the component cost. From a safety and efficiency perspective of the maintenance tasks, the MSP also seeks information about health, safety and environmental (HSE) issues, like safety indicators and environmental restrictions.

The Insurance Provider

Insurance companies provide services to cover the costs of various incidents that might occur during the operational phase of the WF. This can include [13] damage to the WTs and associated equipment due to storms, thefts, malicious actions, or fires, costs of spare parts, loss of revenue, damage to third party property or environmental damage. Consequently, the insurance provider is mainly interested in the health status, failure history and the HSE aspects.

Utility and Grid Operator

According to the European grid codes, all the energy produced from wind has to be bought by an electrical companies, i.e a utility. This stakeholder is usually interested in the energy production of the WF, the future expectations of production and the electricity price. In addition to the utility, the integration of energy produced from wind into the grid is a challenge for the Grid Operator [14–16] . This stakeholder is interested in performance, stoppages and energy production, power quality and other quantities that can affect grid stability.

Government, Public and End Users

Here we identify and group together stakeholders that are not technically involved in a WF's operation. First, the governments regulate the activities of the wind industry through regulatory bodies. Non-compliance with these laws and regulations can result in penalties and subsequent withdrawal of operating license. The public expects protection of the environment and minimum interference of the plant with adjacent living communities. Finally, the end users expect competitive prices of energy in comparison to other sources. Consequently, public opinion and political decisions may affect the profitability of a wind power project, since their support of wind energy can have an economic impact on the project, e.g. in terms of subsidies. In summary, this group of stakeholders is mainly interested in the efficiency of the WF, the electricity price and the environmental impact of the project.

An obvious conclusion that can be derived from the above listing of the most important stakeholders, is that their needs are frequently overlapping. This characteristic, along with the fact that it will facilitate our study of the most important KPIs, guided us when categorizing the stakeholders' requirements. The five chosen categories, as well as the corresponding requirements, are shown in Table 1.

3.2. Definition of the properties

One of the main requests that the industry representatives expressed during the discussion at the JIW was the need to identify the properties of the indicators. In this regard, safety indicators have already been developed for the Offshore wind industry [17], which have guided us to define the necessary properties.

As the most important property, KPIs need to be **relevant**, i.e. they have to carry information valuable to stakeholders. Since they have to allow the stakeholder to take informed decisions, the indicators have to be such that they can trigger changes. Another property is that KPIs must be **specific**, meaning that the observed value needs to be well defined, so that it is clear what exactly is being observed and how. In order to have an easily observable value, indicators should be **measurable**, either in a qualitative or in a quantitative way. The measurement can be a numerical value,

Table 1. Categorisation of the stakeholder requirements

Performance	Reliability	Maintenance	Finances	Safety
Efficiency	Failure history	Component cost	Component cost	Environmental issues
Future expectations	Fatigue	Failure history	Current asset value	Health & Safety environment
Production	Health status	Logistics	Debts & Profits	Safety indicators
Production losses	Loads	Maintenance hours	Electricity price	
	Remaining lifetime	Maintenance restrictions	Risks and insurance	
			Subsidies	
			Unnecessary cost	

like hours of operation, or a categorical statement, like "WF is running ok". Stakeholders should be able to use KPIs to compare different assets without much effort; therefore, **comparability** is another necessary property for the KPIs. In this way, WFs with different layout, size and location can be compared to each other, by only looking at the KPIs. To track the wind power project development over time, it is necessary for the KPIs to be **traceable on different timescales**. For some indicators it might be sensible to provide hourly data, whereas for others a yearly summary is more beneficial to the stakeholder. To leave no room for individual interpretations, a standard should be implemented, giving exact definition of all terms and indicators used. With the **standard**, different stakeholders can use the same indicators without worrying about the scope of interpretation. Standardised KPIs enable the comparison of different assets through benchmarking, comparing the performance of a WF to the best performances recorded in the industry [18]. Defining properties for the individual indicators is not enough, since there will be a set of them. This set needs to be able to give a complete picture of the whole WF, both in onshore and offshore cases, with the fewest possible KPIs. Therefore, we are looking for a **minimal set** of KPIs, which are clear and easy to understand. The indicators do not necessarily need to be disjoint, so two or more of them are allowed to present overlapping observations. Sets of KPIs that are disjoint however, should be preferred over non-disjoint sets. For disjoint KPIs, changes in one KPI cannot imply changes in any other KPIs. This means that changes in the observed WF only influence one specific KPI, which makes interpretation of the KPIs easier for the stakeholders. To sum up, effective KPIs need to be **relevant, specific, measurable, comparable, traceable in time, standardised and form a minimal complete set**.

3.3. Review of the existing KPIs and their properties

For each category defined in 3.1, we performed an extensive review of the indicators used in the industry and the ones covered in the literature. The identified metrics are reported here and then assessed with respect to the necessary properties defined in 3.2.

3.3.1. Performance

One of the most important operator's interests is the performance of the asset. The word performance is very broad and can embrace many aspects of the WF operation, from annual energy production (AEP) to generated revenue. We would like to read here WF performance as its efficiency. Indicators should then answer the following question: *is the WF producing as much energy as it could?* The most commonly used indicators are presented subsequently.

Wind / Energy Index [19–22]

First developed in Denmark in 1979, the concept was later copied by other northern countries. It is based on the production of a number of reference WTs over a wide geographic area. It establishes a statistically "normal" period of yearly wind energy content, expressed as 100%, so that the operator can distinguish between WT under-performance and wind strengths below expected levels; it allows for comparison of the production of a WF with the available wind resource. Although it fulfils many of the properties stated in 3.2, it does not provide the operator with sufficient information so that informed decisions can be solely based on the index.

Capacity Factor [23,24]

Defined as the energy generated during a period of time divided by the WF rated power multiplied by the number of hours in the same period. Since the denominator is a constant, it does not represent the theoretical energy production according to real on-site wind conditions. Although it is a valuable indicator during feasibility and wind project development stages, we believe it is not an effective indicator for evaluating WF operational efficiency.

P_{50} deviation [25]

During the process of wind resource assessment, the P_{50} energy yield gives the level of AEP that is expected to be exceeded with a probability of 50%. Many operators currently look at the deviation of the actual AEP from the calculated P_{50}, especially when looking into deviations of planned budget. From our experience, the P_{50} is subject to important uncertainty. Furthermore, there is no standard procedure to obtain this figure.

Time-based availability [26]

Defined as the accumulated time that the WT is operational divided by the total period of time. This indicator is specific, since the observed value is clearly defined and is the time that a WT is operational; measurable and easy to understand, it is relatively easy to distinguish periods of power production from periods of inactivity; strategies to reduce the downtime result in an increase of this metric. Despite existing technical specifications for its calculation, no international standard exists. Furthermore, it does not provide information about WF efficiency or power losses due to unavailability. The existing standard [8] defines four technical indicators, namely T1 T6, T7 and T15 which relate the total operating time with downtimes due to maintenance activities. TBA comprises the information included in these three technical indicators but it does not consider that the operating time of the wind turbine is influenced by the wind conditions.

Energy-based availability [27,28]

Defined as the ratio between the real energy production and the actual energy available. In our opinion, it illustrates the ”real” efficiency of a WT or WF since it reveals the percentage captured from the available energy. It is a more objective indicator for comparison between different assets, but difficult to implement. Although it is very easy to measure the produced energy over a certain period of time, it is quite difficult to precisely define the actual available energy for the same period. Therefore it is very challenging to define a standard procedure. Current approaches rely on theoretical production calculation from an operational power curve based on SCADA data.

3.3.2. Reliability

Reliability is defined as the “ability of an item to perform a required function under given conditions for a given time interval” [9]. Applied to a WT, its reliability can be defined as its ability to perform properly, without failures, during specified site wind conditions for the whole lifetime (defined to be at least 20 years) or in a specific time window. WT reliability is compromised by component failures, leading to downtime. For that reason, the industry currently uses different metrics to assess WT reliability [29] by answering questions like: *How often does a WT fail?* and *Which WT downtimes are associated with which failure?* [9]. The indicators are summarised below.

Mean Time between Failures (MTBF) & Failure rate [9,30]

The MTBF expresses the total operational hours divided by the number of failures for a specific component or for the whole WT. The term MTBF is frequently used to describe reliability, as well as its reciprocal value, the failure rate. Both indicators satisfy the majority of the identified properties for KPIs. However, an effective comparison between WTs or WFs will not be possible until a standard WT taxonomy is defined. Even though some recent approaches have been published, like RDS-PP [31] and ReliaWind [32], there is still no agreement on a unique and standard designation. This issue has been discussed in detail by Reder et al. [33]. MTBF is defined in the standard [8] as the technical indicator T17.

Mean Time to Repair (MTTR) & Repair rate [9,30]

The MTTR is the average time to return a WT to its functional state [9]. This can imply either a repair or a full replacement of the faulty component, leading to the term of restoration, as defined in [8]. This indicator can be assessed by dividing the total time of restoration by the number of failures. Given the definition in the maintenance standards [9] this term should rather be referred to as mean time to restoration. Nevertheless, we stick here to the designation as mean time to repair due its widespread used in the industry. The reciprocal of the MTTR is the repair rate. As well as the previous indicators, they meet all the desired properties and their definition is specific and standardized within the industry. But again, comparison is limited due to the lack of a standard WT taxonomy and the inconsistency of intervention specific failure definitions. MTTR is defined in the standard [8] as the technical indicator T21.

Mean Time to Failure (MTTF) [30]

The MTTF is similar to MTBF but it is used to describe reliability of non-repairable systems. Non-repairable refers to systems that are replaced after a failure because there is no possible maintenance action that can make them work properly. Hence, over the lifetime of a non-repairable system, this fails once and the MTTF measures the average time until this unique failure occurs.

Availability [34]

The time-based availability (3.3.1) is the amount of time that a system or component is available for use divided by the total amount of time in the period of operation. From the previous metrics, it can be defined as the ratio between the MTTF and the sum of MTTF and MTTR. In our opinion, availability is most closely related to energy production. Thus, the previous metrics seem to be more adequate to assess WT reliability.

The identified indicators satisfy most of the necessary properties for KPIs. Nonetheless, we believe that it is difficult to make them comparable due to the lack of a standard WT taxonomy and due to potentially different component behaviour in different WTs, especially with regard to differences in turbine size and technology [33]. Moreover, data collection on wind turbine failures is not standardised and there is an important lack of failure data, contributing to a high level of uncertainty related to the indicators. We would also like to mention the importance of initiatives for standardisation of data and reliability analyses like [35] and [36].

3.3.3. Maintenance

Maintenance activities are crucial to keep a system in good condition. In general, these activities can be divided into corrective and preventive actions, including both time-based and opportunity-based maintenance. While preventive maintenance intends to avoid failure, corrective actions are implemented once a component has already failed. Maintenance indicators assess the quality of the maintenance, in terms of time consumed for different interventions and related costs. The reported indicators are presented in the following.

Response time [37–41]

Defined as the time between failure occurrence and maintenance intervention, it informs about the efficiency in maintenance planning. Since it is often difficult to detect the failure starting time, it can be redefined as the time between failure detection and intervention. This new indicator is then specific and measurable. However, since the sensors and alarm systems vary between different WT types [42], this indicator is not comparable.

Number of interventions [37–41]

An intervention is the fieldwork conducted to keep a WT in good condition; it implies a displacement of the maintenance crew. Monitoring the number of interventions, both scheduled and unplanned, can show the results after an optimisation of the O&M strategies. In case of higher WT reliability, less interventions should be needed; this would result in lower O&M costs, especially in offshore cases where the number of interventions is related to the necessary vessel transfers. Nevertheless, there is no agreement on the definition of intervention; during a maintenance work one intervention could be accounted for the entire WF or per WT intervened. Even though this indicator could easily fulfil most of the necessary properties with a consensual definition, the comparability between assets remains difficult. This is not only due to possible differences in terms of size of the WFs, but also to the duration of the interventions, and their related costs. Comparability could be improved by normalising the number of interventions by the number of turbines in a WF, but their duration should be definitely included. Further research would be needed on this issue.

Corrective maintenance (%) [37–41]

Defined as the ratio of the purely corrective interventions over the total number of interventions, this indicator meets all the properties and defining a standard is possible. Since corrective interventions are generally more costly than preventive actions, it also allows the assessment of the success of new O&M strategies. Indeed, some operators are experiencing a decrease of this percentage after the introduction of condition-based strategies. The existing standard [8] includes two organizational indicators (O16, O18) which describe the corrective maintenance activities and the immediate corrective maintenance activities, respectively. Our indicator does not distinguish between immediate and non-immediate activities. These two indicators are expressed in man hours instead of number of interventions.

Schedule compliance (%) [37–41]

It is defined as the ratio between the scheduled maintenance tasks completed on time and the total number of tasks. This indicator fulfils most of the properties and a standard can be easily defined. Furthermore, it can be used to assess the efficiency of maintenance execution or accuracy in maintenance planning. The organizational indicator O22 in [8] also describes this.

Overtime jobs (%) [37–41]

Defined as the ratio between the overtime working hours and the planned working hours (working hours per worker and per size of the workforce), this metric can be measured on different time-scales. It is comparable and a standard can be defined. It informs about effectiveness of maintenance planning, worker health or ideal work force size. The organizational indicator O21 in [8] describes this in terms of internal man hours. We do not distinguish between internal and external man hours.

Total Downtime [37–41]

Since downtime is affecting the WT availability, we presented this in the Sections 3.3.1 and 3.3.2.

Equipment reliability [37–41]

We also do not show the equipment reliability here, since it was already presented in section 3.3.2.

Backlog [37–41]

It can be defined as the list of maintenance work that still needs to be completed. Hence, its size might sound like a very intuitive way to measure the effectiveness of maintenance execution. However, there is no specific definition for this effectiveness and it cannot therefore be measured. Indeed, it is possible to sum the time for the expected scheduled interventions but it might not correspond to the exact time that will be finally needed. Furthermore, a big backlog can be due to very different reasons, among them poor planning, poor execution or too small workforce.

Labour costs versus total maintenance costs (TMC) (%) [37–41]

The labour costs, expressed as a percentage of the total maintenance costs (TMC), inform about the effectiveness of maintenance execution; most operators agree on the importance of having qualified maintenance staff to ensure an ideal percentage of labour costs. It fulfils most of the properties defined and can be easily standardized. The standard [8] defines two economic indicators (E8 and E9) describing the total internal and external personnel cost, respectively. Again, we do not make a distinction between internal and external personnel cost.

Cost of spare parts versus total maintenance costs (TMC) (%) [37–41]

The cost of spare parts, expressed as a percentage of the TMC, is directly related to the number of failures followed by replacements. Moreover, historical values might help in the budget planning. This indicator provides information about the proportion of cost of spare part cost of the TMC. Other factors to the TMS include equipment hire, consumables and labour costs. Moreover the indicator fulfils many of the desired properties for KPIs. However, its specificity and standardisation depends on the costs included in the definition.

Total annual maintenance cost versus annual maintenance budget (%) [37–41]

Setting the TMC in relation to the annual maintenance budget (AMB) can give insight into the quality of maintenance planning and is therefore relevant to stakeholders. Defining the indicator as three categories ($TMC<AMB \equiv green$, $TMC \approx AMB \equiv yellow$, $TMC>AMB \equiv red$) is specific and measurable. It can further be compared between WFs, is traceable in time and can be defined in a standard. The stakeholders can use this indicator to know, whether they are spending as much as anticipated or more on the maintenance of their asset. Using three different colours is intuitive and very demonstrative.

The standard [8] includes many more indicators concerned with the cost of maintenance and materials, e.g. T16, E11. However, the indicators presented here are a comprehensive overview of the most important aspects of the maintenance phase of a WF.

3.3.4. Finance

The financial status of the wind power project is a general concern throughout its entire lifetime. Financial KPIs are fundamental tools for making an asset status summary or for comparing different investment options. Consequently, they can be used as a feedback mechanism for management decisions evaluation. Some might be more useful during the feasibility phase, as they can influence the decision of undertaking the project [43,44]. As the investment is already made in the O&M phase, the main interest is to know about the financial status of the operating asset; any decision-making process seeks to maximise the return on the investment. The most widely used indicators are summarised in the following.

Operational Expenditures (OPEX) [43]

The OPEX include the cost of operating the site, planned O&M and unscheduled maintenance. These costs can be grouped into two different categories: the O&M costs, which represent approximately 60% of the OPEX and tend to increase as the WF reaches the end of its lifetime [45]; the other category covers other operating costs like rent, taxes and insurance. In order to be comparable, this metric should be normalised by WF installed capacity.

Earnings Before Interest, Taxes, Depreciation, and Amortisation (EBITDA) margin [46,47]
The EBITDA margin is a financial metric used to assess profitability by comparing revenues with earnings. It is defined as the percentage of the revenue remaining after covering the OPEX. This indicator meets all the desired properties and is used to track changes due to new O&M strategies. Its drawback is the omission of the capital expenditures (CAPEX). Even if a negative margin undoubtedly indicates profitability problems, a positive margin does not necessarily indicate that the WF generates cash. Indeed, this metric cannot track changes in working capital, CAPEX, taxes, and interest rate. In our opinion, CAPEX should be included when evaluating the profitability of a WT or WF project. Hence, the EBITDA margin could be considered as a good KPI allowing the comparison between different WFs profitability, but it should be presented in conjunction with another KPI which includes the CAPEX.
Loan Life Coverage Ratio (LLCR) [46,48]
Defined as the ratio between Net Present Value (NPV) of the cash and the amount of debt, it informs about loan repayments. Financial modelling of LLCR is now a standard metric calculated in a project finance model and has been standardised. Apart from other properties that this metric clearly fulfils, it has a special relevance since it provides the WF Operator with information about the ability to repay the debt over the whole lifetime of the asset.
Debt-Service Coverage Ratio (DSCR) [46,49]
The DSCR is the ratio between the available cash for debt payment and the sum of interest, principal and lease. It is an accepted financial KPI in industry for the measurement of an entity's ability to balance debt payments with produced cash. The main difference with the LLCR is that it measures the ability to pay the debt in a specific year. Similar to the LLCR it meets all the desired properties for KPIs.
Free Cash Flow to Equity (FCFE) [46,50]
The FCFE is a measure of how much cash can be paid to the equity shareholders of a company after all expenses, reinvestment and debt repayment. FCFE takes into account the net income, the depreciation of amortisation, the change in working capital and the net borrowing. A standard definition can be found in [46,50]. Although it provides the investor with relevant financial information, this indicator cannot be used for benchmarking since it is not comparable between assets.
Levelised Cost of Energy (LCOE) [7,51]
The LCOE is probably the most popular financial KPI in the wind industry and particularly useful for investors seeking to compare different generation sources. It allows to compare different WFs in terms of financial status. The LCOE takes into account the CAPEX, the installed capacity, the capital recovery factor, the discount rate, the WF lifetime, the OPEX and the annualised energy production. A complete definition can be found in [7,51]. A standard methodology was proposed, discussed and approved in [7]. This KPI is now a standard and specific indicator and includes both CAPEX and OPEX. However, the suggested methodology was criticized, since the normalisation for benchmarking is done in terms of installed capacity (MW); indeed, the LCOE could be better described in terms of $€/m^2$ of rotor swept area since it would be directly related to the WT energy production. Unfortunately this would require a much more complex model and further data uncertainties. In any case, this KPI remains as a very effective indicator to evaluate the financial performance of an operating asset. As an example, many recent studies are mostly focused on improving the LCOE [51].
Other indicators
Some other more complex indicators might be found as the wind speed dependent cash flow, semi-elasticity (function of averaged weighted payment duration and interest rate) and relative convexity (ratio between convexity of cash flow and semi-elasticity) [52]. The break-even price of energy (BEPE) for renewable energy projects, defined in [53], tries to overcome the omission of the legal framework in the LCOE by taking into account parameters such as inflation and tax rate. Given that the renewable energy sector is highly influenced by local conditioning factors, the suggested metric seems to be an interesting alternative to the LCOE.

3.3.5. Safety

In the RAMS literature [54], KPIs for the system performance are often distinguished from indicators monitoring the safety of a system (safety indicators). KPIs are more focused on system performance and output in terms of financial gain. Safety indicators on the other hand help to monitor the safety of both the system and the workers. We want to refer to an analysis by Scottish Power [55] concerned with major hazard risks, as an example for system safety indicators. For the worker health and safety, we want to refer to a publication on safety indicators for offshore WFs

[17]. Safety indicators enable the operator to track changes in the worker health and safety for different maintenance strategies, legal regulations and specific procedures.

4. Discussion

The review of the indicators showed some of the shortcomings of the potential KPIs in terms of fulfilling all properties. For the KPIs describing **performance**, the energy-based availability allows to have a better tracking of variations in the WF energy efficiency. However, theoretical production cannot be measured accurately and neither indicator is standardized. Although time-based availability does not inform about power losses, it can be helpful for illustrating downtime reduction. All of the indicators concerned with **reliability** fulfil all properties except for being standardised, due to the lack of a common WT taxonomy. Since there is a common understanding in RAMS literature, defining a standard seems feasible and much effort is currently devoted to nomenclature standardisation. In any case, the suggested KPIs allow to track the progress towards increased WT reliability. Also the KPIs for the **maintenance** category lack the definition of a standard. This should be a common goal of the wind energy industry and academia for the future. All discussed **financial** KPIs fulfil the necessary properties and can be used as they are, allowing to reveal variations in the financial status of the asset. An overview over the proposed indicators and their properties can be found in Table 2.

Table 2. Proposed list of indicators and their properties, as listed in section 3.2. The property of a minimal set of indicators is not included in the table. A checkmark indicates that the indicator fulfils the properties, a crossmark that the indicator does not fulfil a property and the asterisk indicates indicators that are not yet fulfilling the property in question but can be modified to do so.

	Relevant	Specific	Measurable	Comparable	Traceable in time	Standard
Performance						
Time-based availability (%)	✓	✓	✓	✓	✓	✗
Energy-based availability (%)	✓	✓	-	✓	✓	✗
Reliability						
MTBF & Failure rate (%)	✓	✓	✓	✓	✓	✓*
MTTR & Repair rate (%)	✓	✓	✓	✓	✓	✓*
MTTF	✓	✓	✓	✓	✓	✓*
Maintenance						
Interventions per WT	✓	✓	✓	✓*	✓	✓*
Corrective maintenance (%)	✓	✓	✓	✓	✓	✓*
Schedule compliance (%)	✓	✓	✓	✓	✓	✓*
Overtime jobs (%)	✓	✓	✓	✓	✓	✓*
Labour costs vs. TMC (%)	✓	✓	✓	✓	✓	✓*
TMC vs. AMB (%)	✓	✓	✓	✓	✓	✓*
Finance						
OPEX	✓	✓	✓	✓	✓	✓
EBIDTA margin	✓	✓	✓	✓	✓	✓
LLCR	✓	✓	✓	✓	✓	✓
DSCR (historical & expected)	✓	✓	✓	✓	✓	✓
LCOE	✓	✓	✓	✓	✓	✓

5. Conclusions and further work

In this paper the topic of key performance indicators for the wind industry has been discussed. After defining properties and a thorough review of existing indicators, we propose a list of possible key performance indicators that fulfil these properties or can be modified to do so. The work was based on discussions with representatives from industry. However further numerical validation with real WF data is highly recommended to make a quantitative evaluation among different KPIs both for onshore and offshore cases.

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A.4 Paper 4

Using a Langevin model for the simulation of environmental conditions in an offshore wind farm.

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Using a Langevin model for the simulation of environmental conditions in an offshore wind farm

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Abstract. For the planning of operations and maintenance in offshore wind farms, many simulation models exist. Many rely on artificially generated weather time series to test different strategies. In this paper, we present a novel approach to modeling both the significant wave height and wind speed based on measurements from the site. We use a stochastic process called the Langevin process. First, equations are fitted to the available data, which are then used to generate the artificial weather data. The properties of these artificial weather time series are very close to the properties of the actual weather. Mean and standard deviation as well as the overall distribution and seasonality can be captured by the new model. Additionally, the persistence of waves and winds is replicated. This is especially important, as the length of weather windows is an important factor in operation and maintenance planning.

1. Introduction

Both in research and the wind industry, simulation models are often used to improve the operations and maintenance for offshore wind farms. There are research groups looking into optimal vessel routing, preventive maintenance strategies, optimization of corrective maintenance and condition monitoring among other topics. In order to provide simulations of an offshore wind farm, many of the existing models use weather time series to model the weather conditions, with significant wave heights and wind speeds. In order to model a specific location, without the risk of finding an optimal solution for a specific historical weather dataset, some researchers want to use artificial weather data. This artificial weather data should represent the given location and have the same properties, such as annual mean wind speeds or persistence of wave heights. The advantage with artificial weather data over historic weather data is that a natural variability of the weather can be achieved, without loss of site specific properties. Even if a model can theoretically be used with historic weather data, this data is not available of an appropriate length and quality for some locations. Also in this case, researchers benefit from artificial weather time series. In order to generate this artificial weather data, different methods can be used. Today, the three main choices for the simulation of weather conditions are Gaussian statistics, Auto RegressiveMoving-Average (ARMA) processes and Markov processes [1]. Different weather generation models have been developed using these methods and are being used in decision support tools. Dinwoodie et al. [2] use a multivariate autoregressive (MAR) process, an improved MAR process is described in detail by Dalgic et al. [3]. Scheu et al. [4] use a Markov chain approach which is described and analyzed in [5]. This approach was developed further to include more weather parameters by Hagen et al. [6]. Hersvik and

Endrerud [7] present an improved Markov chain process. In this paper, we want to introduce a novel approach to generating artificial weather series, based on the Langevin equations. In Section 2, this method is explained in more detail. Then we briefly explain the data sources used in this paper in section 3. An analysis of the generated weather is conducted in section 4, before we discuss the results in section 5. Finally, we conclude and give an outlook to further work in section 6.

2. Methodology

In this paper, we investigate a new approach to weather simulation, a Langevin process. Czechowski and Telesca [8] already fitted a Langevin type equation to wind speed data and the Langevin approach [9] has already been used to model turbulent wind velocities by Reinke et al. [10]. To our knowledge, the Langevin approach has not been applied to model the behavior of wind speeds on the scales used in offshore wind farm operation and maintenance models. Hadjihosseini et al. [11, 12] applied the approach to ocean waves, studying rogue wave phenomena, using data from Japan. They have shown that it is possible to use the Langevin approach to generate surrogate data sets and even forecast extreme wave events. However, the data used in their analysis had a sampling frequency of 1 Hz and the approach has not yet been used on data with a lower sampling frequency. As Hadjihosseini et al. [12] were interested in the study of rogue waves, they have not investigated other properties of the surrogate data, like the persistence of significant wave heights.

The Langevin process is a stochastic process governed by the Langevin equation.

$$\frac{\mathrm{d}X}{\mathrm{d}t} = F(X,t) + G(X,t,\Gamma) \tag{1}$$

This is a stochastic differential equation, including a deterministic term $F(X,t)$ and a stochastic term $G(X,t,\Gamma)$. Those terms are often referred to as drift and diffusion function and depend on the first two Kramers-Moyal coefficients $D^{(1)}(X)$, $D^{(2)}(X)$

$$F(X,t) = D^{(1)}(X)\tau \tag{2}$$

$$G(X,t) = \sqrt{D^{(2)}(X)\tau}\Gamma_t \tag{3}$$

where τ is a time-increment. It is important to note, that the coefficients depend on the observation X (in our case wave height or wind speed) as well as time t. Γ_t represents the stochastic forces. Hadjihosseini et al. [11] and Reinke et al. [10] have shown that the Langevin process can be described by the so-called Fokker-Planck equation, shown in Appendix A.1. The Kramers-Moyal coefficients can be defined as an expression of the conditional moments of the trajectory, as presented by [13], see Appendix A.2. The interested reader can find the derivations of the equations for the Langevin process and a detailed mathematical description in e.g. [11, 10].

When fitting the model to wave height data the two functions describing the dependence of the deterministic and stochastic contribution on the observation are estimated and later used for modeling. We will refer to these functions as the “parameter functions”, the “drift-” ($D^{(1)}(X)$) and “diffusion- ($D^{(2)}(X)$) polynomial” and will use $D^{(1)}$ and $D^{(2)}$ as notation in the remainder of the paper.

In the analysis presented in this paper, we used the software R and the package 'Langevin' developed by Rinn et al. [14]. First, the parameter functions ($D^{(1)}$, $D^{(2)}$) were estimated based on the data. The software package, developed by Rinn et al., estimates the parameters for discrete points and reports back the estimated coefficients, their respective estimation errors and other information such as the mean and density of observations bin (interval) of the data used to estimate the coefficients.

In the second step a weighted linear regression taking into account the uncertainty of the estimate was conducted. The point estimates provided in step one where weighted with the inverse of the square of their respective error. For the wave heights, quadric polynomials were fitted for both parameter functions. Quadratic functions were chosen, based on the fit of the linear models to the estimated parameters. For the wind speed, a linear drift ($D^{(1)}$) and a quadratic diffusion ($D^{(2)}$) function were chosen based on best fit to the estimated parameters.
Following these two steps, the obtained parameter functions were used to generate artificial weather time series. This is done by using the quadraticlinear functions estimated previously as an input to the data generation. The timeseries generation function from Rinn et al. [14] had to be modified in order to generate realistic results for our specific case. The original function 'timeseries1D' generates non-negative as well as negative observations. Since a negative wave height is not meaningful in this context, the function was modified in order to assure only non-negative observations. In the modified function, the Langevin process is allowed to continue into the negative domain, but observations are only added to the simulated weather time series once the process crosses back into non-negative values again. The artificial time series and properties are compared to the original time series in Section 4.

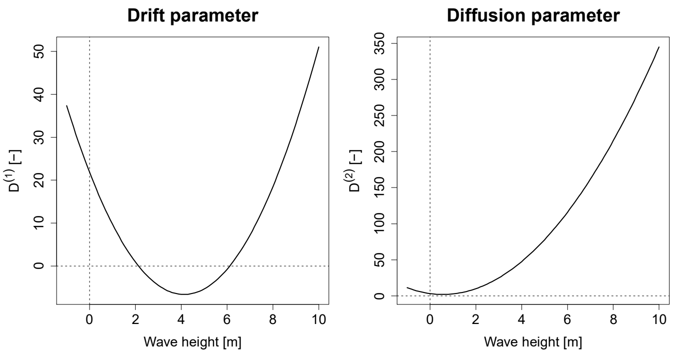

Figure 1. The drift and diffusion polynomial for the significant wave height in January, based on the data from FINO 1. The parameters $D^{(1)}$ and $D^{(2)}$ in the Fokker-Planck equation depend on the wave height.

3. Data

For our analysis, we investigated two different publicly available datasets. The re-analysis data from the ECMWF [15] is available in different resolutions, and we used the data that we already used for a different study [16]. These data have a resolution of six hours, providing one measured wave height and wind speed in the center of each six hour interval.
Additionally, data from the FINO measurement campaign [17] was used for the measurement platform FINO1 next to the Alpha Ventus wind farm in the North Sea. Here the significant wave height is provided in 30 min mean values and wind speed measurements are available in 10min mean wind speed steps.

4. Analysis of the artificial weather data

In this section the properties of the artificial weather series are compared to those of the actual weather data to see how well the Langevin approach captures the site specific weather properties.

Results are presented for both datasets. Not every investigation is shown for both sites, the performance of the model is similar in both cases and we have chosen to show plots from different sites in order to represent different weather conditions.

Table 1. Statistics of the wave height simulations based on the FINO 1 data.

Wave height	Mean	Maximum	SD
Data	1.44	9.77	0.93
Simulation	1.51	7.49	0.92
Simulation without seasonal effect	1.44	8.62	0.93
Simulation based on six-hour data	1.44	9.90	1.0

Table 1 shows some of the statistics of the data for significant wave height for the measurement at FINO 1. We included the mean, maximum and standard deviation from the original data and three different simulations based on the Langevin process. The first simulation, referred to as "simulation" later, is based on one Langevin process. The equations for this process were fitted to the whole data set, therefore the model is not able to capture any seasonality in the weather. The second simulation is based on Langevin equations that have been estimated based on the data for each month, we will refer to this as the "seasonal model" or "seasonal simulation" later in the paper. There are two equations for January, two equations for February and so on. An example of these parameter equations can be seen in Figure 1 for the month of January for the FINO 1 data. The third model is based on six-hour data and is obtained by fitting monthly Langevin equations to data that was previously filtered to have one observation every six hours. This model will also be referred to as "six-hour simulation" in the remainder of the paper. Table 1 shows that mean and standard deviation are replicated quite well by all different simulation models.

Table 2. Statistics of the wind speed simulations based on the FINO 1 data.

Wind speeds	Mean	Maximum	SD
Data	9.99	37.01	4.66
Simulation	9.83	35.57	4.38
Simulation without seasonal effect	10.03	36.25	4.34
Simulation based on six-hour data	10.0	25.68	4.01

The same can be seen in Table 2 for the wind speeds. Also here, the same three kinds of simulations are presented and the mean and standard deviation are again reproduced well. The maximum value in the simulation shows a greater discrepancy. The reason for this lies presumably in the generation of the six-hour data. When calculating the mean over six hours, the extrema are smoothed out. By using the six-hour data to fit the Langevin equations, the extreme values can then not be reproduced by the model.
An important aspect of the weather properties at a given site, is of course seasonality. The weather is generally harsher in winter months, with higher waves and wind speeds. In order to capture the seasonality, different Langevin equations where fitted for each month, as described

above. To see whether this is sufficient to capture the seasonality, we investigated the monthly means of both significant wave height and wind speed. Figure 2 shows box-plots for the original data and simulation of the significant wave height and wind speed at a location off the British coast, where data from the ECMWF was available. It can be seen that the seasonality in both the significant wave height and wind speed is captured well by the new model based on the Langevin process.

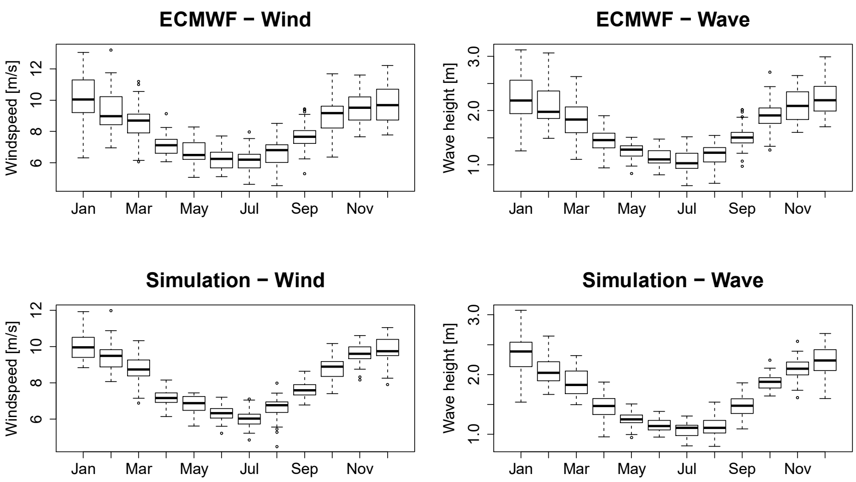

Figure 2. Monthly means of the significant wave height and wind speed at a British offshore location.

Not only the seasonality is an important characteristic of the local weather. Also the distribution of the wave heights and windspeeds throughout the year should be similar to the actual observations. In Figure 3, the distribution of the wave heights is shown for the location of FINO 1. Here the effect of using the simulation based on multiple Langevin equations can be observed. The simulation that was based on one separate set of equations for each month performs better than the simulation without seasonal effect. The same has been observed for the other location.

For the wind speed simulation, the distribution is not matched as well as for the wave heights as can be seen from Figure 4. The same observation of the distribution of simulated wave heights and wind speeds can be made for the British offshore site A1. One possible explanation is that the Langevin process is better at capturing the wave specific properties and it might not be the correct way to model wind speeds. Hadjihosseini et al. [11] have proven that the Langevin process can be used to describe ocean waves. In the absence of a similar investigation for wind speeds, we have in this study assumed that the Langevin process can also be used. It is possible that this assumption does not hold up, this will be the basis for new investigations. Even if the assumption holds, it might be that the type of equations that we fitted with the linear regression, were indeed not suitable to capture all properties of the wind speed.

To show the difference in wave height distribution between winter and summer, January and August were chosen as representative months in Figure 5. It can be seen that the wave height is subject to more variation in the winter, with a higher mean significant wave height. For both

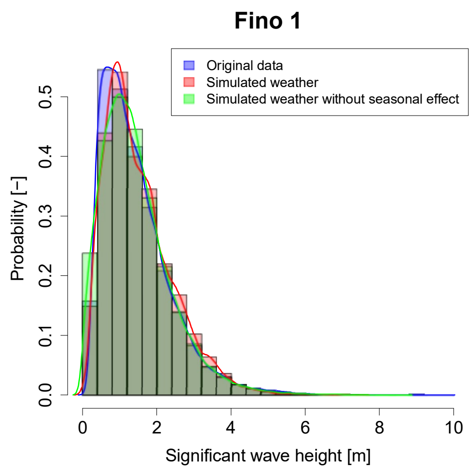

Figure 3. Distribution of the wave heights over one year for the FINO 1 data, seasonal simulation and simulation without the seasonal effect.

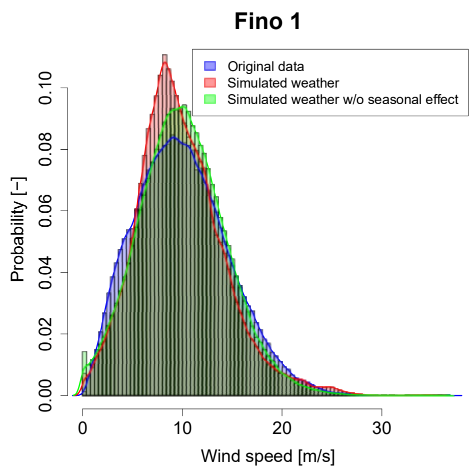

Figure 4. Distribution of the wind speeds over one year for the FINO 1 data, seasonal simulation and simulation without the seasonal effect.

months, the distribution is well matched by the artificial wave height series. Similar observations can be made for the simulations based on the FINO 1 data.

Figures 6 and 7 show the cumulative distribution functions (CDFs) of the wind speed and wave height respectively for each a summer and a winter month for the location of FINO 1.

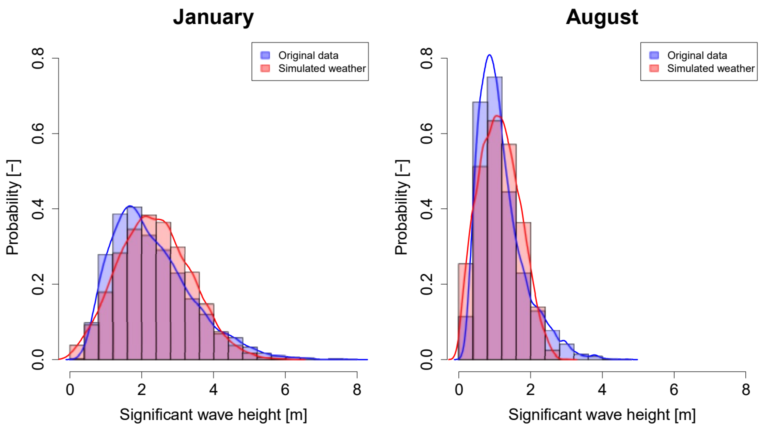

Figure 5. Distribution of the significant wave heights over one year for the ECMWF data. One month in summer and one month in winter were chosen. For both months, the distribution of the original data and of the artificial data are shown.

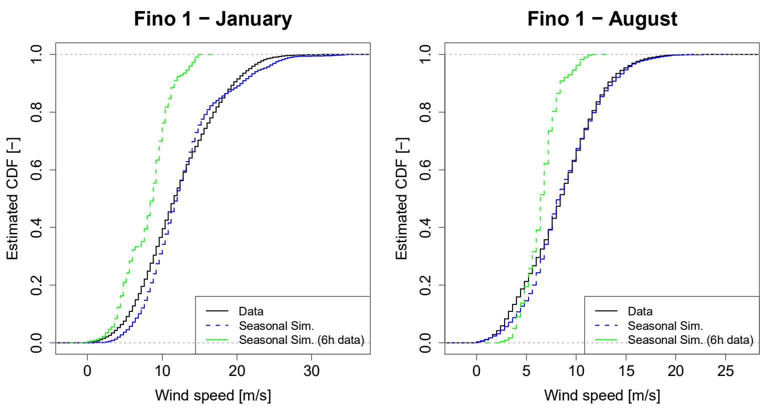

Figure 6. Cumulative distribution function of wind speeds for a winter and a summer month at the location of FINO 1.

Figure 6 shows the CDF of the wind speeds for a winter month and a summer month. It can be observed that the simulation based on six-hour data under-estimates the wind speed at the given site for January. For August, the model also under-estimates the wind speeds. However, it can be seen that the occurrence of wind speeds below $5m/s$ is also under-estimated. The model based on the original data replicates the CDF of the wind speeds much better. here, in both months the occurrence of low wind speeds is slightly under-estimated and the CDF is replicated better for the summer month. For the wave heights, the CDF is shown in Figure 7, again for a summer and a winter month. Also here, we observe that the resolution in the data used for

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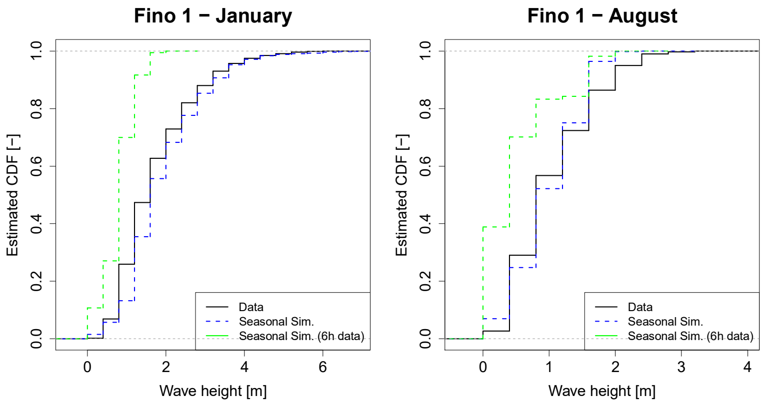

Figure 7. Cumulative distribution function of wave heights for a winter and a summer month at the location of FINO 1.

fitting the equations has an influence on how well the CDFs are represented. Contrary to the wind speed simulations, CDF of significant wave heights is better matched by the simulation for the winter month.

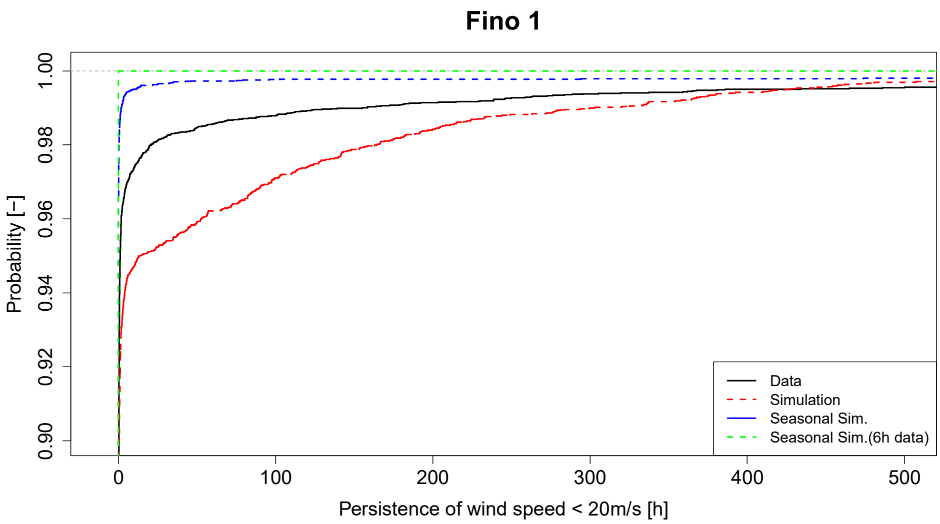

Figure 8. Persistence of wind speeds below $20m/s$ for the location of FINO 1. The data is compared to the simulation without seasonal effect, the simulation with seasonal effect and the simulation with seasonal effect, based on 6 hour data.

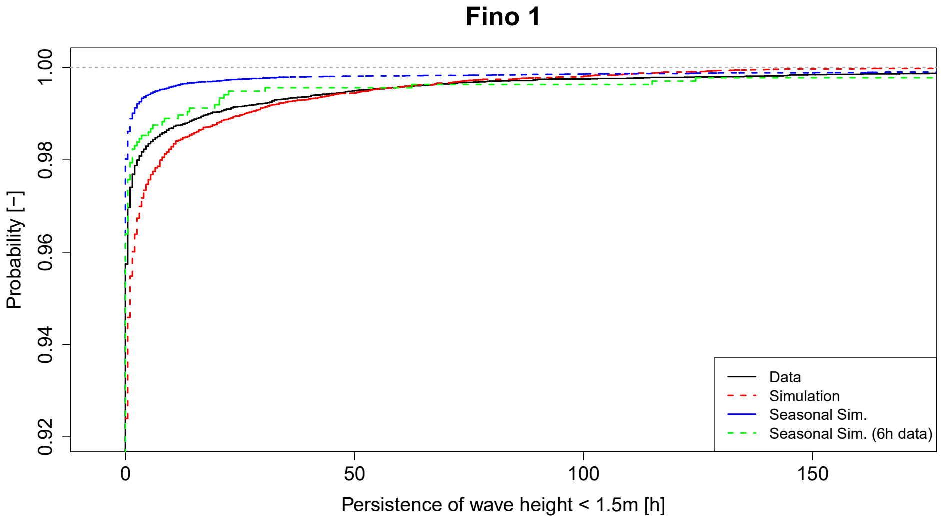

Figure 9. Persistence of wave heights below $1.5m$ for the location of FINO 1. The data is compared to the simulation without seasonal effect, the simulation with seasonal effect and the simulation with seasonal effect, based on 6 hour data.

For the planning of operations and maintenance, weather windows play an important role. In order to see whether the length of these windows is adequately represented in the artificial weather series, we also investigated the persistence of waves and wind speeds. Anastasiou and Tsekos [18] define the persistence of wave height below a threshold level as "the time interval between a down-crossing of that threshold and the first subsequent up-crossing". For the wave height, a threshold of $1.5m$ height was chosen and for the wind speeds a threshold of $20m/s$ was used to investigate the persistence. These values were chosen based on typical wave height and wind speed limits for different vessels used for operation and maintenance (e.g. crew transfer or lifting operations).

Figure 8 shows the persistence of wind speeds below $20m/s$ for the location of the FINO 1 measurement platform. It is necessary to note that the distribution of the persistence could not be calculated for the simulation based on the six-hour data. In the simulated time series, no value above $20m/s$ was present. Therefore, the probability of having a persistence lower than $20m/s$ of the length of the dataset it one. The length of suitable weather windows is over predicted by the seasonal simulation model and under-predicted by the model without seasonal variation. The Kolmogorov-Smirnov-(KS-)distance of the distribution of the persistence is slightly bigger for the non-seasonal model (0.16) than for the seasonal model (0.14), but both are in the same magnitude and it cannot be rejected that the samples come from the same distribution as the data (p-values > 0.8 for all three simulations). Depending on the application (e.g. turbine performance calculation, scheduling a lift operation), the more conservative model might be chosen.

Figure 9 shows the persistence statistics for wave heights below $1.5m$ for the location of FINO 1. Also for the waves, the simulation without the seasonal effect under-predicts the lengths of weather window, whereas the model with seasonal variation over-predicts the lengths.

Calculating the KS-distance shows that the maximum distance between the persistence-curves of the two seasonal simulations (0.04 for both models) is not significantly different (p-values > 0.95) from the persistence of the original data. This means that the over- and under-prediction of the two models are of the same magnitude. The KS-distance of the simulation without seasonal effect (0.08) is about double the KS-distance of the two seasonal simulations. Also this model does not show a significant (p-value > 0.9) difference from the original persistence distribution.

5. Discussion

The popular Markov Process uses discrete time steps. One challenge when using Markov chains is the change from one transition probability matrix to the next. This happens e.g. when switching from one month to the next in the model presented by [4]. The last value generated in a month needs to be used for the generation of values in the next month. However, if this value has an occurrence probability of zero in the new matrix, the process cannot select a first value for the new month.

The Langevin process however is a continuous process and does not have any issues with different starting values for the process. Here, the last generated value for a month can be directly input as a starting value for the next month's process. Additionally, for the Langevin process fewer parameters need to be estimated and therefore less data is needed to fit the model. While for the Markov chain, many transition probabilities need to be calculated and large matrices handled, the Langevin equations can be describes with a handful of parameters.

Having fewer parameters that describe the Langevin model compared to the Markov model, has the disadvantage that some of the properties of the data cannot be replicated as well as with the Markov model. Usually, models with fewer parameters need fewer observations to estimate these parameters. In the given application this would mean that a shorter weather observation period can be used to base the site weather model on. This might especially be useful to optimize the operation and maintenance for new wind farm projects, where data is collected for a short period of time. Additionally, an advantages of the Langevin model is that the model does not require the handling of large matrices and random sampling with discrete probabilities. The analysis of the properties of the artificial weather data generated based on the Langevin process showed that the properties of the site specific weather conditions are conserved well enough to use the model for operation and maintenance optimization. It is necessary to note that the Markov model with its many more parameters is (for the location and dataset used in this study) superior in replicating the site properties of the weather. A comparison of the distribution of the significant wave height and wind speed for the data from the British offshore site and the simulations of this site with the (seasonal) Langevin model and Markov model can be found in the Appendix in Figure A2.

The possible correlation between wave heights and wind speeds are missing in both applications. Previously, a correlation matrix has been used by [4] to generate the wind speeds from the wave height simulation. Using a multidimensional (2D) Langevin process could also solve the issue of correlation.

6. Conclusion and further work

In this paper we have shown, that for the type of application that was the focus of our investigation, namely generating artificial weather time series for operations and maintenance simulations, a Langevin process can be used. The properties of the waves are represented well, both in terms of distribution of the significant wave height and in terms on persistence of waves. As with most data-driven models, the performance of the Langevin process improves with the quality and sampling frequency of the data used to fit the equations. Higher data sampling frequencies lead to a better representation of the site conditions. Especially the persistence is an important property that is needed for O&M simulations, since the length of weather windows

plays an important role in deciding e.g. a maintenance strategy.
In the future, the Langevin approach might be a tool that can assist in propagating site specific properties of the waves without relying on simulations. It might also be used as an alternative input to closed form models like the one from Feuchtwang and Infield [19] or the simulations models mentioned above. The Langevin model presented here models the mean wind speeds and wave heights independently. Hagen et al. [6] have presented a multivariate approach for the Markov chain model to capture correlations between different weather parameters. Capturing the correlation between wave heights, wind speeds (and other weather parameters) should be possible by using a two (multi) dimensional Langevin process. This is another topic for further research.

Acknowledgments
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Appendix

$$\frac{\partial P(X)}{\partial t} = \left(-\frac{\partial}{\partial X}D^{(1)}(X) + \frac{\partial^2}{\partial X^2}D^{(2)}(X)\right)P(X) \tag{A.1}$$

Equation A.1: Fokker-Planck equations, describing a Langevin process.

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$$D^{(n)}(X) = \lim_{\tau \to 0} \frac{1}{n!\tau} M^{(n)}(X, \tau) \tag{A.2}$$

Equation A.2: Equation for the Kramers-Moyal coefficients, where τ is a time increment and $M^{(n)}(X, \tau)$ is the conditional moment of the Langevin processes' trajectory in time, with respect to τ.

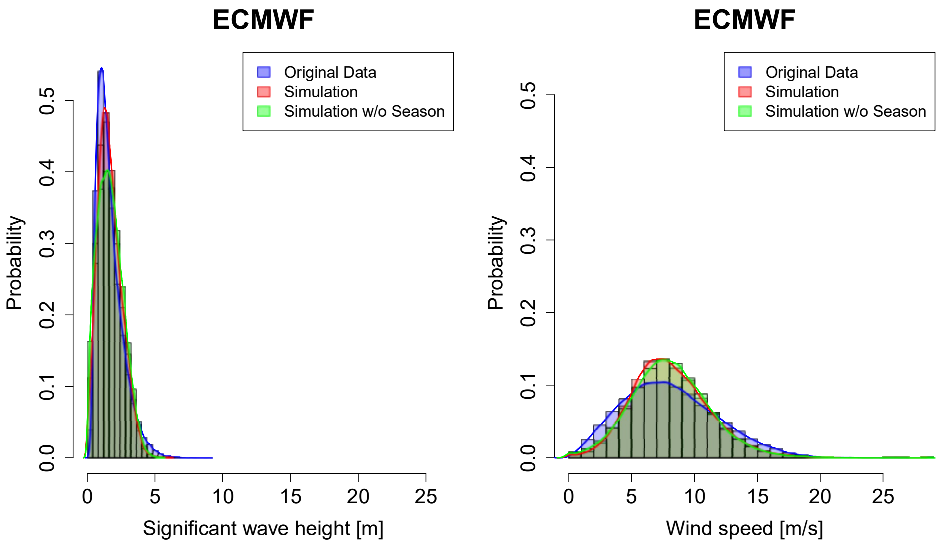

Figure A1. Distributions of the significant wave height and wind speed for the British offshore site. Blue line and shading show the distribution of the original data, red shows the simulated weather based on the seasonal Langevin model introduced in this paper and the green line and shading show the distribution of the Langevin model without taking into account seasonal effects.

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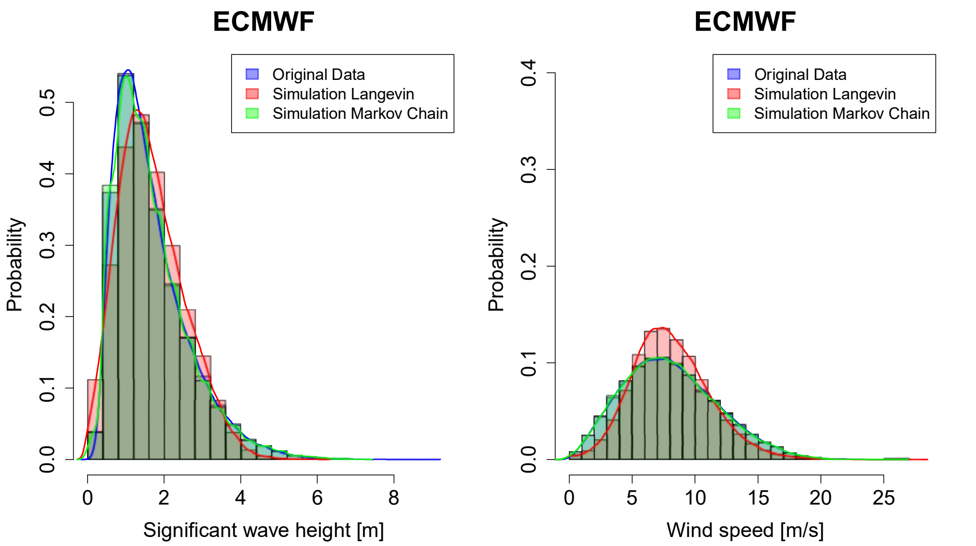

Figure A2. Distributions of the significant wave height and wind speed for the British offshore site. Blue line and shading show the distribution of the original data, red shows the simulated weather based on the Langevin model introduced in this paper and the green line and shading show the distribution of the artificial weather generated by a Markov chain model.

A.5 Paper 5

How does accuracy of weather forecasts influence the maintenance cost in offshore wind farms?.

Seyr, H. and Muskulus, M.

Proceedings of the Twenty-seventh (2017) International Ocean and Polar Engineering Conference ISOPE, 2017.

A.6 Paper 6

Interaction of repair time distributions with a weather model.

Seyr, H. and Muskulus, M.

Proceedings of the 29th International Congress on Condition Monitoring and Diagnostics Engineering Management COMADEM, 2016.

Interaction of repair time distributions with a weather model

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Abstract. Maintenance costs make up for a large part of the total cost of energy in offshore wind farms. We investigate the influence of uncertainty in the repair time duration on the production losses due to maintenance. This is done by using a distribution for the repair times and calculating the expected delay due to sea state. We calculate the production loss based on the mean repair times and compare it to the production loss with the repair time distribution. The findings are that the expected production loss is higher when taking the distribution of repair times into consideration. We elaborate these findings with a case study and compare results for three different turbine subsystems.

Keywords: Maintenance, Repair time, Uncertainty, Offshore, Wind turbines, Weather

1 Introduction and Methodology

Operations and maintenance costs account for up to 30% of the total cost of energy in an offshore wind farm [1]. To lower these costs, several approaches have been developed in the last years. Besides from condition monitoring and early failure detection [2], improving the scheduling of corrective maintenance has been in the focus of research [3]. Optimal scheduling of maintenance is influenced by several factors. Availability of transport vessels, cranes, crew and spare parts determine logistic constraints. Maintenance access is not possible in too harsh conditions, so wave height and wind speed result in weather constraints. It is well known that the weather forecasts used while scheduling are subject to uncertainties that need to be considered in the model. We investigate the influence of information about the repair time to the maintenance costs using a simple cost model, based on an analytical model [4].

The model calculates the delay due to weather constraints based on the distribution of wave heights at a given location. The delays in the execution of repairs occur, because maintenance access is not possible when waves at the location exceed a given threshold. To conduct repairs the weather conditions need to be calm enough for at least as long as the repair time, otherwise the repair has to be completed at a later point in time. We study the interaction between the weather model and the repair time both for mean repair times and for a statistical distribution of repair times with the same mean. We use data for a 2.5 MW turbine [5], since this is the turbine size closest to the mean currently installed capacity offshore for which data was available. The delay model and the distribution of repair times are presented in section 2. Next we include the distribution of the repair times in a simple maintenance cost model that calculates the production losses (PL) caused by the downtime due to failures and the resulting repair actions. Here we also include the delays in repairs due to harsh weather conditions. The occurrence of a failure is modeled with failure rates taken from [6]. We compare the outputs of the cost model for the mean repair time to the output for the distribution in section 2. We investigate, whether using a distribution instead of a deterministic repair time significantly influences the results. We calculate the expected maintenance cost for turbine components in section 3 and discuss the results and ideas for further work in section 4.

2 Maintenance Cost Model

First we develop the model without delay, include a deterministic expected delay in a second step and finally include the expected delay model.

2.1 Repair time distribution

From [5] we get the mean times to repair (MTTR) for certain turbine components. We assume that the repair times are exponentially distributed with this MTTR as the mean. The probability density function (pdf) for the repair time is then

$$f(t;\lambda) = \lambda \mathrm{e}^{-\lambda t}\chi_0(t), \tag{1}$$

$$\text{where } \lambda = \frac{1}{\mathrm{MTTR}} \text{ and } \chi_0(t) = \begin{cases} 1 & \text{for } t \geq 0 \\ 0 & \text{for } t < 0 \end{cases}.$$

2.2 Expected delay

For the expected delay due to sea-state, we use the approach presented in [4]. The model assumes random occurrence of faults with only one failure at a time. They further assume only single trips to conduct repair, so for multiple turbines failures, each turbine is investigated individually. The model assumes wind and wave correlation and does therefore not include a separate wind restriction limit. The correlation between wind and waves has also been investigated by [8] and we support this assumption. We calculate the expected delay with the formula presented in [4] and demand the weather window to be at least as long as the repair time for each turbine component. [4] describe five types of delays representing wave height threshold exceedance (type 1), duration of too short calm weather (type 2a), fault occurance too late within the calm weather (type 2b), delay caused by storm following a type 2 delay (type 3) and delays for a threshold exceedance following a type 1 or type 3 delay (type 4 and higher). As wave height constraint we use 1.5m as suggested by [4].

2.3 Production loss

The maintenance costs consist of the PL due to downtime, the wages of the maintenance workers, and the costs for transport and spare parts. The most uncertainty lies in the PL, since the downtime varies depending on weather delays and repair times. We will therefore focus on the PL in our analysis. The production loss y is the lost revenue due to downtime of a turbine because of a failure and subsequent repair. Therefore the production loss depends on the installed capacity, length of the downtime, the wind speeds during the downtime, power curve of the installed turbine and the current electricity price or feed-in tariff (fit). To simplify, one can multiply the installed capacity with the capacity factor (CF) [7] instead of calculating the exact power output from the wind speeds and power curves. The losses can then be calculated by multiplying this value with the electricity price or feed-in tariff.

In a first step, we analyze the production loss, without the delay caused by sea-state. The production loss y is then a function of the repair time t such that $y = g(t) = C \cdot t$, where $C = \text{installed capacity} \cdot \text{CF} \cdot \text{fit}$. The pdf for the production loss of a single failure event becomes

$$f_Y(y) = \frac{\lambda}{C} \mathrm{e}^{-\frac{\lambda}{C} y} \chi_0(y) \tag{2}$$

The probability p that a failure occurs in a given year, the annual failure rate [6], enters in a Poisson model, where the probability of observing exactly k failures in a year is $f_k = \frac{p^k \mathrm{e}^{-p}}{k!}$. The total production loss over one year is then

$$f(y) = \sum_{k=1}^{\infty} \frac{p^k \mathrm{e}^{-p}}{k!} f_Y^{*k}(y) \chi_0(y), \tag{3}$$

where $f_Y^{*k}(y)$ is the $(k-1)$-fold convolution of the pdf for a single failure

$$f_y^{*k}(y) = \frac{\lambda^k}{C^k} \mathrm{e}^{-\frac{\lambda}{C} y} y^{k-1} \chi_0(y). \tag{4}$$

The expected production loss, is due to the linearity of the expectation

$$E(y|t \sim exp(\lambda)) = E(y|E(t)) = E(y|t = MTTR) = \frac{1}{\lambda} Cp.$$

For a constant delay d and $y = g(t) = C \cdot (t + d)$, similar considerations lead to

$$f(y) = \sum_{k=1}^{\infty} \frac{p^k \mathrm{e}^{-p}}{k!} \frac{\lambda^k}{C^k} \mathrm{e}^{-\frac{\lambda}{C}(y - kCd)} \frac{(y - kCd)^{k-1}}{(k-1)!} \chi_{kCd}(y), \tag{5}$$

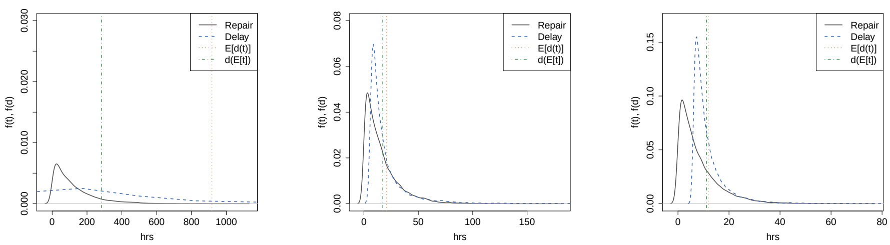
with expectation $E(y|t \sim exp(\lambda)) = [E(y|t = MTTR) = \left(\frac{1}{\lambda} + d\right) Cp$

For the delay according to [4], there exists no analytical inverse function of $y = C(t + d(t))$ and we can therefore not calculate an analytical expression for the pdf. We analyze the pdf of the delay numerically in the following section.

3 Case Study

We now investigate the distribution of the production loss with a delay according to Feuchtwang and Infield [4]. We use the software R [9] to model the delay due to sea state. We generate a random sample of 10000 different repair times for each component and calculate the delay for each. To obtain the density for the delay time, we use Kernel density estimation [10]. The pdf of repair time and delay time for a single failure for three different components, calculated based on [4,5] are plotted in Figure 1. The expectation of the delay for a single failure

Fig. 1. Pdf for the repair time and delay time distributions for the (a) Gearbox (b) Pitch/Hydraulic system (c) Power electronics



(a) (b) (c)

event, calculated based on the distributed repair time, is compared to the delay based on the MTTR in Table 1 for the same three components. It can be seen that for longer repair times, the variations in repair times have a larger influence on the expected delay. When investigating multiple failures, we can again use the linearity of the expectation, and get for exactly k failures, an expected delay

$E[d_k(t)] = E[\sum_{i=1}^{k} E[d(t)]] = kE[d(t)],$ which gives an expected production loss of

$$
\begin{aligned}
E[y] = E\left[C\sum_{k=1}^{\infty}\frac{p^k\mathrm{e}^{-p}}{k!}\left(d_k(t)+t\right)\right] = \\
= C\sum_{k=1}^{\infty}\frac{p^k\mathrm{e}^{-p}}{k!}\left(E\left[d_k(t)\right]+E\left[t\right]\right) = Cp\left(E\left[d(t)\right]+MTTR\right).
\end{aligned}
$$

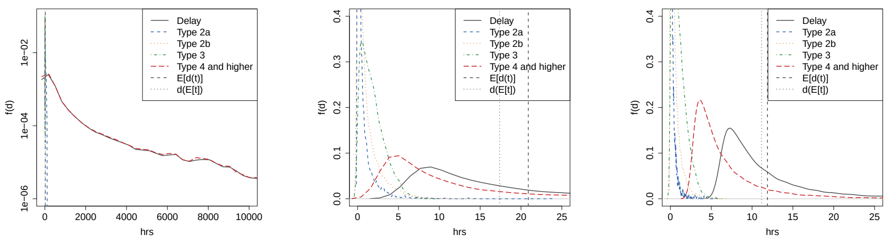
The values for the expected production loss, are presented in Table 1.The values in the last column are for a constant delay $d = d(\mathrm{MTTR})$. In a last step we conduct an analysis of the delay time distribution to see which types of delays, as defined in [4], had the largest influence on the delay time. Figure 2 shows the

Table 1. Calculation results with data from [5, 6] including the delay from [4]. Since the cost factor C is unknown, we present the unit-free values for the production loss.

Component	$E[d(t)]$	$d(E[t])$	$E[y\|d(t)]/C$	$E[y\|d(\mathrm{MTTR})]/C$
Generator replacement	917.5	286.0	103.8	40.4
Pitch/Hydraulic system	20.9	17.4	8.5	7.4
Power electronics	11.9	11.2	11.3	10.9
Units	hrs	hrs	unit-free	unit-free

distribution of the delay and the distributions of the different types of delays. An analysis of the influence of the repair time distribution on the individual delay types is presented in Table 2. We see that the largest discrepancy exists for a delay of type 4 or higher which is consistently and substantially underestimated when using the MTTR. The delay of type 3 is consistently overestimated by a small amount. The type 1 delay does not depend on the repair time and is thus not investigated.

Fig. 2. Pdf for the delay time distributions and distributions for the individual delay types for (a) Gearbox (b) Pitch/Hydraulic system (c) Powerelectronics



(a) (b) (c)

Table 2. Difference $d_i(E[t]) - E[d_i(t)]$, for each delay type $i \in \{2a, 2b, 3, 4\}$

Component	Type 2a	Type 2b	Type 3	Type 4
Generator replacement	-1.9	3.0	1.5	-636.2
Pitch/Hydraulic system	-0.28	-0.22	0.22	-3.23
Power electronics	-0.07	-0.11	0.09	-0.62
Units	hrs	hrs	hrs	hrs

4 Discussion

The analysis presented here, demonstrates the influence of the distribution of the repair times on the production losses. For components with short mean repair times, using the expected repair time instead of an accurate representation of the distribution has a small impact on the overall result. For components with longer repair times, as shown for the example of a gearbox replacement, the influence of the variation in repair times is amplified. We therefore strongly suggest using an accurate representation of repair times and encourage further research in distributions of repair times. For multiple turbines in a wind farm, the effects on the results of using a distribution are expected to be even larger, as the repair times influence the scheduling of maintenance actions in a nonlinear way.

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A.7 Paper 7

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

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

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

1. Introduction

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

2. Methodology

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

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

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

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

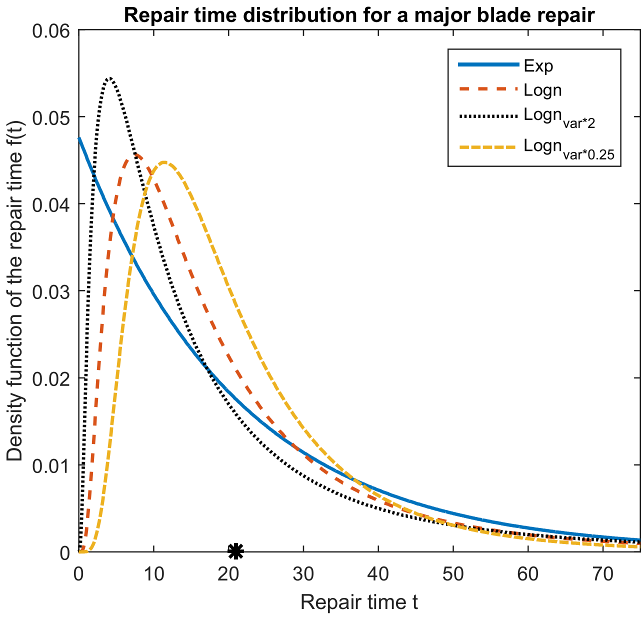


Figure 1: Density functions for different repair time distributions for a major blade repair. The mean time to repair of 21 hours is marked with a black asterisk.

3. Value of information of repair time

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

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

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

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

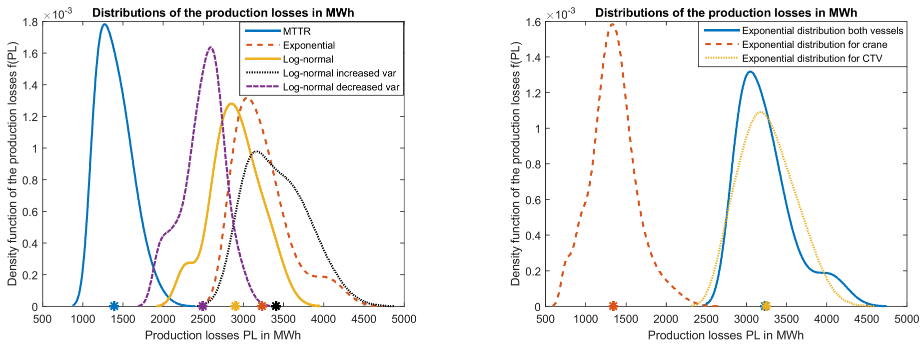
Table 1 shows the mean values for the annual lost production in MWh per turbine over 25 simulation years for different simulation scenarios. The most important observation is that the production losses increase, when uncertainty in the repair times is included. The leading cause seem to be those turbine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

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

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

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

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



(a) (b)

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

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

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

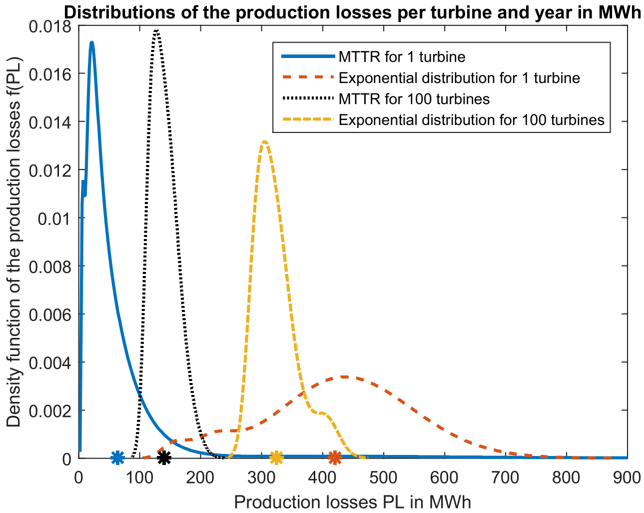


Figure 3: The distribution of the production losses per turbine for a wind farm with 100 turbines, and for a wind farm with one single turbine.

4. Conclusion

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

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A.8 Paper 8

The Impact of Maintenance Duration on the Downtime of an Offshore Wind farm - Alternating Renewal Process.

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The Impact of Maintenance Duration on the Downtime of an Offshore Wind farm - Alternating Renewal Process

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ABSTRACT

Maintenance costs in offshore wind farms are one of the main reasons why it is still not competitive with its onshore counterpart. To lower the price of energy, the authors want to improve the modeling of offshore wind farms in order to help improving the applied maintenance strategies. In this paper, we investigate the repair of wind turbine components as an alternating renewal process. The time it takes to repair (renew) a component in a turbine, directly influences the downtime of this turbine, or even larger parts of the wind farm. This downtime leads to production losses, which in turn raise the cost of energy. Previous investigations by two of the present authors showed that a variation in repair times has a significant influence of the production losses. In this paper, an alternate renewal process is investigated as tool to calculate the influence of the repair time duration on the production losses. We show that if we assume an exponential distribution of repair times, the distribution of the downtimes can be calculated analytically. The results are demonstrated with a case study, based on available failure rates and repair times. For other distributions, the calculation has to be done numerically, after fitting the parameters of the distribution to the available data. Further work with other distributions and actual repair time distributions is planned.

Keywords: Offshore Wind Energy, Failure Modelling, Maintenance Optimisation, Stochastic Modelling, Alternating Renewal Process.

1. Introduction

The offshore wind industry is a growing industry in Europe and other continents. However, Operations and Maintenance (O&M) costs still account for a significant part of the total cost of energy [1]. Lowering these costs will lower the cost per kilowatt of power produced and hence make offshore wind sources competitive to other energy sources. In order to reduce the O&M costs, many approaches are currently followed in research. These include condition monitoring, optimizing the preventive maintenance, and inventing components that are more reliable.

In order to reduce the costs of corrective maintenance, repairs following a failure that could not be avoided by preventive measures, decision support tools are being developed by several research groups. These aim to help for wind farm (WF) operators and maintenance service providers in deciding which maintenance strategy to use in order to minimize costs or maximize availability. Most of these models rely on simulations of the operation phase of the WF. The operation of the WF, its availability and production as well as the maintenance costs, are influenced by several factors. These factors include the failure rates of wind turbine components, the distance of the WF from an onshore maintenance base, the weather at a given location, the types of maintenance vessels, number of vessels, the number of workers and the turbine model. Two of present authors started to investigate variations in the repair times and their influence on the unscheduled downtimes of the wind farm [2, 3]. They have shown that a variation in the repair times can lead to a significant increase in downtimes and hence in production losses. These production losses in turn raise the cost of electricity produced.

In this paper, we want to present an approach based on a stochastic process named alternating renewal process to investigate this same influencing factor. Alternating renewal processes can be used, as soon as we assume random failure and repair times and a repair that is a renewal. The paper is structured as follows. Section 2 gives an overview of the methods used, the results of the analysis are presented in Section 3 and demonstrated in a case study in Section 4. Finally, we conclude the work and give an outlook to future work in Section 5.

2. Methodology

In order to define an alternate renewal process, we need to take some assumptions. First, we assume that the lifetime duration of a turbine component is random, and that it is following a given distribution. We further assume that the maintenance duration, the repair time, follows a different distribution. The distributions used in the paper are only examples and not based on actual wind park data. For the failures, we assume a constant failure rate, which leads to an exponential failure distribution. For many wind turbine components, the failure rate is assumed to follow a bathtub curve, a constant repair rate is then realistic for most of the lifetime [4-6]. Exponential distributions for the failures are common in the literature [7-12].

Also for the repair time, we use a constant rate for a first analysis. Since there has not been done any analysis on the actual distribution on repair times yet, this is a very strong assumption. However, this is a first analysis for a first example of a distribution. Other types of distributions should be investigated as well as fitting the distribution parameters to actual wind park data.

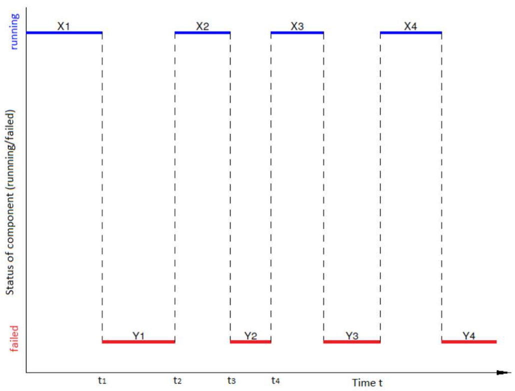
It is further assumed that each repair is a renewal, replacing the faulty component with an identical new one. A renewal is for many wind turbine components, like gears or electrical equipment a common form of repair.

The theoretical distribution for the downtime is calculated based on the distributions for the lifetime and repair times. We show that it is possible to do this calculation analytically for any failure and repair rate and the distribution of the downtime is presented dependent on the two rates.

3. Analytical results

In this section, we present the results of our analysis. An example figure of an alternating renewal process is shown in Figure 1. The turbine component that is considered has two different states – running or failed. In the given example, the component is running until time t_1. At time t_1, it fails and stays in state "failed" until its repair is completed at time t_2. The process continues like this; the turbine is running from t_2 to t_3, when it fails again. The next renewal is finished at t_4, and so on. We are now interested in the distributions of the X_i and Y_i, the durations during which the component is running or failed respectively.

Figure 1. An example of an alternate renewal process. The X_i



show the durations of operation (up states) and the Y_i show the downtimes (down states).

The failure dates $(t_1, t_3, \dots)$ depend on the failure distributions and failure rate. As stated in the previous section, we are assuming an exponential distribution of the lifetime durations X_i, with a constant failure rate. Failure rates for different wind turbine components can be found in e.g. [5, 6]. If we assume a known constant failure rate λ, the probability density function of the failure distribution can be written as:

$$f(t) = \lambda\, e^{-\lambda t}. \tag{1}$$

We also assume an exponential distribution of the repair durations Y_i, which are corresponding to the downtimes, with a constant repair rate μ. The probability density function for this distribution is then:

$$g(t) = \mu e^{-\mu t} \tag{2}$$

The presented density functions represent the density of one failure and one renewal respectively. In order to know the distribution of a sum of lifetime durations $X_1 + \dots + X_n \sim ?$ we calculate the n-th fold convolution of $f(s)$ with itself:

$$F^{(n)}(t) = \int_0^t F^{(n-1)}(t-s) f(s) ds = \lambda e^{-\lambda t} \frac{t^{n-1}}{(n-1)!} \tag{3}$$

Since we are interested in the duration of the total downtime of the component, we introduce the following notation. $N(t)$ is the number of up states during $[0, t]$ and $D(t)$ is the amount of time spent in down state. We are now focusing on the calculation of the distribution of this $D(t)$, starting with the description of an event "$D(t) \leq x$". Since the total downtime is the sum of all downtimes, we have:

$$D(t) = Y_1 + \dots + Y_n \text{ if } N(t) = n. \tag{4}$$

The probability of an event "$D(t) \leq x$ "is then:

$$P(D(t) \leq x) = \sum_{n=1}^{\infty} P(Y_1 + \dots + Y_n | N(t-x) = n) \cdot P(N(t-x) = n) \tag{5}$$

Since when the failure occurs, n lifetimes have been completed, X_n has ended. As soon as X_{n+1} starts, the renewal has already taken place. Therefore the probability of having exactly n failures is the same as having a lifetime between $X_1 + \dots + X_n$ and $X_1 + \dots + X_{n+1}$. The probability $P(N(t) = n)$ can be simplified

$$P(N(t-x) = n) = P(X_1 + \dots + X_n \leq t - x \cap X_1 + \dots X_{n+1} > t - x). \tag{6}$$

leading finally to

$$P(N(t-x) = n) = F^{(n)}(t-x) - F^{(n+1)}(t-x), \tag{7}$$

where $F^{(n)}(t-x)$ is as in Equation (3). For the conditional probability of having the downtime below a value x, while having exactly n failures we get

$$P(Y_1 + \dots + Y_n \leq x | N(t-x) = n) = G^{(n)}(x), \text{ where} \tag{8}$$

$$G^{(n)}(x) = \int_0^x G^{(n-1)}(x-s) g(s) ds \tag{9}$$

and $g(s)$ the probability density function of Y_i. As for $F^{(n)}(t)$ in Equation (3), this simplifies to

$$G^{(n)}(x) = \mu e^{-\mu x} \frac{x^{n-1}}{(n-1)!} \tag{10}$$

By plugging the simplifications from Equations (7) and (10) into Equation (5), the distribution of the downtime $D(t)$ can now be calculates as

$$P(D(t) \le x) =$$
$$= \sum_{n=1}^{\infty} G^{(n)}(x)\left(F^{(n)}(t-x) - F^{(n+1)}(t-x)\right) = \tag{11}$$
$$= e^{-\mu x - \lambda(t-x)} \sum_{n=1}^{\infty} \frac{\mu^n \lambda^n x^{n-1}(t-x)^{n-1}}{(n-1)!\,(n-1)!}\left(1 - \lambda\frac{t-x}{n}\right)$$

solving to

$$P(D(t) \le x) =$$
$$= e^{-\mu x - \lambda(t-x)}\, 2\sqrt{\lambda}\left(\sqrt{\mu x(t-x)}I_0 + (x-t)\sqrt{\lambda}I_1\right) \tag{12}$$

Where I_0 and I_1 are the modified Bessel functions [13] of the first kind of order 0 and 1 respectively.

4. Case Study

In this section, we want to illustrate the analytical results from the previous section with a small case study. We use information about the repair time and failure rates provided in [6]. As discussed in the analysis above, we assume a constant failure rate and therefore exponential distribution of the up states. For the repair time we also assume an exponential distribution with a constant repair rate. The repair rate is calculated as the inverse of the mean time to repair (MTTR) given in [6]. Those parameters are summarized in Table 1.

Table 1. Parameters used in the case study.

	Gearbox replacement	Pitch system minor repair	Conductor/ Circuit breaker/ Relay system
Failure rate λ [failures per annum]	0.154	0.824	0.326
Mean time to repair 1/μ [hours]	231	9	4

Using the analytical results from above we use the software R [14] to calculate and visualize the downtime distribution for the three different components and repair types. In other words, we use equation (12) and plug in the numbers for λ and μ that we obtain from [6]. With these parameters, the probability of the downtime is calculated for possible lengths of downtime up to 365 hours with a resolution of one hour. The reason to calculate the pointwise probability is that there exists no simple method to visualize a multidimensional probability distribution of the form presented in (12). Therefore, we chose to calculate the probability of single points and fit a surface plot for visualization purposes. In Figure 2, those plots are shown for the three different components. The diagonal in the plot corresponds to the case, where the total time of observation is downtime. The MTTR for a gearbox replacement is much larger than the MTTR for the other investigated repairs and it can be seen in the leftmost graph that the probability of having a downtime equal to the total observation time is much larger than for the other two repairs. The reason for this high probability is that the maximum observation length is less than 60% more than the MTTR. Additionally, it can be observed that the most probable downtime lengths are significantly lower than the total time of observation, this is best seen in the figure for the conductor system, indicated by the "ridge" in the graph. The figure for the downtime of the pitch system shows the same "ridge" although less pronounced. The reason is the difference in MTTR between the different components.

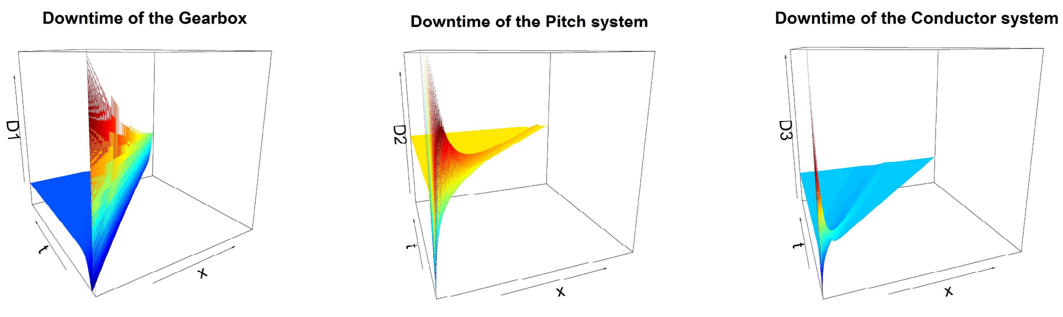


Figure 2. Distributions of the downtime for three different wind turbine components. From left to right: Gearbox, Pitch system minor repair and Conductor/Circuit breaker/Relay system.

5. Conclusions and further work

In this paper, a first step has been taken to investigate the downtime of a wind turbine component as alternating renewal process. We have shown that for a constant repair rate, the distribution of the downtime can be calculated based on this repair rate and the corresponding failure rate of the component. This calculation is in principle possible for any repair duration distribution, but will need to be evaluated numerically in most cases, e.g. a Gamma distribution. The present authors are planning to investigate the properties of further distributions in the future. Additionally, we want to use real wind park data to investigate the actual repair time and run time distributions to conduct a more thorough case study.

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Use of Markov Decision Processes in the Evaluation of Corrective Maintenance Scheduling Policies for Offshore Wind Farms

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Abstract: Optimization of the maintenance policies for offshore wind parks is an important step in lowering the costs of energy production from wind. The yield from wind energy production is expected to fall, which will increase the need to be cost efficient. In this article, the Markov decision process is presented and how it can be applied to evaluate different policies for corrective maintenance planning. In the case study, we show an alternative to the current state-of-the-art policy for corrective maintenance that will achieve a cost-reduction when energy production prices drop below the current levels. The presented method can be extended and applied to evaluate additional policies, with some examples provided.

Keywords: maintenance planning; maintenance strategy; maintenance; corrective maintenance; repair; offshore wind energy; maintenance scheduling; optimization; modeling

1. Introduction

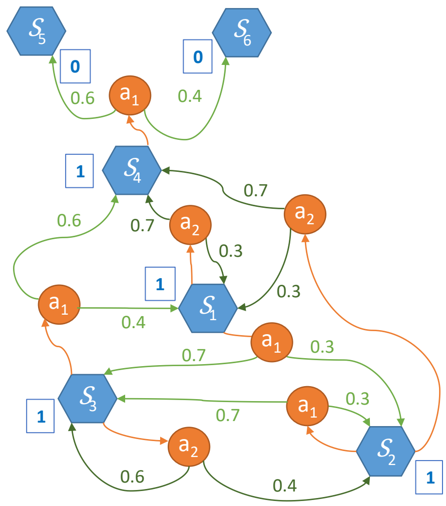
Offshore wind energy is an established form of energy generation in Europe and is globally gaining interest in countries all around the world, especially in East Asia. However, in most places, electrical energy produced by offshore wind farms (OWFs) is still more expensive than other electricity generation methods. Many improvements have already been achieved for different factors influencing the cost of electricity generated from wind. The size of the wind turbine support structures has been optimized, by e.g., minimizing the use of expensive materials. Turbine efficiency has been improved by e.g., optimizing the shape and materials of turbine blades. The overall production of a wind farm can be improved by studying wake effects and optimizing the control of individual turbines. Within the offshore wind research community, the optimization of operation and maintenance has recently been gaining interest from researchers all around the world. One reason for this is the high share of operation and maintenance cost in the overall energy costs up to a third of the price of electricity produced is due to operations and maintenance [1]. Reducing these operation and maintenance costs will improve the total cost of energy production and help achieve cost competitiveness with other generation methods, such as onshore wind or solar energy. Different groups have developed simulators that model the operation of OWFs, as reviewed in [2]. With these simulators, the researchers are able to investigate different maintenance scheduling policies by comparing the simulation results of different policies. Existing models depend almost exclusively on Monte Carlo simulations, i.e., running a large number of simulations with the same inputs, in order to investigate uncertainties and variations in different inputs and variables (wave heights, wind speeds or failure occurrence) used. Additionally, different policies can only be evaluated manually, by implementing each strategy individually in the model. Some exceptions to the dependency on Monte Carlo simulations are some newer approaches, using stochastic models [3] or genetic algorithms [4]. The influence of uncertainties on the optimal scheduling of corrective maintenance has been investigated for the repair time [5], and the weather forecast [3,6].

In this paper, we present a method that can be applied to compare different maintenance scheduling policies for an OWF at a given location (with known weather) for a specific failure type with a known repair time. In contrast to most of the existing tools and models, no simulations are required and expected values for different performance indicators [7], like downtime or production losses can be compared for the different policies. With the presented method, including uncertainties is straightforward—it can be included directly into the model as opposed to running Monte Carlo simulations with different parameters, as has been done by most of the existing models. Uncertainty in the sea state is included in the presented case study. Section 2 explains the details of the method used and gives the details about the mathematical structure. Implementation of the method is explained in Section 3. Section 4 presents a case study applying the presented method. Discussions and an outlook on alternative policies that could be evaluated with this framework are given in Section 5.

2. Methodology

2.1. Markov Decision Process

The method we present in this paper is based on a Markov decision process (MDP). A MDP is a stochastic control process that can be seen as an extension of a Markov chain, adding actions and rewards [8]. The MDP can be described as a 5-tuple: $(\mathcal{S}, \mathcal{A}, \mathcal{P}, \mathcal{R}, \gamma)$, where $\mathcal{S}$ is a set of states, $\mathcal{A}$ a set of actions, $\mathcal{P}$ the transition probabilities between states, given actions, $\mathcal{R}$ a real-valued reward (or penalty) function that calculates the reward (or penalty) of any given state and γ a discount factor. As the name suggests, this process assumes the Markov property, therefore the effects of an action taken in a state only depend on that state and not the prior history of the process. An example of a Markov decision process is presented in Figure 1. In the present framework, the set of states $\mathcal{S}$ includes an finite number of states—in the example in Figure 1, six states are shown. (Infinite sets of states are possible in the framework of Markov decision processes. For more information about the mathematical concept, please refer to the literature, e.g., [8].) Each state can be described by one or multiple properties. These can be e.g., a location (distance from some fixed point), reward given in the respective state, or, in the case of offshore wind farm maintenance, the status of the turbine, a sea state observation, or the time needed to complete a repair. Each state differs from all other states in at least one characteristic, so no duplicates exist. The actions in the MDP can be either deterministic or stochastic. Deterministic actions lead to a (fixed) new state that the process will continue in after the current state. A stochastic action specifies a probability distribution over the next states. The transition probabilities between states depend on the action undertaken in that state and specify the new state, subject to that action. Therefore, for each state and possible action in that state, there is at least one positive transition probability to another state. For each state and action, the transition probabilities sum to one. A deterministic action is a special case of a stochastic action, with exactly one positive transition probability equal to one. The example in Figure 1 includes two stochastic actions and the associated transition probabilities. The reward function is a real valued function, assigning a value to each state and action combination. When a negative value is assigned by the reward function, it is often called a penalty function instead. In the example in Figure 1, each of the six states has one of two reward values, namely 1 and 0.



$\underline{\pi(S_i) = a_1}$

$$\begin{array}{c|cccccc} & S_1 & S_2 & S_3 & S_4 & S_5 & S_6 \\ \hline S_1 & 0 & 0.3 & 0.7 & 0 & 0 & 0 \\ S_2 & 0 & 0.3 & 0.7 & 0 & 0 & 0 \\ S_3 & 0.4 & 0 & 0 & 0.6 & 0 & 0 \\ S_4 & 0 & 0 & 0 & 0 & 0.6 & 0.4 \\ S_5 & 0 & 0 & 0 & 0 & 0 & 0 \\ S_6 & 0 & 0 & 0 & 0 & 0 & 0 \end{array}$$

$\underline{\pi(S_i) = a_2}$

$$\begin{pmatrix} 0.3 & 0 & 0 & 0.7 & 0 & 0 \\ 0.3 & 0 & 0 & 0.7 & 0 & 0 \\ 0 & 0.4 & 0.6 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{pmatrix}$$

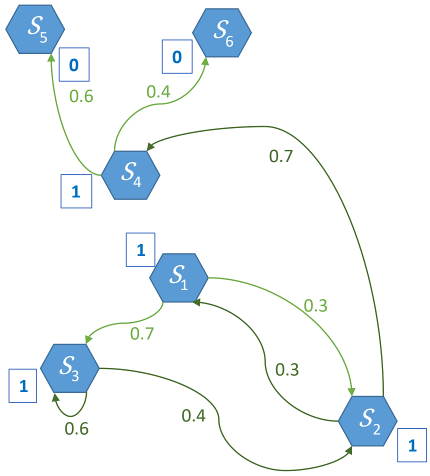
Figure 1. An example of a Markov decision process (**left**). The blue hexagons represent the states, with their rewards indicated in blue boxes next to the state. Orange circles indicate the two actions that can be taken in each state. Subject to the action, the transition probabilities are indicated with green arrows and the value displayed next to the arrow. Transition probabilities following action a_1 are shown in light green, while transition probabilities following action a_2 are shown in dark green. The policies "choose action a_1 in all states" (upper) and "choose action a_2 in all states" (lower) are presented by their transition matrices (**right**).

In addition to the Markov decision process that describe how the system works, our setup contains a set of policies Π. A policy $\pi \in \Pi$ is a mapping from $\mathcal{S}$ to $\mathcal{A}$, and can be understood as a decision makers rule for choosing one of the possible actions $a \in \mathcal{A}$ in each state. In order to follow a policy, one must (a) determine the current state s, (b) determine the action to be executed in that state $a = \pi(s)$, (c) determine the new state s' and continue, alternating (b) and (c). The goal of using a MDP is of course to find an optimal (or at least better than existing) maintenance strategy. In the framework of the MDP, this is done by finding an optimal policy π. In order to evaluate a policy (and ultimately finding the optimal policy), it is necessary to determine expectation of the total reward gained by following it (in order to optimize it). Intuitively, one could try to sum all rewards obtained in the MDP when following the policy, but this can quickly become overwhelming. (Typically, summing all rewards will yield an infinite sum, namely for all MDPs with either infinite state space or for MPDs with infinite horizon. For more information about these cases, refer to e.g., [8].) The solution is to use an objective function to map the sequence of rewards to (single, real) utility values. Options to obtain an objective function are (1) setting a finite horizon, (2) using discounting to favour earlier rewards over later rewards and (3) averaging the reward rate in the limit.

Instead of optimizing the policy, in some cases, it might be desirable to compare different policies with each other. When combining an MDP with a fixed policy that chooses exactly one action for each state, the result is a Markov chain. This is because all of the actions are defined by the policy and one is left with the transition probabilities between states. One example of a resulting Markov chain is visualized in Figure 2. In this Markov chain, the value of each state S_i can be calculated based on the reward $\mathcal{R}(S_i)$ of that state and based on the values of the states that can be reached. It is calculated as

$$V(S_i) = \mathcal{R}(S_i) + \sum_j \mathrm{P}_{ij} V(S_j), \tag{1}$$

where P_{ij} is the transition probability between state S_i and state S_j from $\mathcal{P}$. The equations in (1) are known as Bellman equations, named after Richard Bellman. We can solve the linear equation system (LES) defined by the transition probabilities and reward function to find the values $V(S_i)$ for each state. When comparing two policies, one can look up the value of a specific state one is interested in, usually a 'starting' point. In the case of OWF maintenance, this could e.g., be a state in which a failure occurs and the value could then be representative of the time it takes for this failure to be corrected, with a penalty incurred for each step taken without resolving the failure. A case study comparing different policies is presented in Section 4.



$$\pi^*(S_1) = a_1$$
$$\pi^*(S_2) = a_2 \qquad V^*(S_1) = 6.36$$
$$\pi^*(S_3) = a_2$$

$$\begin{array}{c|c}
 & \begin{matrix} S_1 & S_2 & S_3 & S_4 & S_5 & S_6 \end{matrix} \\
\begin{matrix} S_1 \\ S_2 \\ S_3 \\ S_4 \\ S_5 \\ S_6 \end{matrix} & \begin{pmatrix} 0 & 0.3 & 0.7 & 0 & 0 & 0 \\ 0.3 & 0 & 0 & 0.7 & 0 & 0 \\ 0 & 0.4 & 0.6 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0.6 & 0.4 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{pmatrix}
\end{array}$$

Figure 2. An example of a Markov chain (MC), as the result of selecting one policy in the setup of Figure 1 (**left**). The policy displayed on the right-hand side is the optimal policy for this MDP, when starting in S_1. The transition probabilities for the MC are shown in the matrix (**right**).

In the example shown in Figure 1, a possible policy would be to always choose action a_1. The corresponding Markov chain is presented on the right-hand side of the figure in the form of its transition probabilities. The rewards (presented in the figure in blue next to the states) are $\mathcal{R}(S_1) = \mathcal{R}(S_2) = \mathcal{R}(S_3) = \mathcal{R}(S_4) = 1$, and $\mathcal{R}(S_5) = \mathcal{R}(S_6) = 0$. In order to calculate the value of each of the states, we solve the equation system defined by the Bellman Equation (1):

$$\begin{pmatrix} V(S_1) \\ V(S_2) \\ V(S_3) \\ V(S_4) \\ V(S_5) \\ V(S_6) \end{pmatrix} = \begin{pmatrix} 1 \\ 1 \\ 1 \\ 1 \\ 0 \\ 0 \end{pmatrix} + \begin{pmatrix} 0 & 0.3 & 0.7 & 0 & 0 & 0 \\ 0 & 0.3 & 0.7 & 0 & 0 & 0 \\ 0.4 & 0 & 0 & 0.6 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0.6 & 0.4 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{pmatrix} \begin{pmatrix} V(S_1) \\ V(S_2) \\ V(S_3) \\ V(S_4) \\ V(S_5) \\ V(S_6) \end{pmatrix},$$

$$\begin{pmatrix} -1 & 0.3 & 0.7 & 0 & 0 & 0 \\ 0 & -0.7 & 0.7 & 0 & 0 & 0 \\ 0.4 & 0 & -1 & 0.6 & 0 & 0 \\ 0 & 0 & 0 & -1 & 0.6 & 0.4 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{pmatrix} \begin{pmatrix} V(S_1) \\ V(S_2) \\ V(S_3) \\ V(S_4) \\ V(S_5) \\ V(S_6) \end{pmatrix} = \begin{pmatrix} -1 \\ -1 \\ -1 \\ -1 \\ 0 \\ 0 \end{pmatrix}.$$

The values of the states are then

$$\begin{pmatrix} V(S_1) \\ V(S_2) \\ V(S_3) \\ V(S_4) \\ V(S_5) \\ V(S_6) \end{pmatrix} = \begin{pmatrix} 5.05 \\ 5.05 \\ 3.62 \\ 1 \\ 0 \\ 0 \end{pmatrix}.$$

If one is interested in comparing the value of a specific state under two different policies, the calculation is repeated for that policy and the values compared. It is also possible to find the *optimal* policy without comparing the values based on the resulting Markov chains. In order to find the optimal policy, we define the optimal value function V^* by the recursive set of equations

$$V^*(S_i) = \mathcal{R}(S_i) + max_{a \in \mathcal{A}} \left[\sum_j \mathrm{P}(S_j | S_i, a) V^*(S_j) \right], \tag{2}$$

so the optimal value of a state S_i is the reward in the state, plus the maximum over all actions we could take in the state. This is a the generalized form of the Bellman Equation (1) for policies. In the example shown in Figure 1, the possible actions are a_1 and a_2. The idea behind this maximum is that in every state we aim to choose the action that maximizes the value of the future. The optimal value function V^* can be found by e.g., value iteration. When V^* is known, the optimal policy π^* can be found by picking the action that maximizes the expected optimal value:

$$\pi^*(S_i) = argmax_{a \in \mathcal{A}} \left[\sum_j \mathrm{P}(S_j | S_i, a) V^*(S_j) \right]. \tag{3}$$

In the example shown in Figure 1, the optimal policy is to conduct action a_1 in states S_1 and S_4, and a_2 in states S_2 and S_3. Figure 2 shows the Markov chain corresponding to the optimal policy.

2.2. Probabilistic Weather Input

In the modeling of offshore wind farm maintenance, the uncertainty in the local weather, and more specifically the wave height, is often included. In the given framework, the local weather can be included into the model by adding a sea state (wave height) property in the definition of the states. Some of the existing maintenance approaches [2] use Markov chains to model the weather. Similar to these approaches, transition probabilities between different wave height bins can be used in the MDP. Given some source of historical weather data, the wave height data are sorted into so-called "bins"-categories summarizing wave heights in a given interval. The size of these bins should be adjusted based on the application, for offshore wind farm maintenance 0.4 m is a useful interval step [5]. Then, the probabilities to transition from one bin to all other bins are calculated based on the number of occurrences of transitions between these bins in the given data source. In order to be able to investigate seasonality, one can calculate separate matrices for e.g., each month of the year.

2.3. Repair Time Modelling

Another factor that influences the decision-making in offshore wind farm maintenance is the time it takes to bring a wind turbine component that has failed back to an operational state. Throughout this article, we will use the term "repair time". This repair time is the cumulative amount of time spent during maintenance actions, and we assume a fixed repair time, without uncertainty. The repair time should not be confused with the time between a failure and its resolution, which we will refer to as "downtime". The repair time can be included into the MDP as a parameter to the states. During maintenance, the MDP will move from states with a high remaining repair time, to states with a lower remaining repair time, until a state with no remaining repair time is reached, where the process will stop.

2.4. Calculation of Production Loss

We want to use the MDP to evaluate different policies for offshore wind farm maintenance. One aspect to compare is the production loss of a turbine or wind farm under a given policy. The production loss can only be estimated, as explained in [7], as we cannot measure the absence of production. Therefore, a method to estimate the production loss is needed. Given information about the wind speed from e.g., measurements and a knowledge about how the power production dependents on the wind speed, it is straightforward to find an estimate of the production losses. One could include the wind speed as a parameter into the states of the MDP as was done with the wave height. As we do not need to use the wind speed as a decision criterion for the policies, we use a matrix with conditional probabilities of wind speed values given a wave height, similar to how it has been presented in [5]. Given some source of weather data, the wind speeds are first sorted into bins—a bin size of 1 m/s is sufficient for production loss calculations. For each state in the MDP with a given wave height parameter, the conditional probability for each wind bin is populated in a matrix that can later be used to look up these values. The expected production loss for each state in the MDP can be calculated based on these relative probabilities and a power curve for the turbine type of interest. A power curve can be either obtained directly from the manufacturer or a linearized power curve can be used, based on the turbine model. If one does not have information about an actual turbine model, reference turbines like [9] or [10] can be used. In order to obtain the (expected) production loss, the production values for each discrete wind speed bin, as obtained from the power curve, are weighted (multiplied) with the (conditional) probability from the matrix. The sum of these weighted production values is then the production loss for the state. For a state S_i, given n discrete wind speed steps with conditional probabilities $\mathrm{P}(u_k|S_i)$ for $k = 1 \ldots n$, and a power curve $p(\cdot)$ the expectation of the production loss $L(S_i)$ is

$$E(L_{S_i}) = \sum_{k=1}^{n} p(u_k)\mathrm{P}(u_k|S_i). \tag{4}$$

3. Implementation

In order to use the presented method to evaluate different maintenance policies, it is necessary to implement it in a programming language. The resulting program can then be used to evaluate well-known policies and compare them to alternative options. In our analysis, the implementation was conducted in Python 3.

In order to define the MDP, we define the states, actions, policies and the reward function. The set of states $\mathcal{S}$ can be generated, by defining the composition of a state and then generating a list of possible states. A state could e.g., be a tuple of several parameters $S_i = (p_1(i), p_2(i), p_3(i))$, where each of the parameters can take different values (e.g., $p_1(i) \in \{0, 0.4, 0.8, 1.2, \ldots, 10.0, 10.4\}$ a wave height, $p_2(i) \in \{5, 4, 3, 2, 1, 0\}$ the number of remaining repair hours, and $p_3(i) \in \{\text{'at shore'}, \text{'offshore'}\}$ the vessel location). The different actions $a \in \mathcal{A}$, will have different outcomes depending on the state. Possible actions for an implementation for the offshore wind maintenance planning could be "go out to the wind farm", "repair the turbine", and "return to shore". As described above, each policy $\pi \in \Pi$ is a set of rules, defining which action should be taken in which state. It can be implemented as a set of conditional expressions ensuring that only transitions between states which correspond to the actions defined by the policy are possible. When investigating multiple policies with similar rules, a high level policy can be implemented first, and the characteristic parameter changed for each individual policy in the evaluation. The reward function is a function assigning a real value to each state. It is also possible for the reward value to be dependent on the action taken to reach the state. Implementation of this reward function highly depends on the structure of the states; in most cases, it will be a function depending on one or more parameters of the state.

In order to calculate the value of a policy, the first step is to define the equation system resulting from plugging the policy into the MDP, thereby forming a Markov chain. The LES has been observed to follow some rules and the matrix defining it can be produced following these steps:

1. Find the number of states n, and find a mapping of the states, assigning each of them a natural number, effectively applying an order to the states.
2. Create the $(n \times n)$ matrix containing the transition probabilities for the investigated policy.
3. Calculate the entries of the reward vector, where the i-th entry corresponds to $\mathcal{R}(S_i)$.
4. The matrix $\mathcal{P}$ and vector $\mathcal{R}$ define an equation system

$$(\mathcal{P} - I_n)V = -\mathcal{R},$$

which can be solved using a linear algebra routine in e.g., Matlab or Python. Depending on the structure of the matrix and vector, different algorithms might be used to achieve fast computation.
5. In order to investigate different properties of a policy, the same matrix is used in a LES combined with different reward functions for each property.

4. Case Study

4.1. MDP Definition

In this case study, the states $S \in \mathcal{S}$ of the MDP are tuples of the form $S = (\text{location, wave height, repair time left, steps waited})$, where 'location' can take on either of the values 'port' or 'turbine'. The significant wave height ('wave height') takes values in steps of 0.4 m between 0 m and 10.4 m. The 'repair time' starts off with an initial value, specific to the turbine component that is investigated. The values for repair time are taken from [11], the most recent source for offshore wind turbine failure and repair data. Different components and types of repairs have been investigated in this case study, each with a distinct mean time to repair and worker requirement. For the example of the major blade repair, with 21 h mean time to repair, the values for the 'repair time' range from 0 to 21 h in steps of 1 h. For other components and repair times, the values have a different range. The steps are, however, set to 1 h, for all repair types and components investigated. This results in a different number of states for different types of repair. The 'steps waited' also take steps of 1, starting at 0 and ranging up to 3 depending on the maintenance policy. A summary of the parameters for the states is shown in Table 1. The set of actions $\mathcal{A} = \{\text{stay, wait, reset wait time, go out, repair, return}\}$, where the actions 'wait' and 'reset wait time' are only used in some of the policies. How the actions are used in the different policies is detailed below in Section 4.4, a summary of the possible actions is provided in Table 2. The transition probabilities between states $\mathcal{P}$ depend on the transition probabilities of the significant wave height values. These probabilities are calculated based on the weather data from FINO 1 [12]. More details on how the probabilities are calculated are given in Section 4.2. The reward function $\mathcal{R}$ is used to evaluate different aspects of the maintenance policies. To evaluate the influence of the policy-change on the expected downtime of the turbine, a penalty is used for the steps it takes to end up in a repaired state. To calculate the expected production losses, the reward function $\mathcal{R}$ represents a penalty of the production losses. These are calculated based on the correlation of wind speeds and wave height and a linearized power curve for the NREL 5 MW turbine [9]. The details of this calculation are presented below in Section 4.3. Discounting is not used in this case study and hence the discount factor set to $\gamma = 1$. To evaluate a maintenance policy, we investigate the value of the initial states. These states are those in which the failure occurred and hence the repair has not started. As we assume cumulative repairability (i.e., when a repair has to be interrupted, progress is kept and the repair can be continued at a later stage), these are all states with the initial repair time values. Since the failure can occur at any wave height, multiple states with this repair value exist. These are weighted with their probability of occurrence and the values summed before reporting.

Table 1. The different parameters of the states and their possible values.

Parameter	Possible Values	Comment
Location	$\{port, turbine\}$	
Wave height [m]	$\{0, 0.4, 0.8, \ldots, 10, 10.4\}$	
Repair time [h]	$\{0, 1, 2, \ldots, max - 1, max\}$	maximum (max) depends on component
Steps waited	$\{0, 1, 2, 3\}$	depends on strategy

Table 2. The different actions and how they influence the parameters of the next state.

Action	Parameters for Next State
stay	
wait	steps waited +1
reset wait time	steps waited = 0
go out	location = turbine
repair	repair time −1
return	location = port

4.2. Weather Input

In this case study, the weather data used to calculate the transition probabilities between wave heights (and subsequently states) comes from the FINO 1 measurement campaign. The data from the FINO 1 measurements have some missing observations. Additionally, the wind speeds are provided in 10 min aggregated means while wave height measurements are provided for 30 min intervals, which is not convenient for the calculation of production losses (Section 4.3). The transition probabilities have therefore been calculated based on the interpolated time series also used in [13,14]. In order to calculate the transition probabilities, the significant wave height is categorized in steps of 0.4 m first. This means that all wave height observations between 0 m and 0.4 m will be collected in one so-called bin. The same is done for the values between 0.4 m and 0.8 m, and so on. We have chosen to calculate separate matrices with the transition probabilities for each month, by sorting the data beforehand. This has the advantage that we can investigate and observe how the season affects the optimal policy.

4.3. Calculation of Production Loss

As described above in Section 2.4, the expected production loss for each state is calculated based on probabilities of the wind speed given the sea state, and a power curve. The probabilities are based on data from the FINO 1 measurement campaign. The same 1 h-interpolated FINO 1 data [13] that was used to calculate the wave height transition probabilities was used. For each observation point, a wave height value and a wind speed value are known. The wave height and wind speed are then categorized. For the wind speed, the step size is 1 m/s, so each observation for wind speeds between 0 m/s and 1 m/s will be collected together. The same is done for wind speeds between 1 m/s and 2 m/s and so on. The wave heights are categorized as described in Section 4.2. Then, the conditional probabilities of these wind speeds subject to the wave height at the same point in time are gathered. For the calculation of the production loss, information about the power curve is needed in addition to the weather. In our case study, a linearized power curve is used for the NREL 5 MW turbine [9], as was also done in [5]. The linearized power curve is based on the cut-in and cut-off wind speed as well as the wind speed where the rated power (5 MW) is reached. When solving the MDP, the production loss values are used to calculate the reward of each state. The weighted values of the initial states are then summed and reported, as described above in Section 4.1. The loss of production is calculated in terms of electric power (kWh). If one is interested to compare this directly to the cost of maintenance, the energy needs to be valued in terms of money. This can be done by either using a (variable) electricity market price or a (fixed) feed-in-tariff.

4.4. Policies

This section presents the different maintenance policies that are investigated and compared in the case study. As described in Section 2, a single policy assigns an action $a \in \mathcal{A}$ to each state $S \in \mathcal{S}$. A summary of all policies, with different parameters is shown in Table 3. For each policy, the possible actions under this policy are listed.

Table 3. Names of the different policies investigated in this article, as well as the maximum number of steps that can be waited under this policy and the possible actions.

Policiy Name	Max (Steps Waited)	Possible Actions
go-right-away	0	stay, go out, repair, return
wait-1-step	1	stay, wait, reset wait time, go out, repair, return
wait-2-steps	2	stay, wait, reset wait time, go out, repair, return
wait-3-steps	3	stay, wait, reset wait time, go out, repair, return
0.8 m-limit	0	stay, go out, repair, return
1.2 m-limit	0	stay, go out, repair, return
2.0 m-limit	0	stay, go out, repair, return
2.4 m-limit	0	stay, go out, repair, return
2.8 m-limit	0	stay, go out, repair, return

4.4.1. Go-Right-Away

In order to be able to conduct maintenance, a vessel has to be at the turbine and the wave height needs to be below a defined threshold of 1.6 m. This is a value, based on the often presented wave height limit of 1.5 m for vessel access [15], modified to fit the wave height resolution of the case study. In this strategy, as soon as the wave height is below the threshold of 1.6 m, the vessel is sent to the wind turbine. We assume a travel time of one step (1 h) in this case study, which might be short compared to some wind farms. However, since we are using weather data from FINO 1, which is next to the Alpha Ventus wind farm in the North Sea, we are already assuming a wind farm relatively close to shore which will have a shorter travel time. Once the vessel reaches the turbine, repair is conducted if the wave height is still below the threshold. As soon as the wave height crosses the threshold, the repair is interrupted and the vessel returns to port. We assume that the repair is cumulative, i.e., when the repair is interrupted, it can be continued at a later stage without any loss of progress. The return to port takes one step (1 h) again. As soon as the wave height crosses below the limit again, another access is made until the turbine is repaired. We do not take into account any restrictions to the working time of the maintenance crew or vessel crew, so it is possible to have one access and conduct the full repair without ever returning to port. This is a simplification that could be justified, if the boat has living quarters and enough personnel on board to rotate in shifts. Figure 3 shows a decision diagram for this policy. In every state of the Markov decision process, the diagram can be used to find the action that the policy prescribes for that state. In Figure 4, a minimal MDP is shown for this policy. Here, two steps of repair are required and two wave heights are considered, namely below and above the limit. The probability to stay below the limit is denoted as P(−,−), the probability to change wave height from below the limit to above the limit is denoted as P(−,+) and so on. Assuming the state is ('port', 'above limit', '2'), the first check is whether the repair time is greater than zero, which it is. The next check is whether the vessel is at the turbine, which it is not. Thus, the next inquiry is whether the wave height is below the limit, which it is not. The action is then 'stay'. The state will be the same in the next step with a probability of P(+,+) and will change to ('port', 'below limit', '2') with a probability of P(+,−). In this state, the action will be 'go out'.

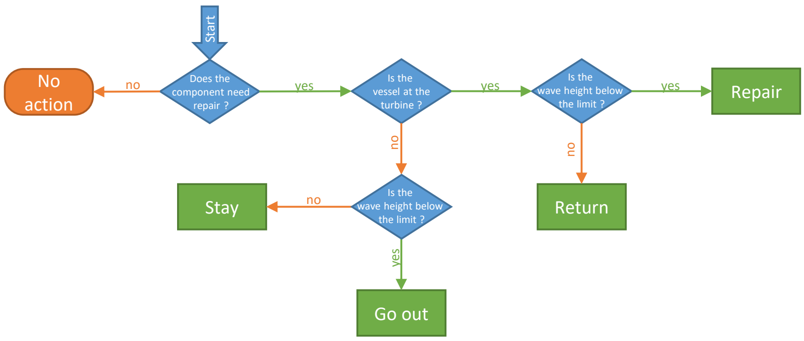


Figure 3. The decision tree for the original (go-right-away) policy. This assessment is conducted for each state and influences the transition probabilities in the MDP, by choosing an action for each state. An example of how the policy is applied can be seen in Figure 4.

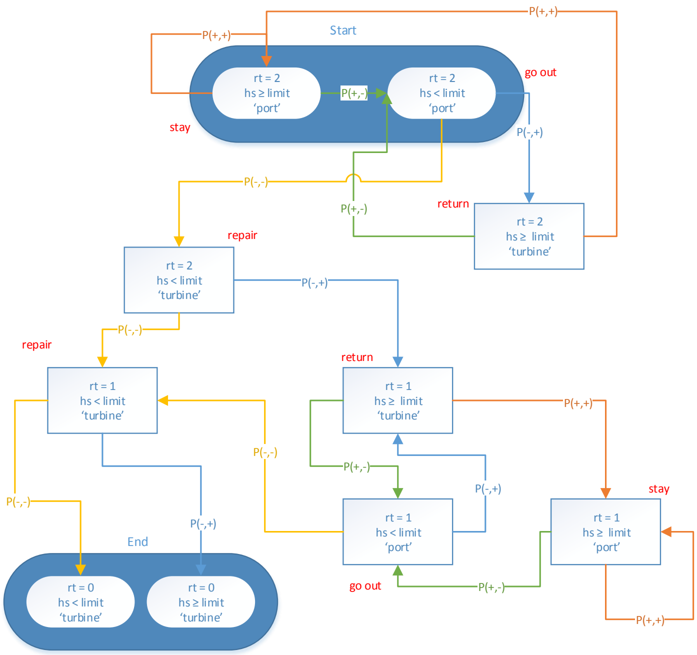


Figure 4. A minimal example of the process for the original (go-right-away) policy. Here, only two steps of repair are shown. The process starts in states with repair time (rt) equal to 2 h (rt = 2), which is then reduced to 1 h (rt = 1) and finally 0 h (rt = 0). The wave height (hs) is categorized as being below (<) or above (≥) the threshold (limit), and transition probabilities are adjusted to accommodate this simplification. P(+,−) is the probability to get from a wave height above threshold (hs ≥ limit) to a wave height below threshold (hs < limit). With 'start', we mark the states in which a maintenance decision maker would start the decision of when to repair, i.e., the point in time when the failure occurs/is reported. The decision taken in each state is marked in red, next to the respective state. How the decision is made, based on the state and maintenance policy can be understood from Figure 3.

4.4.2. Wait-n-Steps

An alternative to accessing the wind farm as soon as the wave height is below the threshold is to wait a certain number of steps in good weather, before going out with the vessel to conduct maintenance. The intuition behind this policy is that, if the sea has been calm for several time-steps, it is more likely to stay calm (i.e., below the wave height limit) due to persistence. Waiting a certain amount of time in good weather assures that the observation below the limit was not just an outlier and one can avoid interrupting the maintenance operations. In the investigated policies, the number of waiting steps is fixed and independent of the observed wave height in the state. In our case study, we investigated wait-times of one step, two steps and three steps. Each step represents 1 h. The other aspects of the strategy remain as before. Again, the repair is assumed to be cumulative, so, if the repair is interrupted, progress is kept and it can be continued and completed at a later stage. The maintenance is aborted and the vessel returns to shore as soon as the wave height is above the threshold. The time it takes to access the turbine and return to port respectively is one step (1 h). The decision diagram for this policy is shown in Figure 5.

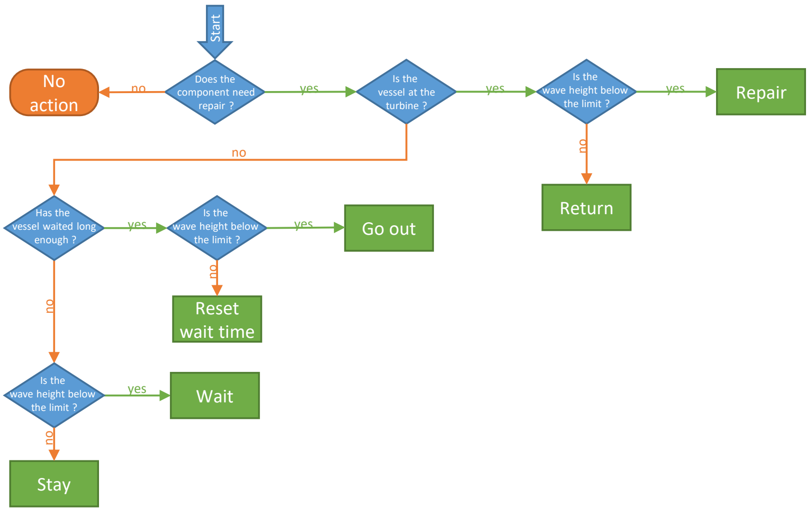


Figure 5. The decision tree for the wait-n-steps policy. First, the decision maker checks, whether a repair is necessary (repair time > 0). Depending on the location (at turbine), a wait-time check is conducted. This depends on the number of wait steps specified by the policy (1 h, 2 h, 3 h). Finally, the weather is checked and the correct action chosen for this state. This assessment is conducted for each state and influences the transition probabilities in the MDP, by choosing an action for each state.

4.4.3. Different-Limits

The third type of policy that is being investigated in this article has a second wave height threshold. One limit (new) is used for the decision of going out to the wind turbine and the other (original) threshold of 1.6 m is used for the decision to start and continue the repair. It is also used for triggering a possible return of the vessel to the harbour. We investigate both lower (stricter) and higher (laxer) wave height limits for access (new limits), specifically we investigate the limits 0.8 m, 1.2 m, 2 m, 2.4 m, and 2.8 m. The repair is again assumed to take a fixed amount of time and can be completed by accumulating enough maintenance (repair) actions. Again, as soon as the wave height is above the (original) wave height threshold, the repair is aborted and the vessel returns to shore. The decision tree for this policy is identical to the one of the go-right-away policy shown in Figure 3, only that the weather check uses a different threshold in a port and at the turbine. The go-right-away policy is a special case of this strategy, where both limits are 1.6 m.

4.5. Repair Data Input

For the repair time values, data from [11] are used. They present the mean time to repair [h], number of workers needed and mean annual failure rates for 19 wind turbine components. For each component, three types of failures are distinguished, namely 'major replacement', 'major repair' and 'minor repair'. Each of these have their own values, leading to a total of 57 different combinations of component and repair type, with specific repair time and worker requirements. We have investigated some selected turbine components and failure types, namely major gearbox replacement, major blade repair, and minor electrical repair. The repair time value is used to generate the possible states for the MDP, whereas the worker requirement is used for cost calculations. The values that have been used are summarized in Table 4.

Table 4. Turbine components that are investigated in the case study and their repair parameters.

Component	Cumulative Repair Time [h]	Average Number of Workers Needed
Gearbox, major replacement	231	17.2
Blade, major repair	21	3.3
Electrical, minor repair	5	2.2

4.6. Cost Data Input

The costs for vessel and workers are dependent on the number of accesses, the total operation time (travel time and working time combined), the vessel charter costs, the vessel hourly costs, the number of workers needed for the repair, and the worker hourly wages. In the case study, these costs are all set according to values from the literature, provided in Table 5. In order to value the production losses in terms of money, the market price for electricity or feed-in-tariffs can be used. Since the price of electricity varies a lot, both between seasons, time of the day and countries, not a single "correct" electricity price can be used to analyze the production losses. In order to show the variation in electricity prices and their influence on the optimal maintenance policy, we include an analysis of the corrective maintenance cost in the case study. In order to gain some insight into the electricity prices in Europe, we used [16,17].

Table 5. Input used to calculate the maintenance cost.

Hourly vessel	287.5 €	calculated from daily cost from [13]
Hourly worker	55.3 €	calculated from annual worker salary
Mobilisation vessel	1000 €	arbitrary (similar to number from [18])

4.7. Results

In this section, some aspects under which the different maintenance policies have been compared are presented. Some of these aspects are similar to the key performance indicators presented in [7].

4.7.1. Repair Actions

The number of repair actions with each policy can be used as a control in order to detect possible mistakes in the implementation of the strategy. All policies include cumulative repair, no degeneration and the work is not continued after the repair is completed. Therefore, the expected repair time calculated and returned by each maintenance policy should be equal to the repair time needed to bring the investigated component back to a state as-good-as-new. Due to memory and rounding errors, this differs insignificantly between policies, in the magnitude of 10^{-10} h in our study.

4.7.2. Downtime

The expected downtime of a maintenance action or repair can be used to evaluate a maintenance policy. The downtime of a turbine is defined as the time the turbine is in a non-operational state caused by either a fault, or by a maintenance action. With an increase in downtime, the time-based availability of the turbine is reduced, often leading to lost production and a lower energy-based availability [7]. The downtime will incur production losses and the decision maker is therefore most likely interested to reduce it. In order to calculate the expected downtime for a policy, the reward function of the MDP is modified such that every step the process takes (i.e., every transition from one state to the next) gets a penalty of 1, representing the time that is lost in this step. When the MDP is then solved, thus the value of each state is calculated, and the average of values of the starting states weighted by the probability of occurrence gives the expected downtime until the cause of downtime (in this case a failure) is resolved. The starting states are those states with a repair time equal to the expected repair time and can be understood as the time of occurrence of the failure. The turbine downtime is, unsurprisingly, higher for the more restrictive policies. For the 'wait-n-steps'-policies, downtime is always higher than for the original 'go-right-away' strategy. For the 'different-limits' policies, those with a less restrictive limit are observed to have a slightly lower downtime than the original strategy. Due to the threshold for access being less restrictive, the vessel is more often at the turbine location. It can be avoided to "waste" one time step of calm weather for the access. This increases the likelihood of the vessel being already at the turbine location when the weather is calm enough to conduct a repair and therefore a faster resolution of the failure. For policies with a stricter limit than 1.6 m, the downtime increases, depending on the repair time and month, to up to three times the downtime of the original policy. Figure 6 shows the downtime for each policy and each month for the major gearbox replacement with a repair time of 231 h.

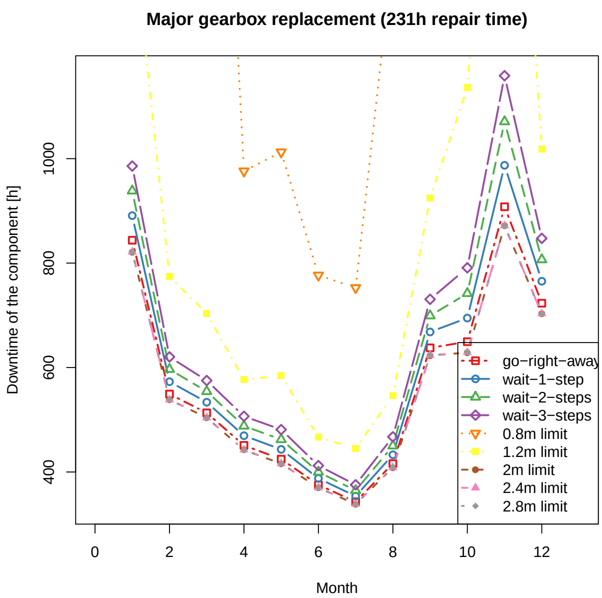


Figure 6. Downtime of the wind turbine due to a major gearbox replacement for different policies. Policies with a less restrictive wave height threshold for the vessel access have a lower downtime than more restrictive policies.

4.7.3. Production Losses

The second aspect that is used to evaluate a maintenance policy is the production lost due to the downtime of the turbine. As explained in Section 2.4, we calculate the production loss based on the wave height in each state. In the MDP, the expected production loss for each policy can be calculated, by using the lost production as 'reward' in the process. Then, the value of the starting states represents the production loss that can be expected by using the evaluated policy. Results for the production loss are shown in Figure 7, for a minor repair of the electrical system. It can be observed that the policies with a laxer wave hold threshold for vessel access have a slightly lower production loss than the original policy. The more restrictive policies on the other hand lead to an increase in lost production, up to more than three times the values of the original policy. For the calculation of the losses in terms of monetary value, different electricity prices have been used in this case study, based on data from Eurostat [16] for various countries. These results are shown combined with other maintenance costs below in Section 4.7.5.

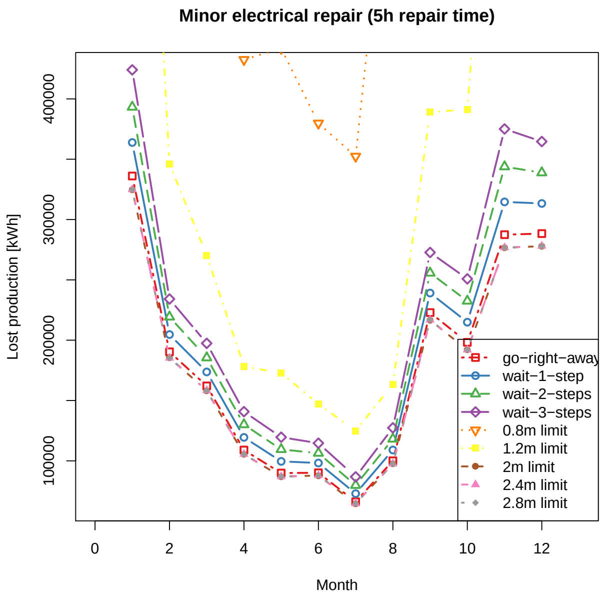


Figure 7. Lost production in kWh for a minor repair of the electrical system, with a repair time of 5 h. The policies with a higher (less restrictive) wave height threshold for vessel access show slightly lower losses in production than the original 'go-right-away'-policy.

4.7.4. Number of Vessel Accesses and Returns

Another aspect that can be used to compare different maintenance policies is the number of vessel accesses. This number is of interest, since usually each vessel mobilization induces a fixed cost for the maintenance provider or wind farm operator. Hence, the decision maker is interested in keeping the total number of vessel mobilizations low, while still trying to conduct a repair as fast as possible. The number of vessel accesses for each policy can be monitored, again by modifying the reward function. The reward is set to 1 for each state in which the selected action is 'go out'. Each time a vessel is sent from the port to the turbine, the reward will increase by one and after the process has finished, the expected number of vessel accesses can be calculated in the same way as the number of repair actions or downtime. As the MDP is stopped as soon as the repair is complete, the number of vessel returns will always be one less than the number of accesses, and can be calculated by following the same logic as for the vessel accesses, switching the action from 'go-out' to 'return'. The number of accesses needed before a completed repair implies vessel and worker costs. Figure 8 shows that the policies with a wave height threshold of 1.6 m ('go-right-away' and 'wait-n-steps') perform very similar in terms of number of vessel mobilizations. The policies with a more restrictive wave height threshold (0.8 m and 1.2 m) show fewer vessel mobilizations. The policies with a higher threshold for waves (2 m, 2.4 m, 2.8 m) show very high numbers of vessel mobilizations, up to 10-times the values of the 'go-right-away'-policy. This is likely caused by the wave height limit for repairs, which remains at 1.6 m also for those policies. When the vessel goes out in harsher weather than is allowed during repairs, and this weather persists for longer than the travel time, the vessel has to return to port right away and no repair can be conducted.

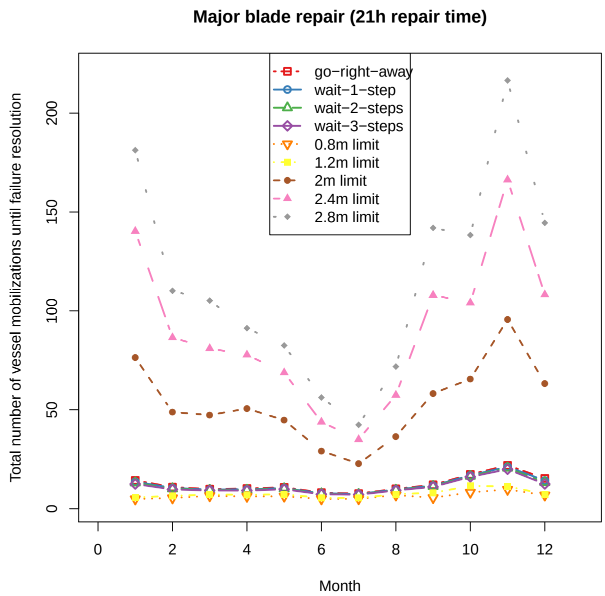


Figure 8. Total number of vessel accesses until the major blade repair is completed—for different policies.

4.7.5. Total Cost of Maintenance

The results for the total cost calculation are naturally the most complex, as they combine the cost calculations with the production losses. In the given framework with cumulative repair and no penalty for an unsuccessful repair attempt, one expects that the 'go-right-away' strategy will be the cheapest option, as this strategy leads to the fastest resolution of the failure. Our case study confirms this under the current electricity prices and assumed worker and vessel costs. Figure 9 shows the example of a major blade repair, and the total cost of maintenance for different policies. Should, however, the electricity price drop, and reach levels below 2.4 Euro-cent, the 'wait-1' strategy surpasses the original (go-right-away) strategy, as the avoidance of unnecessary vessel mobilizations will outbalance the losses due to turbine downtime. This can be seen from Table 6, for the major gearbox replacement for the month of June. As the production losses highly depend on the repair time and weather, no universal "cut-off" point between policies exists, but has to be investigated on an individual basis. Should the current trends of dropping yield for the electricity producer continue, we expect to see novel policies surpassing the cost-performance of the current state-of-the-art policy.

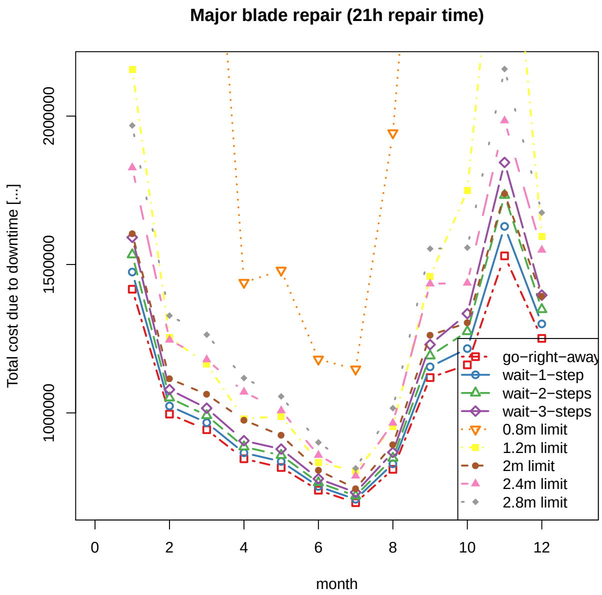


Figure 9. Results for the total costs for the major repair of a turbine blade. We assume an electricity price of 30.84 Euro-cent (Germany second half 2017 from [16]. The original strategy is the cheapest option independent of the season.

Table 6. Electricity price at which a break-even is reached between two policies in €. A value is calculated for each month of the year, for the major gearbox replacement, with a repair time of 231 h. This comparison is not complete and solely meant as an example to show that novel policies indeed become cheaper than the original policy for low enough electricity prices.

Month	simple = wait1	simple = wait2	simple = wait3	wait1 = wait2	wait1 = wait3	wait2 = wait3
1	0.0117	0.0114	0.0110	0.0110	0.0106	0.0103
2	0.0163	0.0153	0.0144	0.0143	0.0134	0.0125
3	0.0118	0.0108	0.0099	0.0098	0.0090	0.0082
4	0.0211	0.0192	0.0175	0.0173	0.0158	0.0142
5	0.0193	0.0178	0.0164	0.0163	0.0150	0.0137
6	0.0247	0.0228	0.0212	0.0210	0.0194	0.0178
7	0.0180	0.0168	0.0157	0.0156	0.0146	0.0136
8	0.0175	0.0158	0.0143	0.0141	0.0127	0.0113
9	0.0113	0.0104	0.0096	0.0095	0.0088	0.0081
10	0.0095	0.0086	0.0078	0.0077	0.0070	0.0063
11	0.0075	0.0070	0.0066	0.0066	0.0061	0.0057
12	0.0223	0.0209	0.0196	0.0195	0.0182	0.0169

5. Discussion

The most important takeaway from this paper should be the methodology that has been presented. The Markov decision process is a powerful tool and yet so versatile that it can be modified to fit a multitude of use cases. Uncertainties in different parameters can be included, by adding a parameter to the state, representing e.g., the probability of a successful repair, or the occurrence of a new failure.

The results presented in the case study Section 4.1 show that the Markov decision process is a valid approach to assess different maintenance policies for offshore wind farms. It has shown that, depending on the circumstances, the current state-of-the-art maintenance policy is indeed optimal. We have further shown that, with an electricity price below 3 Euro-cent, the 'wait-1-step'-policy becomes better than the original strategy in the given framework. This is assuming a crew transfer vessel with the presented values for maintenance costs can be used for the given repair and weather probabilities based on FINO 1 [12].

According to Fraunhofer ISE [17], the wind specific electricity prices in Germany are currently between 8 and 14 Euro-cent, while consumer end prices for electricity were at 31.23 Euro-cent in Germany in the second half of 2018 according to Eurostat [16]. This shows that only a small fraction of the end-consumer price is paid to the wind farm operator, roughly between 26–46% of the consumer end price goes to the energy producer in Germany. Fraunhofer ISE [17] predict the prices in Germany to further drop to around 5 to 11 Euro-cent by 2030.

When applying these percentages to other European countries, like Lithuania with an electricity price of 0.1097 Euro-cent in the second half of 2018 [16], a yield of 3–5 Euro-cent becomes realistic. This is without the prediction of a drop in the share of the percentage of the electricity price that goes to the producer. Factoring that into the previous calculation, a yield between 1.8–0.3 Euro-cent for Lithuania in 2030 can be predicted. Therefore, wind farm operators might soon be interested to look beyond the state-of-the-art strategy and investigate other policies.

Another aspect to consider is the limitation of this study concerning different vessel types. A gearbox replacement usually requires a lifting vessel with a crane, which generally have higher mobilization and hourly hire rates than the ones investigated in the current framework. In reality, the maintenance policy of waiting for a persistently calm sea might therefore already be economically viable in some cases for the current electricity prices.

A similar argument can be observed for wind farms that are far offshore, with longer travel times. The example presented here was based on FINO 1 [12] data, a measurement mast close to the Alpha Ventus wind farm very close to the coast. With an increasing travel time, the cost of a failed maintenance attempt (an unnecessary vessel mobilization) increases and it is expected that another policy than 'go-right-away' will be economically better and possibly already for current electricity prices.

The Markov decision process can be used to study and compare many different maintenance policies that have not been discussed here. It is also very straightforward to use the same process for wind farms with a longer travel time, other site-specific weather conditions, turbine types or cost numbers. Some examples for investigations in the future include:

- Maintenance policies taking into account work-time restrictions or shift lengths.
- Policies including multiple vessels.
- Policies including different vessel types.
- Investigations of multiple failures or turbines.
- A framework that takes into account incomplete repair actions or loss of repair progress in case of interrupted maintenance.
- Wind farms further from shore, with a longer travel time and harsher weather.

6. Materials and Methods

Wind and wave data from the FINO 1 project are provided by the Bundesministerium für Wirtschaft und Energie (BMWi), Federal Ministry for Economic Affairs and Energy and the Projektträger Jülich, project executing organization (PTJ). They can be downloaded from http://fino.bsh.de/ by users from Europe, for research purposes.

The implementation of the method, as used for the case study, is freely available from https://github.com/helenese/MDP, licensed under Creative Commons Attribution—NonCommercial 4.0 International (CC BY-NC 4.0).

7. Conclusions

In this article the Markov decision process (MDP) has been presented as a useful method for offshore wind farm maintenance modeling. The method can be adapted to fit many use cases and uncertainties can be included without relying on Monte Carlo simulations. The case study has validated the use of this concept and further indicates that under a hypothetically, lower electricity price alternative policies for the scheduling of repair will become more efficient than the current state of the art.

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A.10 Paper 10

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Article

Vindby—A Serious Offshore Wind Farm Design Game

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Abstract: To maintain the increasing interest and development in offshore wind energy, novel training tools for engineers and researchers are needed. Concurrently, educational outreach activities are in demand to inform the public about the importance of offshore wind energy. In this paper, the development of a serious game about the design and management of offshore wind farms is presented to address such demands. Such a serious game may enable a new audience to explore the field of offshore wind as well as provide researchers entering the field a better understanding of the intricacies of the industry. This requires a simulation that is realistic but also effective in teaching information and engaging outreach. Ultimately, increased public support and expanded training tools are desired to improve decision-making and to provide opportunities to test and integrate innovative solutions. The work presented here includes the game design and implementation of a prototype game. The game design involves building a game framework and developing a simplified simulation. This simulation addresses weather prediction, offshore wind farm design, operation and maintenance, energy demand, climate change, and finance. Playtesting of the prototype demonstrated immersion and informed decision-making of the players and surveys revealed that knowledge had increased while playing the game. Recommendations for future versions of the game are listed.

Keywords: offshore wind energy; operation and maintenance; serious game; outreach; wind farm design; wind farm siting; metocean conditions; foundation design; installation; decomissioning

1. Motivation

International climate change policies have driven the offshore wind energy sector to immense investments in industry and research globally. Despite the growing success, there are still challenges to overcome before truly competitive costs of energy compared to other energy sources that can be achieved without sacrificing safety or productivity. A frequently referenced challenge that will affect the future of support structures in offshore wind is the transition to deeper water [1], enabling also the construction and use of larger turbines. Additionally, the reduction of uncertainty in weather prediction may improve O&M by allowing for decisions to be more informed in efforts to reduce downtime. To address such specific offshore wind challenges, many studies are being conducted and field tested on cost reducing and production enhancing measures. Some topics at the forefront of research include innovative bottom fixed and floating support structures, improved wind speed and power forecasting methods, intelligent control systems, realistic grid integration sensitive to economic and political objectives, and optimization of operation and maintenance (O&M) strategies under uncertainty. According to Ernst & Young [2], one of the priority measures required to realize the full potential of offshore wind in Europe's future energy mix includes the support of innovation and training and enhancement of synergies to reduce costs.

Offshore wind farm design and operational management is a complex task as is demonstrated by the variety of approaches in practice and research. Even for experienced engineers, it is sometimes difficult to correctly judge the relevance of different cost factors and design drivers in a multidisciplinary field. Additionally, researchers in offshore wind energy often come from diverse backgrounds and often need to collect and understand lots of unfamiliar information in a short amount of time. To maintain the current momentum of increasing investment, interest, and development in the field, there is a need for novel training tools and techniques for engineers and researchers that integrate the work of both industry and academia. Concurrently, the general public is concerned about the price of energy from offshore wind energy and the costs of research to improve it. A list of "wind energy myths" compiled by the European Wind Energy Association [3] highlights misconceptions of wind power: that it is a niche-technology, expensive, unreliable, and bad for health and the environment. To address these concerns, there is therefore also a need for educational outreach activities.

A modern approach to provide this education is the development of a serious game that teaches users' facts and lessons about offshore wind energy. This approach offers the opportunity to integrate both existing and pioneering offshore wind practices in a tool that is as educational as it is entertaining. The game will be driven by an underlying complex simulation based on engineering models, which is packaged in the form of an optimization challenge. The playability and engagement of the game drives how this otherwise non-unique simulation fits into an entirely new context.

The goal of this study is to evaluate a new, alternative form of training and dissemination of scientific knowledge of offshore wind energy in the form of a serious game. This is done by focusing on the simplification of offshore wind farm design, management, and lifetime costs in addition to assessing alternative serious game approaches. The results consist of the development of a playable prototype of a serious game in wind farm design and operational management. The project goals were to:

1. Develop a digital game for the design and the operational management of offshore wind farms to be used for two purposes:
    (a) Training: The game should act as a novel training technique/tool for engineers and researchers to better understand cost and design drivers.
    (b) Dissemination: The game should teach the public important facts about offshore wind energy and serve as educational outreach.
2. Measure game effectiveness in terms of the accuracy and responsiveness of its simulations and its educational power.

The educational goals of the game are different for the two purposes of training and dissemination. For training, users include engineers and researchers who want or need to improve their comprehension of offshore wind farm processes. After playing, these users should be able to describe terminology and design drivers in detail. They should feel more confident and prepared to begin or continue their work in wind energy. For dissemination, users include young adults or adults without prior knowledge of offshore wind who are prompted or interested to gain knowledge on important facts or trends. After playing, these users should be able to generally describe challenges and opportunities of offshore wind as well as basic physical elements and costs. They should feel that they are aware of the basic principles of offshore wind and feel an increased appreciation for the topic.

1.1. Boundary Conditions

This study is conducted under several boundary conditions as follows. The simulation behind the game includes simplified methods of wind farm design and management, with emphasis on future expandability. Minimal effort is put into game production (i.e., making an attractive user experience). Procedural generation using random numbers is used to present a different scenario to the user for each run. The prototype is implemented in Python [4]. The prototype was playtested once with voluntary participants. Lastly, it is assumed that the results of this work may be improved upon and utilized by game developers and producers in the future to create an attractive user experience. To promote development, the game is open source and can be downloaded by anyone from the internet. Currently, the game is hosted at http://folk.ntnu.no/muskulus/vindby/.

1.2. Organization of Research

The three topics explored in this study are offshore wind energy (design, operation, and economics), serious game design, and prototype development. The organization of this paper was constructed in a way to capture the justification behind the major decisions made to produce the resulting prototype. Section 2 presents a review of the definition and scope of serious games in general. Section 3 presents the game, called Vindby, which is then described in detail with respect to the game framework defined by game dynamics, game elements, and game mechanics. This section also covers the offshore wind energy topics demonstrated by Vindby, including the weather simulation created specifically for the game. Section 4 summarizes the outcome of testing the game prototype. Section 5 presents a discussion of the simulation development and key experiences in game development and testing. Section 6 presents the study conclusions and a summary of potential future work.

2. Serious Games

An enhanced understanding of uncertainties by researchers and the public alike can contribute to informed decision-making. Better decisions are desired to enhance progress and reduce costs. Looking to learning methods to enhance this understanding, there is a multitude of various teaching and learning techniques. Some learners prefer to learn by reading a textbook, watching a documentary, studying in a group, or individually. The success of existing serious games indicates that some learners value alternative strategies. This does not imply superiority but rather that a greater number of learners can be reached by increasing the set of learning tools. Serious games provide one more way to explore the topic of offshore wind for a new group of learners [5].

A great deal of practical work and research has been carried out in the field of serious games designed for medical purposes, history, social issues, engineering, and much more. "Serious Games Foundations, Concepts and Practice" by [5] consolidates the work of over 50 authors including researchers and professionals whose expertise or career lies in serious games. Reference [5] define a serious game as a digital game intended to entertain and to achieve at least one supplementary goal. This additional goal is known as a characterizing goal. The characterizing goal for training purposes in the Vindby game is to improve the user's technical judgment of offshore wind farm design and industry. The characterizing goal for dissemination purposes in the game is to enhance the user's sentiment towards offshore wind energy and introduce basic terminology.

Modern serious games are used in schools for many educational purposes because serious games can provide an extrinsic motivation to players who do not have the intrinsic motivation to engage with the subject matter otherwise. Serious game developers use various motivational tools to join fun and learning. They integrate amusing gameplay closely tied to the subject matter, using the power of stories, rules, rewards, and other mechanics to teach principles as well as complex concepts rather than just facts [6]. Some serious games are developed for training in technical areas and decision-making such as in SimPort: a multiplayer management game framework as documented by Warmerdam et al. [7]. The dual characterizing goals of the proposed serious game is what distinguishes it from similar existing games, where either training or dissemination is desired but not both. Additionally, the nature of the game content is highly subject to evolution with time. The game Vindby that is detailed in this article aims to be technically as accurate as possible, while teaching about the technology choices in wind energy. Existing games with wind energy as topic [8,9] do not provide such level of technical details as Vindby. Fu et al. [10] measured the effectiveness of serious games and noted that whether a player enjoyed a game is a key factor in determining whether the player continues to learn from the game. In other words, when the learner is prompted by self-motivation factors in the game, they will choose to devote more time to playing the game and understanding its content. The importance of the game mechanics and engineering principles driving the simulation must not overtake the importance of designing an immersive, fun-to-play game. This distinguishes the product from an engineering simulation because, if the goal to entertain is neglected, the playing experience might result in a failure to achieve the characterizing goal. To properly integrate the subject matter (in this case, the design and operation of offshore wind farms) and enjoyment (fun and amusement), a collaboration between game designers, programmers, artists, and domain experts through the entire development is essential to create a successful serious game. The task of interface development and final prototype development of the game would largely rely on work done by a dedicated game development team.

The content of the game includes the design and maintenance of offshore wind farms. There is a high upper limit for how detailed the content can be in a serious game because it is packaged in a simulation. Scientific simulations focus on accuracy, while ordinary game simulations focus on entertainment. The simulation of a serious game falls between an entertainment and scientific simulation depending on the characterizing goals. For training purposes, such a game is expected to represent the subject matter correctly, like a flight simulator. While an entertainment game eliminates details that are not fun, a serious game relies on realistic details to educate users about the subject. A simulation is always an abstraction of the system it represents. Abstraction of the system can be done by eliminating factors that have little effect, or by simplifying features that contribute to the overall mechanics, but whose inner workings do not significantly change the outcome [6]. In an effort to balance accuracy with fun, the final game design presented here is the product of many iterations internally tested for accuracy of scale, accuracy of weather prediction, and, most of all, playability. Playability is vital to the players' understanding and grasp of game content as well as general enjoyment and can be influenced by the feedback the game provides to the player. Different mechanisms to provide feedback have been tested to achieve playability in the prototype.

The existing body of knowledge on how to design a serious game is extensive. While the majority of the terminology and approaches align between sources, there are several differences in the literature. To maintain clarity and consistency, the guidelines in [5] are generally followed in this paper and supplemented when appropriate. Terminology used throughout is outlined in Table 1. The structure of how the individual terms fit into the concept of serious games can be seen from Figure 1.

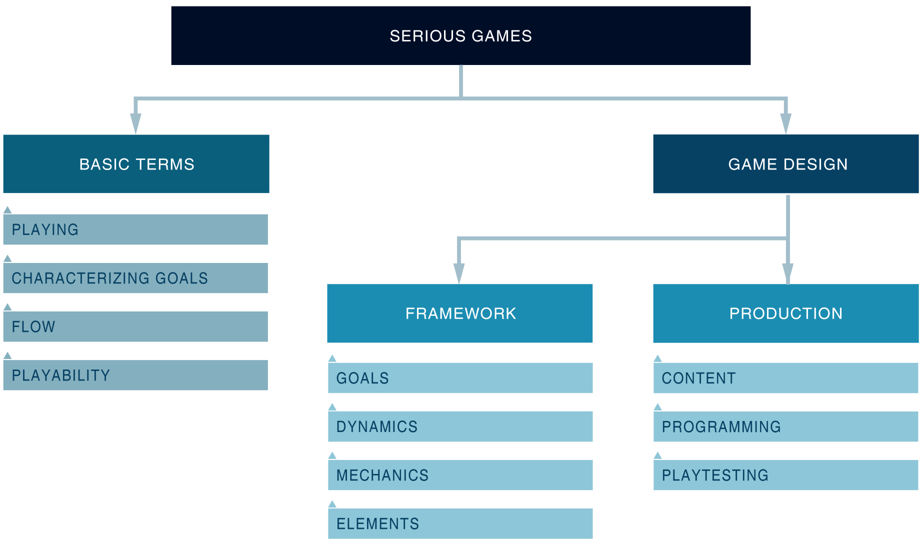

Figure 1. Serious game terminology and concepts.

Table 1. Concepts of serious games and terminology used throughout this article.

Terminology for serious games	
Playing	Playing refers to a user engaging in the serious game for training or dissemination. This includes voluntary or required participation. Characterizing goals refer to the additional purpose of a serious game other than entertainment.
Characterizing goal	The characterizing goal for training is to improve technical judgement of the user. The characterizing goal for dissemination is to enhance the sentiment of the user towards offshore wind energy and introduce basic terminology. These goals are refined throughout the report and summarized in the conclusion.
Flow	Flow is the experience while playing characterized by exclusive concentration on the game, feeling immersed, feeling in control, facing clear goals, and receiving immediate and consistent feedback. Flow should encompass motivation to play, appeal to a spectrum of end users, removing factors that demotivate, and creating meaningful hints with feedback [5,11].
Playability	Playability is the term used when referring to game usability, player experience, and the inclination for continued play. For the sake of simplicity playability will almost always be referred to as a composite measure throughout this study.
Terminology for game design framework	
Goals	Game objectives or game goals are what the player must achieve to win (not to be confused with the characterizing goals). The game goal includes a specific target to reach by playing e.g., an award or a certain number of points.
Dynamics	Game dynamics are the means by which players achieve the goal and can include one or many different dynamics. Common well-known dynamics include race-to-the-finish, construct, solve, and collection.
Mechanics	Game mechanics control the way players interact with the game. This includes specific rules and procedures that guide the player and the internal structure of the game, as defined by game dynamics.
Elements	Game elements are features of the game that keep players engaged such as story, rewards, and scoring. Games use one or more of these elements [12].
Terminology for game production	
Content	Content refers to domain-specific knowledge. In this study, this pertains to simplified offshore wind farm design. This includes the engineering models, weather simulation, assumed parameter values, and formulas used to build the game.
Programming	Programming refers to the relevant algorithms and programming concepts used in the hardware and software arrangements on which the game is played. One of the challenges of programming is to ensure the game runs at a desired speed on different computers throughout the game.
Playtesting	Playtesting is the process of testing the prototype of a game by individuals not involved in the design. Feedback from players after playtesting is used to improve the prototype.

3. Vindby the Game

The game created for this study is called Vindby and will be referred to as such. Vindby is chosen as the name of the game both as an ode to the world's first offshore wind park in 1991 in Denmark and as a translation to Norwegian of "wind city". The serious game must have one or more game goals and a framework to support the players to achieve these goals. The framework for Vindby was established alongside the development of game content and the programming to ensure proper integration of playability while achieving the characterizing goals. In this section, the game framework and game content is described.

3.1. Game Framework

3.1.1. Objectives

The goal of Vindby is to reach a target by building wind farms in a virtual sea within an alloted time and budget. Five different game goals were defined and evaluated during playtesting to compare different game duration, level of difficultly, and interest in the subject. The player can select from the following game goals to play during one game:

1. Profit: Invest all the initial investment (€1 billion) in capital costs and break overall profit by 2025,
2. Compete: Keep playing until 2030 and achieve an overall score higher than any other player,
3. Dominate: Achieve 10% share of all energy supply that can be provided by offshore wind by 2050,
4. Save the planet: Prevent the global temperature from increasing by 2 degrees by 2100, and
5. Free for all: Free play without time limits.

3.1.2. Dynamics

Common game dynamics include: Race to the finish, collection, solve, rescue, escape, and construct [12]. Of these, the main game dynamic of Vindby is constructed in addition to collect or solve, depending on the game goal selected, under time constraints. While the game does impose a time limit to reinforce real-life constraints on renewable energy, it is relatively slow paced and does not require quick reactions since reflective thinking is often necessary for learning. To aid in learning, the player may pause the game at any moment.

3.1.3. Elements

Studies in neural sciences indicate the positive impact of emotional engagement, or immersion, on learning. Game elements provide immersion by creating motivation to the player to continue playing and incentive to achieve the game goals [5]. Elements used in Vindby are rewards, resources, scoring, story, chance, and strategy.

Rewards are used to build player self-esteem. Resources are limited and displayed with transparency to aid in decision-making that results in success and rewards. To maintain immersion, player decisions must be impactful and informed and not tangential to the game goal, hollow, or obvious, so as not to cause disinterest [13]. Scoring indicates progress on a variety of measures not necessarily directly related to the game goal and is used in Vindby to teach the player about how offshore wind energy is affected by a combination of effects. The story of Vindby takes place in a virtual sea given input from a growing energy demand onshore and climate change effects. The player is the designer and operator while other characters include the government, the general public, and shareholders to demonstrate external consequences. Chance is incorporated using random events related to weather and failure, which make each game unique and interesting to play multiple times and demonstrate real world uncertainty. The player's freedom to test various strategies allows for the comparison and contrast of offshore wind concepts and understanding that there is not one solution to all the challenges encountered.

3.1.4. Mechanics

Game mechanics include rules and procedures that guide the player and determine the internal structure of the game. As Vindby is an educational game, game mechanics heavily rely on the serious content to determine rules and processes, although these are sometimes modified to enhance playability. Such rules are typically defined for game space, time, objects, actions, and resources [11]. The game space in Vindby is a virtual sea (referred to as the "sea grid") divided into 100 unique cells. Game time is measured in calendar dates to teach users about realistic timelines. Specific game mechanics are explored in the game content section.

A few game mechanics defined early in the game design include the following. The player is given an initial investment at the start of the game to pay for site investigation, building and maintaining wind farms. The player must not run out of money (or the game is lost). The game is won if the player reaches the target of the selected goal. Additionally, various bonuses, penalties, and special features are revealed throughout playing. Such additional features include the reward and penalty of money and the expansion of design capabilities.

3.2. Implementation

The Vindby prototype was coded using Python (version 3.6) with an object-oriented programming (OOP) approach. OOP is a programming style used to organize code by encapsulating data together with operations that act on it in a single code unit called an object. For preliminary game development, the prototype is minimal but enough to test game mechanics and generate random values. Within OOP, a common game-specific programming pattern is a game loop. The game continuously cycles through process input, update game, render, and a time delay. Each update advances the game time by a specified amount while it takes a certain amount of real time to process the updates. To deal with user defined game speed (slow, normal, or fast) and variable machine capabilities, a catch-up method is used by applying a fixed time step with synchronization. The game runs at a fixed speed and adds a delay to maintain consistent speed. Specifically, each loop in the game is designed to be completed in one real-time second. The user may select to run one hour, one week, or one month of simulation time in that second. If the computation time for one loop is less than one real time second, a delay is added to force the loop to maintain a one real-time second per loop speed.

The terms used to reference measures of time in the simulation are defined as follows. *Game time* is used to measure the time that has passed since beginning the game in units mimicking the game's story line. In the simulation, game time is measured in hours for simplicity in calculations, and presented as calendar dates to the player for relevance. *Game speed* measures the interval of game time that occurs per second of real time. Game speed is chosen by the user. Slow speed runs at one hour (game time) per second (real time), normal speed runs at one week (168 h) per second, and fast speed runs at one month (730 h) per second. For example, at fast game speed, the player may simulate 10 years of wind farm activity in 120 s of real time. *Wind time* measures the number of loops in the simulation that have passed since beginning the game. Each loop represents one hour in the game (theoretically, this interval may be different). Wind time progresses by this interval regardless of the game speed selected. Wind time is used by the simulation to perform ongoing calculations. Specifically, wind speeds and power production must be calculated continuously, regardless of the game speed that the player chooses to use. *Wind time interval* is the amount game time that represents one loop in the simulation. This is equal to one hour in the current version of Vindby, as mentioned above. This was selected because the weather model was built to produce output including hourly wind speed and wave height. For example, one loop in the simulation is performed in one real second at "slow" game speed, and 168 loops in the simulation are performed in one real second at "normal" game speed.

3.3. Game Content

The game content includes the design and maintenance of offshore wind farms. The topics that are integrated into Vindby are weather prediction, wind farm design, operation and maintenance, energy demand, costs, stakeholder influence, and optimization. These topics were identified through many iterations of game mechanics, review of offshore wind current practices, review of ongoing research, and discussions with colleagues regarding areas of interest to potential players.

3.3.1. Weather Simulation

Accurate weather modelling is incorporated to improve the player's understanding of expected energy production and weather windows for construction and operation. This topic is addressed with the most detail in Vindby's development. It is meant to illustrate the game's potential use as an advanced training tool and serves as an example for the other game content topics to be explored in further detail.

The two environmental parameters used in Vindby are significant wave height and mean wind speed. Wind speed is used to determine power production. Both the wind and wave parameters are used to determine persistence of weather windows. Weather windows indicate the availability of a turbine to be repaired, i.e., repairs cannot take place during weather that is unsafe for vessels.

The parameters are modelled probabilistically and realizations are established using a random number generator. The Vindby weather simulation uses 10 min intervals, as this interval is used throughout the wind industry to measure turbulence and reliability of larger wind turbine [14].

A Markov chain model is used for wave (or wind) time series generation in Vindby, but only for one parameter. The second parameter is then generated using conditional probability distributions. A Markov model is a discrete stochastic process. It is a simple and efficient method that assumes the future weather only depends on the current weather state. The development of current to future weather state is described by stochastic transitions. The transitions are established using an existing data set. The transition probabilities are estimated by discretizing the average frequencies of transitions observed in the data and can be presented in matrix form as described by [15]. The data was discretized with bin sizes of 0.4 m and 1.0 m/s, respectively. The wave and wind data used is from FINO1, which is a research platform in the German North Sea near the wind farm Alpha Ventus, 45 km from shore. Year-round seasonality was accounted for by using different matrices for each month.

One challenge while using conditional probabilities between wind and wave data is that the original datasets are at different resolutions. The recorded observations of wave heights were provided by buoy measurements, and the data resolution is more or less one hour, with slight variations in length. For the wind speed, the resolution is uniformly 10 min. Markov transition matrices based on one hour wave data may only accurately model one hour resolution. As the goal was to use 10 min wind speeds to describe the power production, a number of different modeling approaches were tested. The results from these test are summarized in Table 2 and explained in the following.

Two main approaches to capture the correlation between wind speeds and wave heights can be distinguished. The "wave to wind" approach uses a Markov matrix to generate wave heights and then uses a matrix containing conditional probabilities to generate wind speeds consistent with the seastate. The alternative "wind to wave" method uses a Markov matrix to generate wind speeds and then uses conditional probabilities to generate corresponding wave heights. Another distinction was made regarding the method to sample six realizations of 10 min wind speeds for each hour of a seastate, necessary to address the issue of the different timescales. The two approaches used for this were a "Markov" method, that relies on a Markov chain for generating 10 min wind speed values within each hour, versus a "Gaussian" approach that randomly draws wind speed values, based on the measured standard deviations of 10 min speeds within an hour. Although the latter approach does not correctly reproduce correlations in time between the 10 min wind speed values, it was introduced due to its simplicity and since it was observed that the distributions of 10 min wind speeds within each hour appeared consistently Gaussian (for hourly means less than 25 m/s).

Before implementing the weather prediction model into Vindby, the different approaches were tested. Six observations of 10-min wind speeds where aggregated (by averaging) to create hourly wind speed observations. This provides an unbiased estimate of the hourly mean wind speed. It needs to be noted, however, that fluctuations among the wind speeds are smoothed out at the lower resolution. This is unproblematic in this case, but would have to be addressed if also the variance of the wind speeds would be needed (e.g., for modelling fatigue damage). These hourly values were then used to calculate conditional probabilities for observing corresponding wave height measurements (or vice versa), in order to capture the correlation between wave height and wind speed. The different simulation methods were then each run 10 times for 10 simulated years each to establish the effects of the different modeling strategies: (a) 10 min data sampling method (Markov vs. Gaussian), and (b) using a "wave to wind" vs. a "wind to wave" approach. Wave height boundaries of 1.5 m and 2 m, and upper wind speed boundaries of 15 m/s and 20 m/s were used to test persistence of weather windows. A 10-year simulation length was chosen after an analysis of the stability of mean wind speeds after 1, 5, 10, 15, and 20-year simulations. The 10-min wind speed time series and one hour wave height time series generated were compared to the original dataset. After at least 10 years of simulation, the mean of the 10 min wind speeds did not vary more than 1% when increasing the simulation length by another year.

The further results of the weather simulation model (see [16] for details) establish that (using the same dataset and Markov chain for each run) the simulated hourly wave height and wind speed distributions had average percent errors of 2.1% and 1.0%, respectively, from the distributions obtained from the measurement data. The persistence of weather windows for sea states was well represented with a slight underestimation of weather windows for periods of 12 to 24 h.

Somewhat predictably, the simulations using the wind Markov matrices resulted in lower percent errors than for the wind speeds derived by conditional probabilities, and those using the wave Markov matrices performed similarly for the wave height. Interestingly, the hourly distribution of 10 min wind speeds was closer to the observed values using the Gaussian approach. This is probably due to a more accurate parameterization: the Gaussian approach is based on only two parameters that need to be estimated from the data, whereas the alternative Markov approach is based on many more parameters. In the end, the "wave to wind" simulation method with Gaussian sampling was implemented in Vindby, as it enables more accurate wind speeds and wave heights.

Table 2. Weather model results for mean wave height and wind speed for 10-year simulation.

Simulation Hourly	Simulation 10 min	Mean Wave Height [m]	Mean Wind Speed [m/s]	Intra-Hour Variation [m/s]	Error Wave Height	Error Wind Speed
Observed	Observed	1.51	9.37	0.55	-	-
wave to wind	Markov	1.52	9.55	0.75	0.55 %	1.97 %
wave to wind	Gaussian	1.49	9.48	0.56	−1.18 %	1.20%
wind to wave	Markov	1.47	9.38	***0.73***	−2.66%	0.12%
wind to wave	Gaussian	1.47	9.35	0.56	−2.73 %	−0.25%

In order to represent sea-wide weather variation in the weather, it was necessary to include some spatial variation of weather parameters in the game. To demonstrate variations of weather in the offshore environment, Vindby's virtual sea is divided into 100 cells, each with distinct environmental characteristics. All cells use the same Markov matrix, mainly to save setup time and memory. Each occupied cell then runs its own weather simulation (unoccupied cells are excluded to minimize computing time). Cells must have distinct mean wind speeds to demonstrate variation offshore. This is achieved by using a wind speed factor to scale (increase or decrease proportionally) the simulated mean wind speed and wave height magnitudes, while maintaining their distributions. Because Vindby's sea is fictitious, wind speed factors were assigned more or less randomly to different cells, with generally increasing mean wind speed farther from shore. The factors range from 0.5 to 1.3, thereby achieving a range of annual mean wind speeds between 4.7 to 12.2 m/s (the mean of the wind speed measurements was 9.37 m/s).

3.3.2. Wind Farm Design

Intelligent wind farm design is Vindby's most fundamental activity. This section presents how wind farm design translates into game mechanics.

Site Selection: One characterizing dissemination goal is for the player to gain an appreciation for the short-listing process of selecting an adequate site. The characterizing training goal is for the player to learn about relevant offshore parameters that dictate this process. Players are given minimal information about the physical characteristics of each of the 100 cells within the sea grid, each of which is considered one site. The player can then pay for site investigations to gather more details. The full site information includes mean wind speed, water depth, soil quality (poor, medium or good), distance to shore, environmental restrictions, vessel traffic, and whether there are already wind farms built in that cell or not.

Turbine technology: The building blocks of the offshore wind structures in Vindby are turbines (including the tower) and substructures (including a foundation and transition piece). Typically, the wind turbine model is selected before site investigation as it will influence the grid connection and design capacity. Vindby prompts for the turbine selection after site selection because limited prior knowledge of offshore wind farm design may negatively inform the player's selection.

Turbine capacity options are 3, 5, 7, 10, and 15 MW to capture existing and future technology. The 10 and 15 MW turbines only become available after building five wind farms in the game, to demonstrate the development of technology with experience. Vindby addresses different turbine states including "operational", "waiting", "automatic shut down", and "fault shut down". Future versions of Vindby may expand more states to test control system strategies.

Each turbine has its own failure rates based on Carroll et al. [17], who provide failure rates in failure per turbine per year as well as expected costs for minor and major repairs and major replacements. Although failure rates vary throughout the turbine lifetime, the majority of studies and industry practice use the simplification of constant failure rates, as used in Vindby throughout the turbine original 20-year lifetime. The player has the option to extend the farm lifetime by five years, twice. During lifetime extension, turbine failure rates are doubled to add consequence to extending farm lifetime and add weight to decisions. The capacity factors for wind farms in Vindby are updated in each time step and presented to the player to indicate how efficiently wind farms are running and what the consequences of certain O&M decisions are.

Support Structures: The support structure types in Vindby are "monopile", "gravity", "jacket", "tripod", "spar", "semi-submersible", and "tension-leg platform", presented in Figure 2. The three floating concepts only become available to the player after seven wind farms are in operation, to demonstrate industry growth with time and to reward the user for continued play. Floating offshore wind structures are both important to industry development and considered a hot-topic in research and the general public.

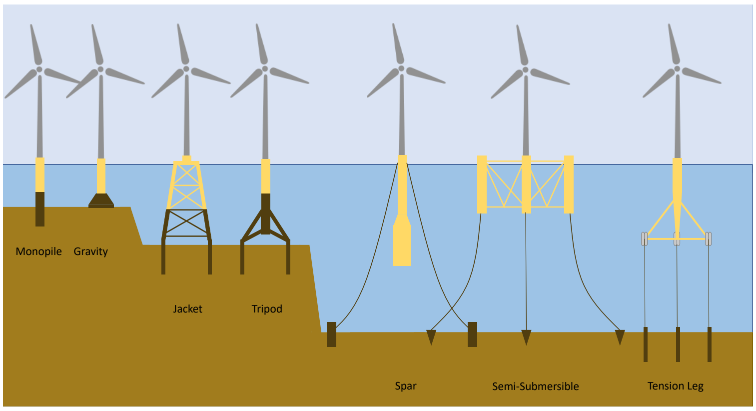

Figure 2. Types of support structure concepts. From left to right: monopile, gravity based, jacket, tripod, spar, semi-submersible platform and tension-leg platform.

One characterizing goal of Vindby is to enhance the players understanding of design drivers. For training purposes, this includes how to address poor soil conditions or rough sea states. For dissemination purposes, this includes recognizing failure modes and the complexity of designing structures offshore. Structural failure rates in Vindby are not designed to represent realistic occurrence probability, rather to direct the player to which parameters affect which substructures. The game mechanics describing these rates is a balancing task between engineering reality and playability. Each substructure has its own failure rates based on the mean wave height, soil quality, structure type, and turbine size. The substructure failure rates used in the game are presented in Table 3.

Table 3. Failure rates per turbine per hour. The failure rates depend on the mean wave height (WH), soil quality (poor/medium/good), turbine size (TS) and type of structure.

	Monopile	**Gravity**	**Jacket**	**Tripod**	**Spar**	**Semi-Submersible**	**Tension Leg**
Scour	poor: 0.0001	poor: 0.0001	0	0	0	0	0
Fatigue	0.00001 × WH	0.00001 × WH	0.000005 × WH	0.000005 × WH	0.00002 × WH	0.00002 × WH	0.00002 × WH
Corrosion	0.00001	0	0.00002	0.00002	0.00001	0.00002	0.00001
Bearing	0	medium: 0.0001 poor: 0.0002	0	0	0	0	0
External load	0.000001 × TS	0.0000005 × TS	0.000001 × TS	0.0000005 × TS	0.000001 × TS	0.000001 × TS	0.0000005 × TS

Vindby uses scour as an example of addressing reliability in structural design. For each new wind farm, the player is prompted to pay for scour protection. If scour protection is not provided but was not needed, nothing happens. If it was needed (i.e., for some concepts in poor soil conditions), scour failure is guaranteed to occur soon after construction. The player must then pay for scour protection for the entire farm at a higher price. The price for installation during wind farm construction is set to €80.000 per turbine and to €150.000 per turbine for later installation of the protection measures. These values have been chosen based on the range of scour protection costs presented in [18].

Layout: Wake effects and losses are not considered in Vindby. Therefore, turbine spacing is constant for all farms. Using a grid layout and 1 km spacing, a resulting cell of 10 × 10 km could hold a maximum of 100 turbines, which falls within the realistic scale of existing farms [19]. To demonstrate sea-wide layout considerations to the player, there are cost penalties for constructing farms relatively close to shore because of visual impact. This specifically considers the possible major, moderate, and minor effects for distances "less than 13 km", "between 13 and 24 km", and "greater than 24 km" from shore, respectively [20].

Grid integration: Vindby simplifies grid integration and teaches the player about subsea cables, wind farm clusters, alternating versus direct current transmission, and onshore versus offshore substations. Subsea cable lengths are computed as straight-line distances from the center of the grid cell to the onshore substation. With a growing number of offshore wind farms, many advantages can be gained through coordination of offshore installations and the use of clustered wind farms that feed their electrical output into common nodes [21]. The player has the option to connect to the closest possible wind farm if it results in shorter cable lengths. Given their connection, grid and cable failures at one farm affect the farms connected via the same cable.

Offshore wind farms require a substation, either onshore or offshore. In Vindby, all farms at a distance greater than 100 km from the onshore substation are required to have an offshore substation. Additionally, the onshore substation starts with a 500 MW capacity, and increases in increments of 500 MW as needed by the construction of the new farms.

Construction: Logistical constraints regarding fabrication yard and port capacity to handle offshore wind farm elements are not included in Vindby because Vindby's onshore infrastructure is not considered in detail. The construction duration is calculated as a sum of installation time for cable length, support structure type, and waiting time considering random construction accidents and delays. Significant detail in construction time calculation and feedback is reduced as it may distract the player and cause impatience (even at maximum game speed) with respect to when the wind farm becomes operational; however, to teach the user about the impact of design choices on construction time, construction time may vary between under a month to several years. Before construction, the player is prompted to provide a name for the new wind farm. If they choose a name of a real offshore wind farm in the North Sea, the construction time is reduced to zero days. This is one of the game's easter eggs, chosen to encourage players to research existing offshore wind farms.

Decommissioning and disposal: The lifetime of all wind farms in Vindby is 20 years. There is no option to decommission early, but it is possible to extend the lifetime by five years, twice. The cost of decommissioning the turbines and substructures is based on Shafiee et al. [22] and includes port preparation, removal, waste processing, waste transportation, landfill, post decommissioning monitoring, and recycling materials. Decommissioning cost for subsea cables is estimated according to Myhr et al. [23].

3.3.3. Operation and Maintenance

Operation activity and costs are greatly simplified in Vindby in order to highlight the high level risks and decisions considered in O&M for both training and dissemination. Maintenance of an offshore wind farm consists of repair, replacement, and annual inspections. The challenge of applying maintenance efficiently for the player is maximizing turbine availability while minimizing costs associated with unexpected failures [22]. Based on a combination of strategy organizations in literature, Vindby offers three maintenance strategies to choose from for each farm. Vindby uses an O&M manager object to manage and repair failures based on the three strategies.

The three O&M strategies in Vindby are: (1) Calendar based maintenance—failures are repaired at the end of the month, accumulating more downtime but saving costs by using the same vessel for multiple repairs, (2) Corrective maintenance—minor failures are delayed for repair at the end of the month, but certain expensive repairs prompt the player to decide if the high cost of immediate repair is necessary to keep the productivity going, and (3) Condition based preventive and corrective maintenance—for an upfront cost for a monitoring system, certain failures can be predicted ahead of time and repaired immediately at a reduced cost, and failures that are not anticipated are either repaired automatically at the end of the month or can be repaired immediately.

Actual repair times and therefore costs are not well understood, largely because of data availability, and the differences among literature regarding the definition of failure. Therefore, repair costs are estimated using a fixed repair duration per failure based on Carroll et al. [17] multiplied by a daily vessel rate plus the cost of the repair itself. Programming of the maintenance strategies involved many iterations to capture accurate representation and playability. One big challenge is to not overwhelm the player with decision-making over maintenance issues so focus can be kept on building farms and achieving the overall goal. Some decision-making is required for the training and dissemination of maintenance knowledge. A possible solution to this issue is improved interface interaction, which is out of scope of this study.

3.4. Power Production

The power production of a wind farm depends on the turbine type, the number of turbines and the weather. To demonstrate the concept of turbine capacity to the user and the importance of wind speed in production, the game uses linearized power curves to calculate the energy production depending on the (10 min mean) wind speed and turbine rating. The power curves are hidden from the player and only the turbine rating is known. This keeps the game experience simple while also giving the player a tool to utilize to improve performance. The parameters defining the power curves used in the game are presented in Table 4.

Table 4. Defining parameters for the linearized power curves used to calculate power production in the game.

Turbine Rating [MW]	Cut-In [m/s]	Slope	Rated Speed [m/s]	Cut-Out [m/s]
3	3	0.3	12	23
5	3	0.5	11	25
7	4	0.8	13	25
10	3	1.2	11	25
15	4	1	15	25

3.4.1. Energy Demand

To give context to the player about electricity supply, there is some electricity demand that must be met. The scale of Vindby in this prototype does not allow for full capacity to be met by offshore wind. One principle that is stubbed out in the game is the investment in other renewables to demonstrate how to address storage and variation in wind speeds. More specifically, an additional characterizing goal may be needed to teach users about long term integration costs of variable renewable energy. Combating climate change and reducing CO_2 emissions are arguably the core goals of why the player should be building offshore wind farms. One characterizing dissemination goal is that the player at a minimum understands that energy produced by offshore wind is replacing energy provided by non-renewable electricity generation means, such as coal, which releases large quantities of CO_2 into the atmosphere, only half of which is absorbed by earth's surface. To enable the player to learn about the reduction in CO_2 emissions, the game provides feedback on the amount of CO_2 prevented from being released.

Relatable feedback is also presented in terms of households powered, equivalent cars taken off the road, and acres of forest reclaimed. The average household demand is assumed to be 3900 KWh per household as presented by [24]. Vindby demonstrates in the graphical user interface (GUI) that, because wind power generation varies with time, the number of homes powered by offshore wind is not constant.

3.4.2. Economics and Costs

Vindby includes resource management of an initial investment, expenditures, revenues, fines, and bonuses. Relevant characterizing dissemination and training goals include recognizing the influence of O&M costs and gaining a sense of scale for offshore wind farm costs. More specifically, the player must use limited resources to make better design and operational decisions. If the player's balance runs out, the game is over. The resource manager object is called the player's "wallet", to which money can be withdrawn and deposited.

Costs for all items in Vindby are based either on realistic values when data is available, or are manipulated to enhance game flow and playability. For example, monopiles typically reach their water depth limit around 30–40 m, when the design reaches engineering limits for pliable diameters and wall thickness. Rather than imposing depth limits in Vindby (also considering that the technology is often upgrading), the concept of building outrageously sized and priced structures is both amusing and indicative of the real world considering unrealistically high costs. Therefore, fictitious cost factors are applied to increase cost dramatically in deeper water. This cost factor is selected based on a careful balancing of all bottom-fixed structure costs with depth to ensure that at different depths and soil qualities, different structures become the most economic option. Table 5 shows examples of the costs of the different substructures at different water depths. Without this consideration, the same structure (i.e., a monopile) would be the cheapest every time.

Table 5. Vindby Support structure cost for different water depths in good quality soil [€ million].

Water Depth [m]	Monopile	Gravity	Jacket	Tripod	Spar	Semi-Submersible	Tension Leg
0	0.0	0.0	0.0	0.0	25.7	11.1	25.8
10	0.8	1.4	1.1	1.6	23.5	9.5	23.6
20	1.6	2.7	2.1	3.2	21.4	8.0	21.5
30	3.3	6.5	3.2	4.8	19.2	8.0	19.4
40	0.4	8.7	4.2	6.4	17.1	8.0	17.2
50	5.4	10.9	5.3	8.0	14.9	8.0	15.1
60	6.5	13.1	6.4	9.6	12.7	8.0	12.9
70	7.6	15.2	7.4	11.2	10.6	8.0	10.8
80	8.7	17.4	8.5	12.8	8.4	8.0	8.7
90	9.8	19.6	9.5	14.4	6.3	8.0	6.5
100	10.9	21.8	10.6	16.0	4.1	8.0	4.4
110	12.0	23.9	11.7	17.6	4.1	8.0	4.4
120	13.1	26.1	12.7	19.2	4.1	8.0	4.4
130	14.1	28.3	13.8	20.8	4.1	8.0	4.4
140	15.2	30.5	14.8	22.4	4.1	8.0	4.5
150	16.3	32.6	15.9	24.0	4.1	8.0	4.5

Costs can also be leveraged to incorporate rewards and repercussions for certain game actions. For example, a reward is offered when a wind farm pays back its initial investment. Fines are deducted when a wind farm is constructed in an environmentally sensitive area without performing mitigation measures.

A wind farm's selling cost is the price at which electricity is purchased and is established following the feed-in tariff (FIT) approach for simplicity. The FIT value depends on technology used, distance to shore, and mean wind conditions on site. The profit that the player is encouraged to realize is the difference between the selling cost and the levelized cost of energy (LCOE). The LCOE is updated monthly to account for maintenance activities and serves as a way to compare wind farms and maintenance strategies within one game.

Various fines and rewards are used in Vindby to introduce positive and negative consequences for specific player decisions. The values are not based on any research, but rather scaled to have an impact on the player's emotion regarding their decision. Some fines include: building in an environmentally protected area, and building in an area with an active vessel route. Some rewards include: breaking even on capital cost of a wind farm, and breaking even on CO_2 emissions during construction of a wind farm versus CO_2 prevented in electricity generation.

3.4.3. Stakeholders

Part of the characterizing training and dissemination goals is to recognize the influence that government, the public, and shareholders have on offshore wind projects. The effect of stakeholder reactions does not consider current research or actual events, but rather is incorporated as points used as indicators for the player. The background behind the satisfaction points belonging to each stakeholder considers a broad understanding of what impacts certain actions have on stakeholders. One example of an increase in stakeholder satisfaction due to game play is an increase by one point for the public, when 1 million additional homes can be powered with the energy produced by a wind farm. Another example is that construction of a wind farm close to shore will result in a decrease in public satisfaction.

3.4.4. Optimization

One of the original sub-tasks of constructing Vindby was to build an optimization algorithm that "solves" the game, which theoretically can determine optimal playing strategies corresponding to optimal design or operational management of a wind farm. Throughout this work, it was agreed that the development of a fully integrated optimizer that acts as the "computer player" is outside of the scope of this study. Nonetheless, using optimization strategies as a form of feedback for the player is incorporated into Vindby in the form of small optimizer functions. Two optimizer functions used are: (a) yearly reports on operation and maintenance costs and downtime, and what they would be under alternative strategies; and (b) information on the potential consequences of alternative substructure choice, in terms of economy and reliability, provided after construction of a wind farm.

3.5. Game Design

The final game design is the product of many iterations internally tested for accuracy of scale, accuracy of weather prediction, and, most of all, playability. Feedback is vital to the player's understanding of game content as well as general enjoyment and experienced the most iteration during programming. Feedback given by the game to the player is done through two means: textual, in the Python console, and by way of a GUI. The GUI presents information that changes throughout the game as well as a graphical representation of the sea grid. The prototype Vindby GUI is shown in Figure 3. In the center, the virtual sea grid is visualised with individual cells, numbered from 1 to 100. Dark blue cells are the default, before any player interaction. Light blue color indicates that the player has already conducted research on the cell in question. In the example shown in Figure 3, cell 34 is an example. Yellow color indicates that a wind farm is under construction in the given cell, shown by cell 27 in the example. Green cells, 17, 22 and 35 host operating wind farms, while the color red (cell 24) indicates a fault that needs attention of a maintenance team. In the bottom of the GUI, the selected goal of the game is displayed, together with information about how close the player has come to achieve this selected goal. The left-hand side of the interface shows information about the selected cell, in the example cell 35. Depending on previous interaction of the player with the game, this information is altered. If a player investigates a cell, additional information is shown. When a wind farm is constructed on a cell, the information about the wind farm is also shown here. The right-hand side of the user interface shows general information about the game progress, like the players' wallets and stakeholder scores.

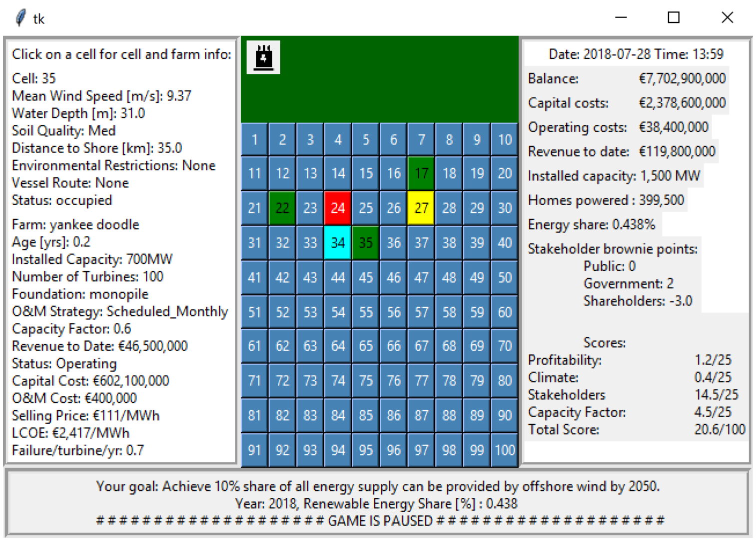

Figure 3. Game graphic user interface. The left-hand side of the user interface shows information about a selected cell. The right hand side of the interface displays general information about the game. In the center, the virtual sea grid is displayed. More information about he colors and the content of the GUI is provided in the main text.

Feedback provided in the console is provided based on individual actions and occurrences in the game and in the form of regular reports. The default report is issued annually and presents game information with additional information about wind farm activity including a list of wind farms, list of investigated cells and their results, construction activity, climate change details, and details about stakeholder satisfaction. Vindby's final game design includes a simulation loop displayed in Figure 4.

The loop begins with the player selecting the scenario they want to play among five possible game choices. The simulation loop then begins by updating the game's weather, energy demand, climate change status, economy, and finances. The interface is rendered displaying the updated information, along with any important notifications about goal progression or game rewards. After this step in the loop, the game continues unless the designated game time for ending the chosen scenario (e.g., 2025 in scenario 1) has been reached, in which case the player is notified whether he or she has won or lost.

If the game is not over yet, the game loop continues to process any input that has been entered. This may include the player's request to perform site investigation, build a wind farm, manage existing wind farms, change game settings, or pause or quit the game. The loop continues to the update phase once again, including the update of all wind farm production and maintenance status. The simulation has been designed such that the loop is continuous, although it can register input at any moment. The input is addressed in the "process input" step. Once the game time which presents the limit for the chosen scenario is reached, the result determines how the player can continue. A loss forces the player to either quit or play again, while a win offers a choice to continue playing the game.

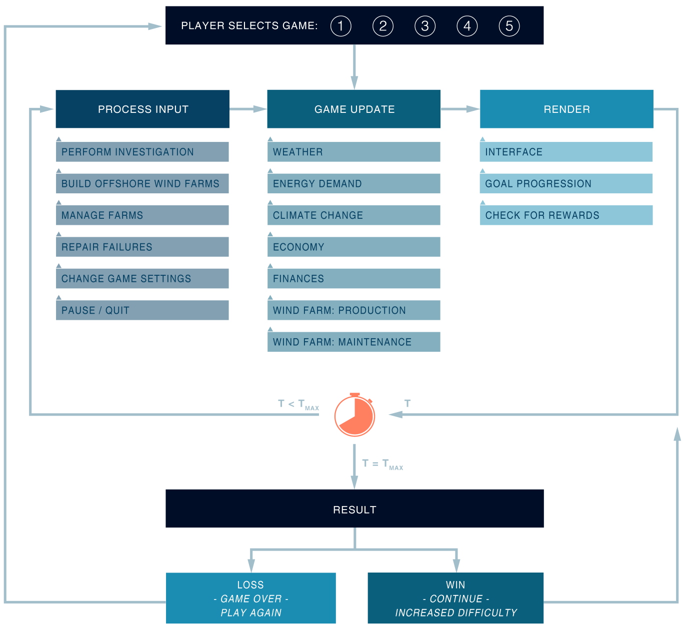

Figure 4. Game design framework beginning with the selection of one of the five game options presented in Section 3.1.1. Please refer to the text for a detailed explanation.

4. Playtesting Results

In order to measure the effectiveness of the serious game and also to ensure playability, it was decided early in the game design phase to involve representatives from both target groups.

First, during the game design, a questionnaire was sent out to collect information on specific areas of interest by potential users. The link to the online questionnaire was sent to students at NTNU (Department of Civil and Environmental Engineering) not working in wind energy, early stage researchers in wind energy in Europe, as well as some members of the general public (selected based on non-work related relationships). The questionnaire was filled out 53 times. An overview over the background of the participants can be seen in Figure 5. Out of all the responses, 40% of participants indicated studying or knowing more about wind energy than the average person. The questionnaire had the option for the participants to provide a free response on what they would like to learn more about by playing the Vindby game. From 53 responses, the two most common topics were "payback period on carbon emissions" and "environmental impacts of offshore construction". These, among other suggestions, were integrated into the game mechanics. Among individuals with some knowledge or background of offshore wind, there was a higher interest in the physical components of offshore wind and the O&M strategies. Participants with little to no knowledge of the topic were more interested in the costs and the stakeholder influence.

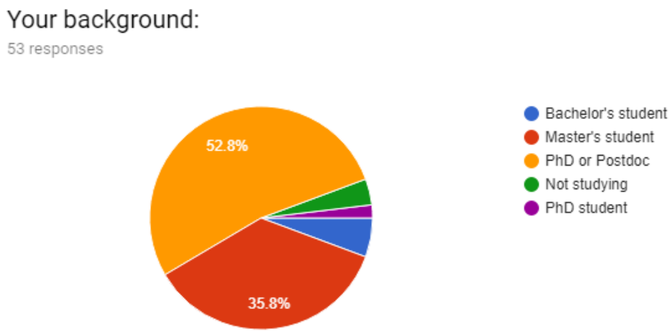

Figure 5. Summary of the replies to the question "What is your educational background?" in the initial questionnaire.

After game development, a playtesting session was organized for volunteers to play the final prototype game to analyze the educational strength of the game. The playtesting session was hosted at NTNU and consisted of volunteers. All of the participants were either Master- or PhD-students at the Department of Civil and Environmental Engineering. Out of the eight participants, four studied a subject related to wind energy. The other four studied another engineering field. Surveys were distributed before and after playtesting to identify potential shifts in knowledge. Additionally, a group discussion after the playtesting was used to identify playability issues and recommendations for improvements of the game.

During playtesting, a total of 203 wind farms were constructed in a total of 24 games played by eight people. The results from each game were saved and post-processed. The variation in wind farm characteristics (number and size of turbines, project costs, and capacity factors) indicate that the game encourages exploration. The degree to which players recognized value of site investigation information was measured by overlapping the investigated sites with sites with constructed wind farms. Across nearly all games played, 99% of wind farms constructed were in cells that had previously been investigated. This indicates that players quickly learned about the value of site investigations to make more informed decisions about building farms, and that they actively sought out that information. The cells that were investigated and not built on were broken down by site conditions to identify where players made informed decisions. Out of 344 instances, 137 of such decisions were made because of a restricted area (environmental or navigation), 92 decisions were made in areas with lower wind speeds (wind speed factor less than 1), and 118 were made in areas with poor soil quality.

Out of 169 farms built on investigated areas, 12% were built on cells with poor soil quality, but all of those farms were constructed using substructures that are suitable for poor soil (not monopile or gravity). This is a strong indicator that players made informed decisions about substructure choice and made use of information provided by the game.

Following playtesting, players shared and expressed their game experience in a group discussion. Players recognized that they felt engaged in the game and wanted to keep playing. The interest to continue playing was also observable in the replies to the post-game survey, where seven out of the eight participants replied that they would like to play the game again. The main point for improvement was considered to be improvements in the feedback provided by the game. Several players felt that they could not properly assess the long-term impacts of certain choices, e.g., for substructure reliabilities. Additionally, the frequent notifications for corrective or condition-based maintenance were deemed distracting, rather than informative, despite being recognized as information necessary to make better O&M choices.

5. Discussion

This section includes discussions on various results and challenges that arose as an outcome of this work.

Weather modeling: As part of the game, a weather simulation model has been developed. The mean hourly wave height is modeled with a Markov chain model. The correlated hourly mean wind speeds are then modeled based on conditional probabilities. From the hourly mean wind speeds, 10 min wind speeds are sampled from a Gaussian distribution with the hourly mean wind speed and its intra-hour variance as parameters. Investigations have shown that this model is capable of reproducing the properties of the data relatively well, both in terms of mean wind speeds for production estimates, and regarding the length of windows for maintenance access. The combination of Markov transitions with sampling from a distribution enables faster modeling time compared to pure Markov chain modeling, while still reproducing the statistical properties of the original data with sufficient accuracy.

Balancing accuracy and playability in game design: The product of this study, Vindby, is an interactive simulation that integrates two topics: simplified offshore wind farm design, and the design of a serious game. A holistic approach to game design was employed throughout this study. This ensured that the game is not a mere add-on to simplified offshore wind farm design, or that a simplified offshore wind farm design was merely added to an unaltered entertainment game [5]. This approach affected decisions made on the overall game dynamics and framework as well as the finer details of the game mechanics and the engineering processes. Great attention and detail were applied to developing an accurate weather simulation model to ensure that each game played is different than the next.

The other offshore wind farm topics were modelled by starting from the basic definition of elements and adding details that would be valuable to the player's learning. This required a method of finding the appropriate level of detail, which was subsequently applied throughout the simulation. For example, substructure definitions were introduced as a fundamental element to offshore wind farm design. Subsequently, the reliability and costs were added to build game mechanics around choosing different substructures for different farms. The reliability and costs of the substructures vary with year of construction and site selection to teach the cost and design drivers to the player. This level of detail was considered sufficient, as there was ample information to generate the same outcome without adding more computations. Playability requires meaningful feedback, and unnecessary details may be detrimental to learning. In the example of substructures, this meant that the choice of the most economic and most reliable structure would be the same with or without further refinement of failure rates and specific costs.

In the end, Vindby managed to incorporate all the investigated game content into game rules and functions that resulted in an engaging game (as shown by the user feedback).

Simulation efficiency: Simulation efficiency directly impacts the speed at which the game runs. A digital game ideally runs at a speed consistent between computers and other platforms (e.g., mobile devices) for all game speed settings (slow, normal, and fast). The analysis of Vindby's performance showed that the game runs with adequate, yet somewhat suboptimal efficiencies.

The random generation of numbers in each game tick greatly slows down the simulation. While the selected weather model suits the game mechanics (reproducing variations in time and space), adjustments should be made to increase efficiency of calculations. This could be achieved by generating random time series for longer periods (e.g., during periods of inactivity, or between games), and then reading values from these series in each game tick.

Memory usage is another factor relevant for simulation efficiency. Values and attributes of nearly all objects are updated or checked every tick of the game loop. The storage of these values was kept to a minimum in the prototype, although it can be further reduced. This is possible by refining the game mechanics and minimizing the storage of unnecessary information. Furthermore, advanced programming concepts may be incorporated for serializing object structure, saving memory in the game module itself. Future programming should improve simulation efficiency without sacrificing feedback necessary for the player.

Alternatively, simulation efficiency can be improved by increasing the game loop interval resolution (currently set to one hour). This value may be increased to a day, or even a week, to decrease the number of updates and checks performed. In this case, adjustments must be made to ensure that production and weather are being updated correctly within the new interval. Additionally, the value of failure rates and unit costs must be either updated to a higher resolution or the code must be adjusted to still update these on an hourly basis.

Optimizer: The optimizer was originally planned as a prominent feature in the game and was intended as a dynamic function capable of independently running the game to produce large amounts of feedback. The development of such a sophisticated optimizer proved to be beyond the scope of this study. Small optimizer functions were created instead to provide feedback to the player on individual topics at specified points in the game. This approach is considered more static as it only runs these functions during specific events (when instructed to do so). This simplified strategy was used during gameplay and may be expanded to cover more topics. Alternatively, the original concept may be revisited through the incorporation of deep learning. The framework of multi-agent systems could be a fitting approach for providing close to optimal benchmark solutions for comparing with player behaviour.

Incompleteness of game development: Development of a serious game for the wind industry is actually an open-ended effort that might never be completely finished. New technologies are being constantly developed and existing technologies improved. Many researchers are working in the field and it is very likely that new concepts will need to be included in a serious game in the future, if this game should be a useful teaching tool or tool for outreach. Additionally, the user interface of the game can (and should be) improved. It was decided to publish the game now at this stage of development, such that others can immediately use it and contribute to further development. The reasons for decisions made in the game development and technical details are explained and documented here, enabling others to better understand and use the game.

6. Materials and Methods

Wind and wave data from the FINO 1 project are provided by the Bundesministerium für Wirtschaft und Energie (BMWi), Federal Ministry for Economic Affairs and Energy and the Projektträger Jülich, project executing organization (PTJ). They can be downloaded from http://fino.bsh.de/ by users from Europe, for research purposes.

The developed prototype of the game is freely available from the webpage http://folk.ntnu.no/muskulus/vindby/, licensed under Creative Commons Attribution—NonCommercial 4.0 International (CC BY-NC 4.0).

7. Conclusions and Future Work

7.1. Conclusions

The goals of this study were to develop a digital game for the design and the operational management of offshore wind farms, to be used for the purposes of training and dissemination, and to measure game effectiveness in terms of its simulations and educational power. After identifying the core components of serious games and methods for simplified wind farm design, a complete game framework was established and integrated into a prototype. The final prototype of the game is a functional simulation capable of reproducing realistic values of offshore wind farm parameters including weather, site investigation, design, O&M, climate impacts, and costs. The game mechanics were constructed around simplified wind farm design and are documented in detail in this study (additional details can be found in [16]). The game was playtested with voluntary participants, who filled out surveys before and after playtesting. A comparison of the answers in the pre- and post-playtesting surveys revealed that learning had taken place during playing the game. Therefore, the effectiveness in terms of the educational power of the game has proven successful at achieving its characterizing goals of learning about offshore wind farms. The engagement and exploration of the players in the game demonstrated that playability of the game was overall achieved.

7.2. Future Work

The game presented in this article is an implementation prototype and it has to be said that the development of a serious game for the given purpose is an open-ended effort as there will always remain potential for improvement. The success of a deployed version of a serious game about offshore wind energy in the future will depend on the improvement on various aspects of game design, simulation improvements, and interface development. A (non-exhaustive) list of recommendations for future work is presented below:

Simulation improvements: The game speeds must be improved to acquire 100% efficiency (i.e., the game must run at the desired speed across all platforms, whereas currently there is some lag when multiple farms are running at the game's fast mode). This may be done by re-examining the simulation resolution. The program may be modified to preserve one hour of weather sampling and 10 min production estimates while performing the remaining calculations (such as checking for rewards and point deductions, updating energy demand, and repairing wind farm failures) once every 24 h only, whereas currently these are updated for every hour of game time. Another approach to improving game speeds is to consolidate the weather generation computations. Rather than generating random values when needed (i.e., in every hour of game time), a synthetic time series may be generated either at the start of every year, or while the game is paused. Waiting times during regular game play will then be minimized or eliminated.

Augmented offshore wind farm design: The simplified offshore wind farm design as represented in the game simulation currently includes a fraction of the possible topics that can be explored and integrated. Some key topics that have been discussed and suggested to add to the game include inter-farm and inter-turbine wake effects, turbine control systems, transmission losses, different types of site investigations, balancing costs in other non-renewable energies, investments in R&D, and more detailed stakeholder influence.

Optimizer: Playtesters paid attention to the small optimizer functions for O&M strategies and substructure selection. Further development of more optimizer functions regarding other design elements such as turbine selection, O&M decisions, and site selection may accelerate learning. Alternatively, a new large-scale optimizer may be developed that solves the entire game and offers complete optimally designed wind farms for the player to study for comparison.

Extensive Playtesting: In order to further validate the effectiveness of this serious game as a teaching tool, we highly recommend further testing of the game with a varied test-group. This group should specifically contain members of the general public with little to no knowledge about engineering.

In order to achieve this variation in background, the members of the test group should be found through other means than university contacts. One possibility to find participants would be to look for volunteers at a local library, sport facility or other community that is not related to engineering.

Expanded platforms and improved interface: To expand the interest in playing, the game should be adapted for multiple platforms and devices. The ability to save and return to games would be valuable for continued use. A multiplayer platform may also broaden the outreach capabilities. Furthermore, an attractive user interface is necessary for deployment.

Author Contributions: M.M. conceived the idea of developing a serious game. H.S. and M.M. outlined the scope of the game. E.D., H.S. and M.M. designed and discussed the mechanics of the game. E.D. programmed the game. H.S. and M.M. reviewed the code and helped with debugging. E.D. developed the surveys, conducted the playtesting and analyzed the participant feedback. E.D. and H.S. prepared the figures for the paper. E.D. wrote the paper. H.S. and M.M. reviewed and edited the paper. H.S. was responsible for the paper submission.

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Appendix B

Abstracts of Additional Papers

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Operation and maintenance models for offshore wind farms - mathematical structure and techniques.

Seyr, H. and Muskulus, M.

Proceedings of the 12th EAWE PhD Seminar on Wind Energy in Europe, 2016.

Abstract: The operations and maintenance costs account for nearly a third of the total cost of energy in offshore wind farms. Several approaches have been taken to address this problem. One focus is to improve the scheduling of corrective maintenance tasks. Today, most maintenance models use different simulation methods, including Monte Carlo simulation and Markov chains. In this paper, we discuss model properties and investigate different modelling techniques. We discuss the differences in modelling techniques and investigate which techniques can be used for modelling the scheduling of maintenance for an offshore wind farm. We find that most techniques can be used for maintenance modelling. Some models have smaller computational requirements, but are less accurate. Other models provide complexity and details while being computational expensive. By benchmarking simple models against complex models, researchers can provide the industry with confidence in models that are fast and cheap in computation, while still accurate.

The Impact of Maintenance Duration on the Downtime of an Offshore Wind Farm - Alternating Renewal Process.

Seyr, H., Barros, A. and Muskulus, M.

Proceedings of the 30th Conference on Condition Monitoring and Diagnostic Engineering Management COMADEM, 2017.

This was awarded "best student presentation".

Abstract: Maintenance cost in offshore wind farms are one of the main reasons why it is still not competitive with its onshore counter part. To lower the price of energy, the authors want to improve the modeling of offshore wind farms in order to help improving the applied maintenance strategies. In this paper, we investigate the repair of wind turbine components as an alternating renewal process. The time it takes to repair (renew) a component in a turbine, directly influences the downtime of this turbine, or even larger parts of the wind farm. This downtime leads to production losses, which in turn raise the cost of energy. Previous investigations by two of the present authors showed that a variation in repair times has a significant influence of the production losses. In this paper, an alternate renewal process is investigated as tool to calculate the influence of the repair time duration on the production losses. We show that if we assume an exponential distribution of repair times, the distribution of the downtimes can be calculated analytically. The results are demonstrated with a case study, based on available failure rates and repair times. For other distributions, the calculation has to be done numerically, after fitting the parameters of the distribution to the available data. Further work with other distributions and actual repair time distributions is planned.

On the effects of environmental conditions on wind turbine performance: an offshore case study.

Gonzalez E, Valldecabres L, Seyr H and Melero JJ.

Journal of Physics: Conference Proceedings, 2019.

The poster presenting this paper was awarded "best communication" at Deepwind 2018.

Abstract: Monitoring wind turbine (WT) performance offers a means of identifying abnormal operation, but only if natural disturbances of the operating regime change can be excluded. WT performance monitoring usually relies on the analysis of operational power curves, generally based on data from the supervision control and data acquisition system. However, these curves do not reflect the source of variability, negatively affecting the capabilities for detecting WT abnormal performance. This work aims at understanding and quantifying changes in WT performance variability due to different environmental conditions during normal and wake-free operating conditions, based on an offshore case study. The magnitude of performance fluctuations is highly influenced by environmental conditions, being higher during high turbulence intensity and low wind shear conditions. The Taylor law, with small time windows, is suitable to describe them for low-mid winds in the absence of dedicated wind measurements, often not permanently available offshore, and could potentially result in more effective performance monitoring solutions. Nevertheless, the heteroskedastic nature of the power deviations negatively affects fitting possibilities. The results support the importance of using low data aggregation periods to understand the dynamics of WT performance.