Risk and Reliability based O&M Planning of Offshore Wind Farms

Asgarpour, Masoud

DOI (link to publication from Publisher):
10.5278/vbn.phd.eng.00029

Publication date:
2018

Document Version
Publisher's PDF, also known as Version of record

RISK AND RELIABILITY BASED O&M PLANNING OF OFFSHORE WIND FARMS

BY
MASOUD ASGARPOUR

DISSERTATION SUBMITTED 2017

AALBORG UNIVERSITY
DENMARK

RISK AND RELIABILITY BASED O&M PLANNING OF OFFSHORE WIND FARMS

by

Masoud Asgarpour

AALBORG UNIVERSITY
DENMARK

Dissertation submitted

.

Dissertation submitted:	November 2017
PhD supervisor:	Prof. John Dalsgaard Sørensen Aalborg University
Assistant PhD supervisor:	Assistant Prof. Jannie Sønderkær Nielsen Aalborg University
PhD committee:	Associate Professor Amélie Tetu (chairman) Aalborg University Associate Professor Sebastian Thöns Technical University of Denmark Dr. Mahmood Shafiee Cranfield University
PhD Series:	Faculty of Engineering and Science, Aalborg University
Institut:	Department of Civil Engineering

ISSN (online): 2446-1636
ISBN (online): 978-87-7210-105-7

Published by:
Aalborg University Press
Skjernvej 4A, 2nd floor
DK – 9220 Aalborg Ø
Phone: +45 99407140
aauf@forlag.aau.dk
forlag.aau.dk

Printed in Denmark by Rosendahls, 2017

CV

Masoud Asgarpour is a Mechanical Engineer specialized in O&M planning, performance monitoring and reliability assessment of onshore and offshore wind farms. He is currently leading the analytics and asset integrity management team in Vattenfall Wind.

SUMMARY

The wind energy with 153.7 GW of installed capacity by the end of 2016 is currently the second largest power generation capacity in Europe. Derived by the continuous pursuit of European countries for environmental friendly and sustainable energy sources, significant further growth of wind energy especially in form of offshore wind farms is anticipated. The offshore wind farms compared to onshore ones have higher energy yield and less environmental impact for humans. However, due to harsh offshore weather condition, the maintenance of unplanned component failures results into high operation and maintenance (O&M) costs. The O&M costs are one of the main cost drivers for offshore wind farms. The main objective of this thesis is to provide smart solutions in form of long-term and short-term O&M strategies to reduce the O&M costs of offshore wind farms to their minimum.

During development phase of an offshore wind farm, the optimal baseline O&M costs (direct cost of maintenance and indirect cost due to lost power caused by downtime of wind turbines) and O&M resources (e.g. vessels, technicians and spares) can be determined based on optimal long-term O&M strategies. Additionally, once the offshore wind farm is in operation, the long-term O&M strategies can be used to optimize the required O&M resources using all available historical O&M data of that wind farm. A long-term O&M strategy is based on reliability and cost models. In this thesis first, based on failure probability of offshore wind components a reliability model is defined and then, a custom Monte Carlo O&M cost model is developed in R programming language. Afterwards, based on the developed reliability and cost models, LCoE and O&M costs of an 800 MW reference offshore wind farm with 8 MW wind turbines on monopiles through several illustrative case studies are estimated and recommendations for optimization of O&M resources are given.

During the operational years of an offshore wind farm, optimal short-term O&M strategies can be used to make sure existing corrective maintenance work orders are executed with minimum cost and downtime and future corrective maintenance actions are avoided as much as possible. The unplanned component failures of offshore wind farms can be avoided if future faults of components are predicted before they occur or be detected as soon as they are initiated and before they lead to a failure.

A short-term O&M strategy is based on diagnostic, prognostic and decision models. In this thesis, a Bayesian based holistic diagnostic model is defined. This holistic multi-agent model is based on confidence and diagnosis matrices to determine confidence (relevance) and result (diagnosis) of each individual diagnostic agent (e.g. vibration, temperature or oil particle analyses) for a given wind farm component. Once both confidence and diagnosis matrices for all diagnostic agents and wind farm components are defined, within a holistic diagnostic framework all individual diagnoses are incorporated into one final verdict on components' fault state.

Furthermore, once sufficient observations on the component fault state (e.g. by inspections) are available, based on the Bayes' rule the initial assumptions made in the confidence matrix can be updated. At last, through several illustrative examples the condition based maintenance of offshore wind farms based on this Bayesian holistic multi-agent diagnostic model is explained.

Fault detection and condition based maintenance of offshore wind components can reduce O&M costs significantly. However, offshore wind O&M costs can be reduced to their minimum only if faults are predicted and maintained by sufficient predictive maintenance work orders. This can be done using a Bayesian prognostic model. The prognostic model defined in this thesis is based on degradation, remaining useful lifetime and inspection threshold models. The degradation model defined in this thesis is an exponential degradation model with stochastic normal distributed scale factor. The initial shape and scale factors of this degradation model can be defined based on failure probability of each component. Once enough observation through inspections or failures is available, based on the Bayes' rule and Normal-Normal model the prior shape and scale factor of an exponential degradation model can be updated. Later, the posterior degradation model is used to define a stochastic remaining useful lifetime (RUL) model. Furthermore, it is discussed that the best trigger for a predictive inspection is a hybrid of degradation and RUL limits to make sure false predictions are very low, enough time for planning, preparation and execution of predictive work orders is available and the predictive maintenance cost is kept to its minimum. At last, within a case study translation of inspections' outcome to degradation level of a component using a degradation matrix is explained and a proposal for validation of predicated degradations based on inspections' outcome is given.

In the last chapter of this thesis scheduling and prioritization of all maintenance work orders, specially condition based and predictive work orders are discussed. It is seen that within a stochastic risk based decision model the optimal scheduling and prioritization of all outstanding work orders according to their defined end date and cost targets can be determined. The application of this model within a case study for the work orders of the reference offshore wind farm is explained in detail and significant O&M cost reduction opportunities for everyday operation and maintenance of offshore wind farms are highlighted.

The discussed risk and reliability models in this thesis for optimal short-term and long-term O&M planning of offshore wind farms are developed in a way to be easily implemented into any offshore wind asset management system. At the end of each chapter of this thesis, clear recommendations for future studies on this topic are given. In future studies on this topic it should be noted that an O&M planning model brings no added value to an offshore wind farm if it cannot be easily implemented into the existing infrastructure of offshore wind farms, no matter how accurate that O&M planning model is.

DANSK RESUME

Vindenergi med 153,7 GW installeret kapacitet ved slutningen af 2016 er på nuværende tidspunkt den andenstørste kapacitet inden for energiproduktion i Europa. Afledt af de europæiske landes stadige stræben efter miljøvenlige og vedvarende energikilder, forventes der en betragtelig, yderligere vækst i vindenergi, specielt i form af offshore vindmølleparker. Sammenlignet med onshore vindmølleparker giver offshore vindmølleparker større energiudbytte og har mindre miljømæssige påvirkninger på mennesker. På grund af barske offshore vejrforhold, resulterer vedligeholdelse af uplanlagte komponentfejl generelt i høje drifts- og vedligeholdelsesomkostninger. Drifts- og vedligeholdelsesomkostninger er en af de store omkostningsfaktorer for offshore vindmølleparker. Hovedformålet med denne afhandling er at bidrage med forbedrede metoder til drifts- og vedligeholdelsesstrategier på både kort og langt sigt for at reducere disse omkostninger.

I løbet af udviklingsfasen for en offshore vindmøllepark, kan den optimale basisstrategi for drifts- og vedligeholdelsesomkostninger (direkte omkostning for vedligeholdelse og indirekte omkostning på grund af tabt strømproduktion grundet nedetid af vindmøller) og ressourcer til drifts- og vedligeholdelse (f.eks. fartøj, teknikere and reserver) bestemmes ved hjælp af optimale langsigtede drifts- og vedligeholdelsesstrategier. Ydermere, når offshore vindmølleparken er taget i brug, kan de langsigtede drifts- og vedligeholdelsesstrategier bruges til at optimere de nødvendige ressourcer ved brug af alle tilgængeligt historisk drifts- og vedligeholdelsesdata for den pågældende vindmøllepark.

En langsigtet drifts- og vedligeholdelsesstrategi baseres på pålideligheds- og omkostningsmodeller. Denne afhandling beskriver først en pålidelighedsmodel baseret på fejlrater af offshore vindmøllekomponenterne og derefter udvikles en Monte Carlo drifts- og vedligeholdelse omkostningsmodel i programsproget R. Herefter estimeres energiomkostninger og drifts- og vedligeholdelsesomkostninger for en 800 MW reference offshore vindmøllepark med 8 MW vindmøller på monopæle ved hjælp af adskillige illustrative case undersøgelser og der gives anbefalinger til optimering af ressourcer for drift- og vedligeholdelse.

I driftsfasen for en vindmøllepark kan optimale kortsigtede drifts- og vedligeholdelsesstrategier benyttes til at sikre at eksisterende korrektive vedligeholdelsesordrer udføres med minimum omkostninger og nedetid og at fremtidige korrektive vedligeholdelseshandlinger undgås så vidt muligt. De uplanlagte komponentfejl ved offshore vindmølleparker kan undgås, hvis fremtidige fejl på komponenter forudsiges før de sker eller opdages så snart de starter og før de fører til fejl.

En kortsigtet drifts- og vedligeholdelsesstrategi er baseret på diagnostiske, prognostiske og beslutningsmodeller. Denne afhandling definerer en Bayesiansk-baseret holistisk diagnostisk model. Denne holistiske multi-agent model er baseret på konfidens og diagnose matricer til at afgøre konfidens (relevans) og resultat (diagnose) for hver individuel diagnostisk agent (f.eks. vibration, temperatur eller oliepartikel analyser) til en given vindmøllepark komponent. Når både konfidens- og diagnosekilderne for alle diagnostiske agenter og vindmølleparkkomponenter er definerede inden for et holistisk diagnostisk rammeværk, inkorporeres alle individuelle diagnoser i en endelig afgørelse af komponentens fejlstatus. Ydermere, når tilstrækkelige observationer af komponent fejlstatus (f.eks. ved inspektioner) er til rådighed, kan de første antagelser opdateres i konfidensmatricen baseret på Bayes' regel. Gennem adskillige illustrative eksempler forklares til sidst den tilstandsbaserede vedligeholdelse af offshore vindmølleparker baseret på denne Bayesianske, holistiske multi-agent diagnostiske model.

Fejldetektering og tilstandsbaseret vedligeholdelse af offshore vindkomponenter kan reducere drifts- og vedligeholdelsesomkostninger betragteligt. Offshore vind drifts- og vedligeholdelsesomkostninger kan dog kun reduceres til deres minimum, hvis fejlene forudsiges og vedligeholdes ved tilstrækkelige prediktive vedligeholdelsesordrer. Dette kan gøres ved at bruge en Bayesiansk prognostisk model. Den prognostiske model der defineres i afhandlingen er baseret på nedbrydning, resterende brugbar levetid og inspektions-grænse modeller. Nedbrydningsmodellen, der defineres i denne afhandling er en eksponentiel nedbrydningsmodel med en stokastisk, normal fordelt skalafaktor. Prior modeller for form- og skalafaktorer i denne nedbrydningsmodel kan defineres baseret på fejlrater for hver komponent. Når tilstrækkelige observationer fra inspektioner eller fejl er tilgængelige, kan den prior modellen for form- og skalafaktorer i en eksponentiel nedbrydningsmodel opdateres baseret på Bayes' regel og en normal-normal model. Senere bruges den bagvedliggende nedbrydningsmodel til at definere en stokastisk model for den resterende levetid. Ydermere diskuteres det, at den bedste trigger for en prediktiv inspektion er en hybrid af grænserne for nedbrydning og resterende levetid til at sikre falske forudsigelser er få, der er nok tid til planlægning, forberedelse og udførelse af prediktive arbejdsordrer er tilgængelige og at den predikterede vedligeholdelsesomkostning holdes på et minimum. Endeligt forklares for en case translationen af inspektionsudfald til et nedbrydningsniveau af en komponent ved brug af nedbrydningsmatricer, og der gives et forslag til validering af prediteret nedbrydning baseret på inspektionsudfald.

I denne afhandlings sidste kapitel diskuteres tidsplanlægning og prioritering af alle vedligeholdelsesordrer, specielt tilstandsbaseret og prediktive arbejdsordrer. Inden for en stokastisk risikobaseret beslutningsmodel ses det, at den optimale tidsplanlægning og prioritering af alle indestående arbejdsordrer kan bestemmes i forhold til deres definerede dato og omkostningsmål. Brugen af denne model uddybes i detaljer i en case for arbejdsordrer til reference offshore vindmølleparker, og der fremhæves væsentlige muligheder for betragtelig reduktion af drifts- og vedligeholdelsesomkostninger for daglig drift og vedligeholdelse af offshore vindmølleparker generelt.

De omtalte risiko- og pålidelighedsmodeller for optimal kort- og langsigtet drifts- og vedligeholdelsesplanlægning af offshore vindmølleparker i denne afhandling udvikles på en sådan måde, så de nemt kan implementeres i et hvilket som helst offshore vind kontrolsystem. I slutningen af hvert kapitel i denne afhandling gives der klare anbefalinger for fremtidig forskning i dette emne. I fremtidig forskning skal det noteres, at en planlægningsmodel for drifts- og vedligeholdelse ikke tilføjer nogen øget værdi til en offshore vindmøllepark, hvis denne model ikke nemt at implementeres i en eksisterende infrastruktur for vindmølleparker, uanset hvor præcis denne planlægningsmodel måtte være.

ACKNOWLEDGEMENTS

This thesis is the final deliverable of an industrial PhD position in collaboration with Aalborg University of Denmark, Norwegian Centre for Offshore Wind Energy (NORCOWE) and Energy Centre of the Netherlands (ECN).

First, I would like to express my gratitude to my PhD supervisor Prof. John Dalsgaard Sørensen from Aalborg University for his continuous support and insightful feedback during past four years of this industrial PhD. Secondly, I would like to thank my family and friends for their loving support through all the ups and downs.

CONTENTS

CHAPTER 1. INTRODUCTION

Offshore wind surely has passed its infancy. Nowadays offshore wind is considered as a solid business case for utilities and not anymore, a proof of concept demonstration handled by research organizations. This chapter is intended to give an introduction to offshore wind energy, to explain why offshore wind matters and why the operation and maintenance (O&M) planning of offshore wind farms is the focus of this thesis. Further on, the objective, approach and outline of this thesis are briefly discussed and a literature review on the state of the art in risk and reliability based O&M planning of offshore wind farms is given.

1.1. OFFSHORE WIND ENERGY

During the last decade, wind energy has been the fastest growing power generation capacity in Europe. As illustrated in Figure 1-1, wind energy with 153.7 GW installed capacity by the end of 2016 has already overtaken fuel oil, nuclear, hydro and coal, becoming the second largest power generation capacity in the European Union. The reason of such a fast growth of wind energy is the continuous pursuit of European countries for environmental friendly and sustainable energy sources.

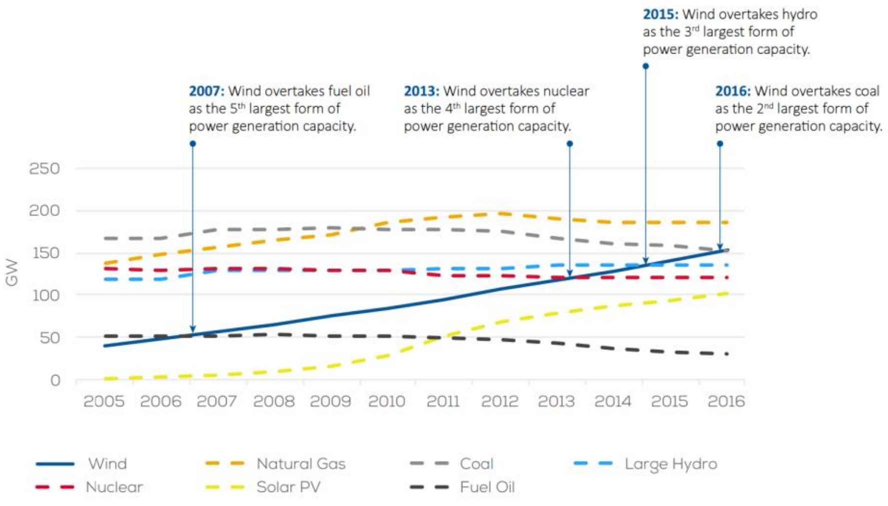


Figure 1-1 Cumulative power capacity in the European Union 2005-2016 (WindEurope, 2017)

The wind energy in Europe is generated from both onshore and offshore wind turbines. The onshore wind energy in Europe is generated from a variety of onshore wind farms, ranging from single-turbine wind farms owned by farmers to 50-600 MW wind farms owned by large utilities. In contrary, nowadays the offshore wind energy in Europe is generated in form of 300-600 MW offshore wind farms owned and developed mainly by utilities, located 30-80 km far offshore and in 20-40 m water depth.

To date, the majority (91.8%) of the installed wind energy capacity in Europe has been onshore and only 12.2% offshore. The reason behind this variation is that the installation and maintenance costs in land are much lower than offshore locations, which results into lower Levelized Cost of Energy (LCoE) and a better business case. Moreover, in the past decades there have been strong governmental subsidy schemes to promote onshore wind energy.

In comparison to onshore wind, offshore wind farms have higher energy yield and lower environmental impact for humans such as noise or shadow disturbance. Additionally, in recent years the offshore wind market has seen a significant growth due to replacement of onshore subsidy schemes with offshore ones. The offshore wind industry is moving rapidly to become a subsidy-free industry. The first breakthrough was announced in 2017 German offshore wind tenders in which two out of three winning bids were with zero subsidy. A similar trend is expected to be seen in 2018 Dutch offshore wind tenders.

This thesis is focused only on offshore wind farms as there are yet excellent opportunities for innovation and cost reduction. In the next sections, first typical components of an offshore wind farm are described, followed by an introduction into offshore wind projects and costs.

1.1.1. OFFSHORE WIND COMPONENTS

An offshore wind farm is consisted of offshore wind turbines and infrastructural components known as Balance of Plant (BoP).

1.1.1.1 Offshore Wind Turbine

According to IEC 61400-3:2009 (Technical Committee IEC 88, 2009) an offshore wind turbine is a "*wind turbine with a support structure which is subject to hydrodynamic loading*" and support structure is a "*part of an offshore wind turbine consisting of the tower, sub-structure and foundation*". In Figure 1-2, the typical components of a three-bladed horizontal axis bottom-fixed offshore wind turbine are visualized.

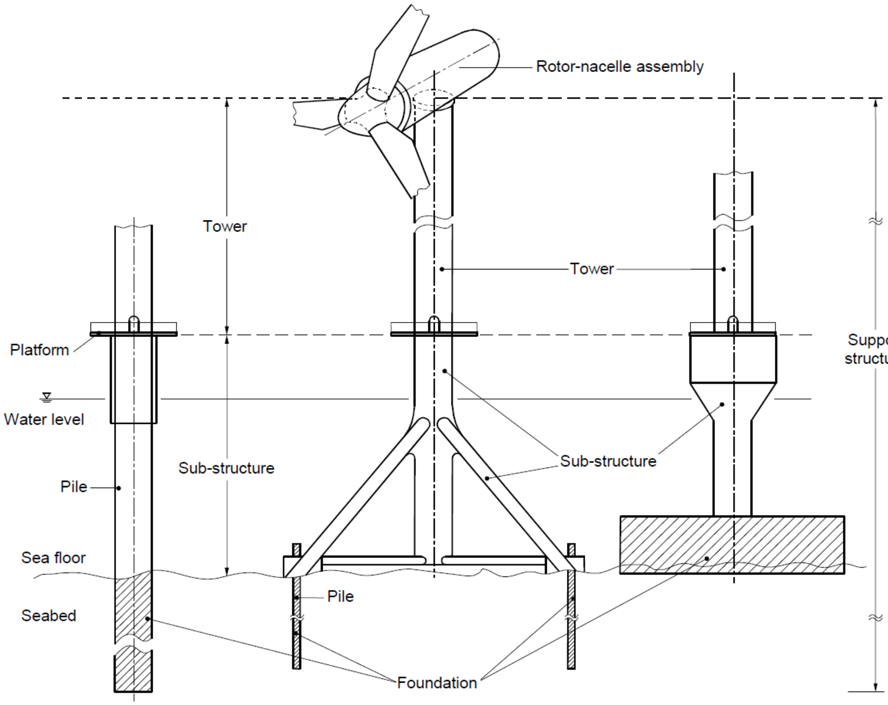


Figure 1-2 Offshore wind turbine components (Technical Committee IEC 88, 2009)

Wind turbine manufacturers which are known as Original Equipment Manufacturers (OEMs) typically only supply the rotor-nacelle assembly and the tower. The rest of support structure (substructure such as transition piece and foundation such as monopiles) is normally designed for each specific site by a third-party engineering office according to the frequency ranges defined by OEMs.

1.1.1.2 Offshore Wind BoP

The second part of an offshore wind farm is balance of plant, which consists of wind farm electrical infrastructure, wind farm Supervisory Control And Data Acquisition (SCADA) as well as occasionally wind farm civil infrastructure.

Wind farm electrical infrastructure is required to transfer the generated electricity by offshore wind turbines to the local onshore grid through a few steps explained in the followings.

First, the array cables collect the generated medium voltage electricity from offshore wind turbines and transfer it to an offshore transformer station. Depending on the type and size of the cable a limited number of turbines can be connected to each array cable string. The offshore transformer station then transforms the collected medium voltage electricity to high voltage electricity.

Second, the AC export cables transfer the high voltage electricity to an offshore converter station, if DC is preferred transmission option. The offshore converter station converts the high voltage electricity from AC to DC, which is a better choice for long distance transfer of electricity to minimize the losses.

Third, the DC export cables transfer the high voltage electricity from the offshore converter station to an onshore station. The onshore converter station converts the high voltage electricity from DC to AC and if required, from high voltage to medium voltage. Eventually, the generated electricity by offshore wind turbines reaches the local onshore grid.

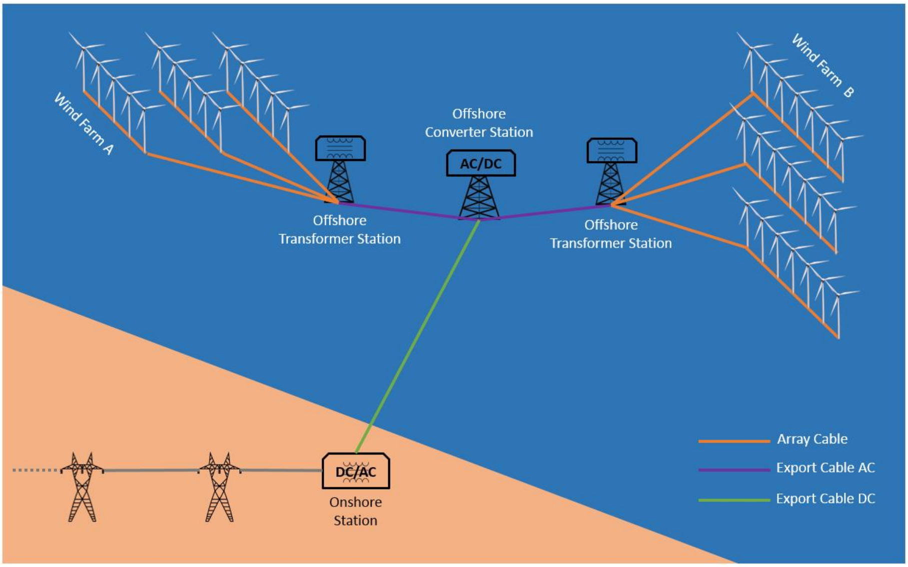


Figure 1-3 Offshore wind balance of plant components

In Figure 1-3, the layout of a typical offshore wind balance of plant is illustrated in which two neighbour offshore wind farms use the same offshore converter station. It should be noted that a variety of different offshore wind balance of plant layouts can be seen in Europe. As instance, if offshore wind turbines are located near shore they can be connected directly to an onshore station (such as Egmond aan Zee offshore wind farm in The Netherlands). Furthermore, depending on the size of an offshore wind farm, the offshore transformer and converter stations can be combined into one station.

The focus of this thesis is all offshore wind turbine components, both wind turbines and balance of plant components. In the next section, a typical offshore wind project is described to give an overview on lifecycle challenges of offshore wind farms.

1.1.2. OFFSHORE WIND LIFECYCLE

Offshore wind farms are complex and dynamic projects consisting of innovative components located in harsh offshore locations. Similar to any other power plant, offshore wind farm projects consist of four main phases, which are development, construction, generation and decommissioning:

- **Development Phase:** to plan, design and permit an offshore wind farm
- **Construction Phase:** to supply and install wind farm components followed by commissioning tests
- **Generation Phase:** to maintain the wind turbines and BoP to maximize the produced power and minimize operational costs
- **Decommissioning Phase:** to decommission and dismantle the wind farm components at the end of the wind farm lifetime

In Figure 1-4, the lifecycle breakdown of an offshore wind farm is illustrated.

Figure 1-4 Lifecycle breakdown of an offshore wind project

It should be noted that the design and manufacturing of offshore wind components is not discussed here and occurs in parallel to this project lifecycle. In the following sections, activities carried out in each phase are described in detail.

1.1.2.1 Development Phase

The offshore wind farms in Europe can be developed mainly through tenders initiated by governments. Development of an offshore wind farm is a costly and time-consuming process which is subject to high risk and uncertainty in early stages of the project. Development phase of an offshore wind project typically is managed by a dedicated development team and consists of all activities from project initiation to project handover to the construction team. In Figure 1-5, breakdown of development steps in an offshore wind farm project is shown.

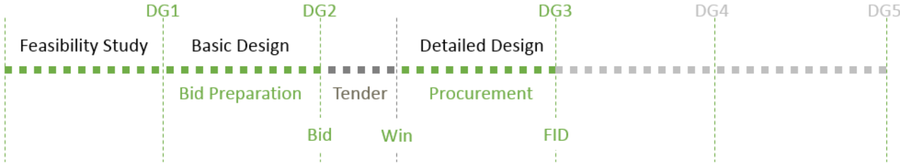


Figure 1-5 Breakdown of development phase of an offshore wind project

At the end of each development step a Decision Gate (DG) is defined to make a Go or NoGo decision to the next development step. The feasibility study, basic design and detailed design steps are briefly discussed in the followings.

Feasibility study

After government positive decision on offshore wind development in a specific region, the development team initiates a feasibility study to roughly determine a potential business case and the suitability of the wind farm within the existing wind asset. The deliverable of the feasibility study is a potential business case presented to the steering committee of the project to make a Go or NoGo decision. This decision step is called Decision Gate 1 or DG1.

Basic design

If the DG1 is positive, the project team enters into the Basic Design step to prepare a bid according to the official governmental tender documents. The deliverable of this step is the basic design of the wind farm and a bid for LCoE. The basic design outlines the layout of the wind farm civil and electrical infrastructure, type of wind turbines and their estimated lifetime energy production within that layout and a baseline O&M strategy, together with an estimation of development and operational costs for LCoE estimation. As deliverable, the basic design document together with the LCoE bid is presented to the project steering committee to make a decision. This decision step is called DG2.

Detailed design

In case of positive DG2, the development team submits their bid into the tender and awaits a few months for the tender results. Only after winning a tender, the development team will move forward into the detailed design and procurement step of the project. If the tender result is a win, the development team enters in negotiations with suppliers and contractors to prepare the detailed design of the wind farm.

The deliverable of the development step is the detailed design document in which all costs, suppliers, contractors, construction and commissioning steps are detailed out. This decision gate is called DG3 or Final Investment Decision (FID). By reaching to an FID, the task of the development team is finished. If the FID by the steering committee is positive, then a construction team takes over the project to bring it to the next step.

1.1.2.2 Construction Phase

If the FID is positive, the project owner commits to all the project costs and by doing so, the project enters into the construction phase managed by a dedicated team. The breakdown of the construction steps of an offshore wind farm project is shown in Figure 1-6 and further explained in the following sections.

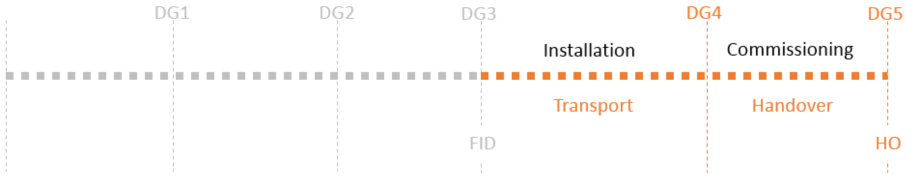


Figure 1-6 Breakdown of construction phase of an offshore wind project

Transport and installation

The first step in the construction phase is transport and installation of offshore wind components, which is typically outsourced to one or several contractors. If only one contractor is in charge of the whole construction phase, then it is called a turnkey project meaning that the contractor will deliver a grid connected wind farm ready to generate electricity to the owner.

Before transportation of wind farm components from suppliers to the location of offshore wind farm, several Factory Acceptance Tests (FATs) is carried out to make sure all components are manufactured as described in the procurement specifications agreed upon in the detailed design step. Typically, also after arrival of components to the wind farm, several Site Acceptance Tests (SATs) are carried out to verify that no damage has occurred during the transportation of components.

After FATs and SATs, the construction contractors normally start with installation of array cables, offshore BoP stations and wind turbine foundations. Afterwards, the installation is concluded by installing wind turbine towers and rotor-nacelle assemblies. Similar to the SAT after transportation of components, another SAT can be carried out to verify that no damaged has occurred during the installation of components.

It should be noted that lifting of heavy turbine components from a jack-up barge can only be done in specific weather windows in which wind speed and significant wave height are both below defined thresholds. Consequently, in case unfavourable weather conditions, the installation step can be delayed several weeks or months. In (Asgarpour, 2016), installation steps of offshore wind farms is discussed in more detail.

The deliverable of the installation step is the actual offshore wind farm together with an installation overview report presented to the steering committee for DG4.

Commissioning

After a positive DG4, the commissioning step is initiated. The commissioning step is intended to detect and mitigate defects before start of the generation phase. During the commissioning step, several inspections and test are carried out to make sure the performance of wind turbines is as expected and power quality of the wind farm follows the grid requirements. Typically, the following Operational Acceptance Tests (OATs) are carried out for each wind turbine during the commissioning step:

- **Trial Operation:** to verify that each wind turbine can be in operation and grid connected for a given time period (e.g. 5 days) according to acceptance criteria defined in the commissioning contract.
- **Short Power Test:** to verify that power performance of each wind turbine in a given time period (e.g. 20 days) is not deviating strikingly from warrantied performance provided by the OEM.

Besides this short-term power performance test for each wind turbine, a long-term performance test campaign will be carried out only for a few wind turbines to investigate their performance in a longer period and in more detail. Typically, during these campaigns an independent meteorological equipment (such as a LiDAR) is used to eliminate the uncertainty of wind speed measurements by the nacelle anemometer of wind turbines. In (Asgarpour, 2016), commissioning steps of offshore wind farms is described in more detail.

After the commissioning step, the construction team prepares a handover (HO) document and presents it to the project steering committee for DG5. If DG5 is positive, the construction phase is officially finalized and the wind farm can be handed over to the generation team.

1.1.2.3 Generation Phase

Generation phase is when an offshore wind farm is truly realized and it is ready to transfer the generated electricity to the onshore grid. The generation team is typically located onshore, in the closest harbour to the offshore wind farm.

Generation team consists of a site manager, an O&M manager and several lead and specialized technicians. In the generation phase the main responsibility of the generation team is to maintain the wind farm in a way to maximize the production and minimize the operational risks such as costs. In Figure 1-7 the breakdown of the generation phase of an offshore wind farm is illustrated.

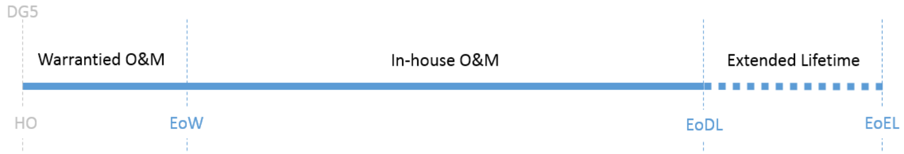


Figure 1-7 Breakdown of the generation phase of an offshore wind farm

The warrantied O&M, in-house O&M and extended lifetime steps and end of warranty and end of lifetime decision gates are discussed in the followings.

Warrantied O&M

The first step of the generation phase is warrantied operation and maintenance phase. In order to reduce the financial risk of offshore wind projects, normally the early years of operation (e.g. first five years) is fully warrantied by the OEMs. This warranty includes maintenance and availability warranty.

The term "maintenance" is defined in detail within section 1.2.1 of this chapter. Within the maintenance warranty period, the OEM is accountable to maintain the component failures and perform the scheduled service of wind turbines, and in some cases, balance of plant components. Next to the maintenance warranty there is typically an availability warranty to reduce financial risks if component failures occur way too often and/or resolving failures takes much more time than expected.

In IEC 60050-191:1990 (Technical Committee IEC 1 & 56, 1990), the term "availability" is defined as "*ability of an item to be in a state to perform a required function under given conditions at a given instant of time or during a given time interval, assuming that the required external resources are provided*". The OEM's warranted availability could be time based or production based.

In IEC 61400-26-1:2011 (Technical Committee IEC 88, 2011), time-based availability is defined as "*fraction of a given operating period in which a WTGS is performing its intended services within the design specification*", given in Equation (1.1). In IEC 61400-26-1:2011 (Technical Committee IEC 88, 2011), unavailability time calculation is described in detail.

$$Time\ based\ Availability = 1 - [Unavial.Time/(Avial.Time + Unavil.Time)] \quad (1.1)$$

In IEC 61400-26-2:2014 (Technical Committee IEC 88, 2014), production-based availability is defined as actual energy production divided by potential energy production, given in Equation (1.2). In IEC 61400-26-2:2014 (Technical Committee IEC 88, 2014), lost production calculation is described in detail.

$$Production\ based\ Availability = 1 - [LostProduction/(ActualProduction + LostProduction)] \quad (1.2)$$

It goes without saying that production based availability is a better deal for wind farm owners since in case of time based availability, one hour of lost energy in high wind condition and one hour of lost energy in low wind condition are considered alike. However, currently the majority of availability warranty contracts are time based. Both availability warranties can be applied to each single turbine or to the average of the whole offshore wind farm.

End of warranty

By reaching the end of warrantied O&M period known as End of Warranty (EoW) decision gate, the wind farm owners have two options, to prolong the warranty period or to do the maintenance by themselves and accept the financial risks. In recent years the latter option is chosen more often since it can reduce the operational costs substantially.

In-house O&M

If the wind farm owner decides to step out of the warranty contract, then the wind farm enters into the in-house maintenance step, which can last for several years (e.g. 20 years). During this period, the generation team has the full responsibility to comply with cost and availability targets and to maintain all offshore wind components. The in-house O&M step is the focus of this thesis as there are several cost reduction opportunities for reduction of O&M costs.

End of lifetime

In the past decade, offshore wind turbines were typically designed for 20 years of lifetime, but nowadays they are designed for 25 years and in some cases 30 years of lifetime. At the End of Design Lifetime (EoDL) the wind farm owners have several options ahead of them.

One option is to extend the lifetime, if wind turbine structural components are still reliable and business case is still profitable. To date, no offshore wind turbine's lifetime has been extended since this is a new practice and still no clear standard and/or procedure is defined for this step.

If the wind farm owner decides to extend the lifetime of the wind farm then a comprehensive study should be carried out to estimate the Remaining Useful Lifetime (RUL) of structural components and post EoDL O&M costs. Typically, the results of this study should be verified by a third-party certification body to permit the wind farm owner for lifetime extension.

1.1.2.4 Decommissioning Phase

If the wind farm owner decides to not pursue a lifetime extension or if the End of Extended Lifetime (EoEL) is reached then, the offshore wind farm reaches its End of Lifetime (EoL) and should be decommissioned and dismantled according to environmental requirements agreed upon in the development phase.

Decommissioning and dismantling

The decommissioning phase can be considered as reverse construction phase. First, turbines should be disconnected from the grid and then, nacelle-rotor assemblies and towers should be dismantled. The final step is take out foundations, array and export cables from the seabed and make sure that marine lifetime is back to its origin as it was before the construction of the offshore wind farm. As instance, a steel monopile foundation can be entirely removed from the seabed by vibration or if it is allowed in the decommissioning document, the monopile can be cut below the seabed. In (Topham & McMillan, 2017) a thorough overview on sustainable decommissioning and dismantling techniques for offshore wind farms is given. The dismantled components can be used as second-hand components or be partially recycled.

Decommissioning and repowering

Instead of full dismantling, the owner may opt for repowering, which means installation of a new wind farm at the same location and if possible, using some or all the balance of plant components of the previous wind farm. The repowering is an interesting option since the existing operational data of the old wind farm can be used to lower the risks and uncertainty of the business case of the new wind farm. Repowering is widely used in onshore wind farms, but so far it has not been applied to any offshore wind farm. In Figure 1-8, the breakdown of the decommissioning phase of an offshore wind farm is illustrated.

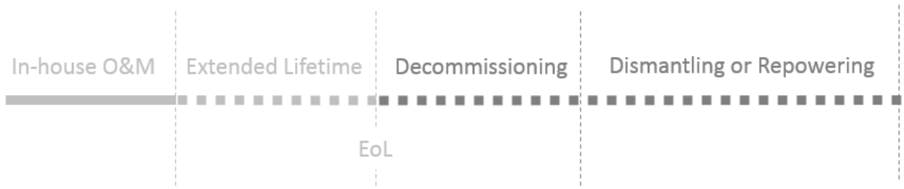


Figure 1-8 Breakdown of the decommissioning phase of an offshore wind farm

As discussed in the generation phase, the focus of this thesis is to reduce operational costs during the in-house O&M step of the offshore wind farms. Before discussing potential cost reduction solutions, it is important to have a clear overview of offshore wind costs during its lifecycle. In the next section, an overview of offshore wind lifecycle costs is given.

1.1.3. OFFSHORE WIND COSTS

In the development phase, it was explained that nowadays offshore wind farms are permitted only through competitive governmental tenders based on the lowest LCoE. Offshore wind energy without relying on subsidies can be a profitable industry only if the LCoE produced by offshore wind farms is reduced substantially and a proper Power Purchase Agreement (PPA) is settled.

The LCoE for an offshore wind farm can be calculated using Equation (1.3):

$$LCoE = (CAPEX \times CRF + OPEX)/(AEP_{Potential} - AEP_{Loss}) \quad (1.3)$$

- CAPEX as initial Capital Expenditure in EUR (project development, supply, installation and dismantling costs)
- CRF as Capital Recovery Factor[1] calculated by Equation (1.5)
- OPEX as the average yearly Operational Expenditure in EUR
- $AEP_{Potential}$ as the average potential Annual Energy Production (AEP) of the wind farm in Watt hour (Wh)
- AEP_{Loss} as the average lost AEP of the wind farm due to unavailability of wind turbines or BoP electrical infrastructure in Watt hour (Wh)

$$CRF = [i \times (1+i)^n]/[(1+i)^n - 1] \quad (1.4)$$

- i as the interest rate
- n as number of wind farm operational years

As instance, in case of 4% interest rate and 25 years of wind farm lifetime the CRF will be:

$$CRF = \frac{[i \times (1+i)^n]}{[(1+i)^n - 1]} = \frac{[0.04 \times (1+0.04)^{25}]}{[(1+0.04)^{25} - 1]} = 0.064 \quad (1.5)$$

The LCoE is normally shown as €/kWh or €/MWh. In the following sections, the remaining LCoE elements are explained in more detail.

1.1.3.1 AEP

The potential AEP of an offshore wind farm is the energy that wind turbines of that wind farm can produce if both the wind turbines and BoP electrical infrastructure are

[1] https://www.nrel.gov/analysis/tech-lcoe-documentation.html

100% available throughout the year. In order to calculate the potential AEP, first the nominal AEP should be calculated.

Nominal AEP

The nominal AEP of a wind farm is calculated based on the nominal AEP of each single wind turbine. The nominal AEP of a wind turbine can be calculated using its warrantied power performance and historical wind condition at its geographical location.

Power performance of a wind turbine is typically presented by means of a Power Velocity (PV) curve. A PV curve consists of an estimated power per each wind speed bin (e.g. 1 m/s). In Figure 1-9, a PV curve for a reference wind turbine with total capacity of 8000 kW is illustrated. Every PV curve can be highlighted with several key wind speeds and state modes. The key wind speeds are:

- **Cut-in Wind Speed:** the minimum wind speed that a wind turbine requires to start producing power (4 m/s in Figure 1-9)
- **Start Rated Wind Speed:** the minimum wind speed that a wind turbine requires to operate at its maximum capacity (13 m/s in Figure 1-9)
- **End Rated Wind Speed:** the maximum wind speed that a wind turbine can still produce at its maximum capacity (25 m/s in Figure 1-9)
- **Cut-out Wind Speed:** the maximum wind speed that a wind turbine can operate (30 m/s in Figure 1-9)

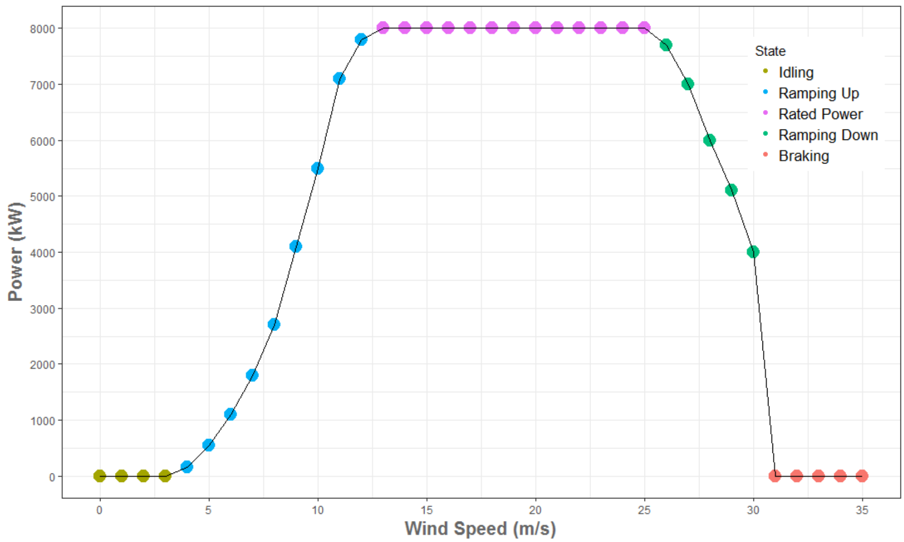


Figure 1-9 Power Velocity (PV) curve of an 8 MW offshore wind turbine

In wind speeds below cut-in, a wind turbine is in the idling state, waiting for preferable wind condition. From cut-in wind speed until start rated wind speed, a wind turbine is in ramping up mode by pitching its blades to maximum lift mode. When a wind turbine reaches the rated power, the wind turbine controller actively pitches its blades to minimize the loads as much as possible and make sure in higher wind speeds the produced power doesn't exceeds the rated power.

The end rated wind speed is the maximum wind speed that a wind turbine can operate at its rated power. Up to a few years back all existing turbines in the market would shut down immediately in wind speeds above the end rated wind speed. Therefore, the end rated wind speed would have been equal to cut-out wind speed for these turbines. In recent years wind turbines have been equipped with extended cut-out features, which allows them to have less immediate shut downs and to produce power in very high wind speeds.

If a turbine is equipped with extended cut-out, for wind speeds above the end rated wind speed the turbine starts ramping down by pitching its blade to decrease the lift and thereby the loads. If the wind speed continues to increase above the cut-out wind speed, then the wind turbine will immediately shutdown to prevent unplanned structural loads.

The historical wind speed condition at a geographical location is typically presented by a Weibull curve. In Figure 1-10, frequency of 11 years wind speed measurements of FINO3 meteorological mast (wind speed measurements at 150 m hub height in 80 km far offshore in the North Sea) supplied by NORCOWE[2] is visualized in red.

[2] NORwegian Centre for Offshore Wind Energy (NORCOWE): https://rwf.computing.uni.no/

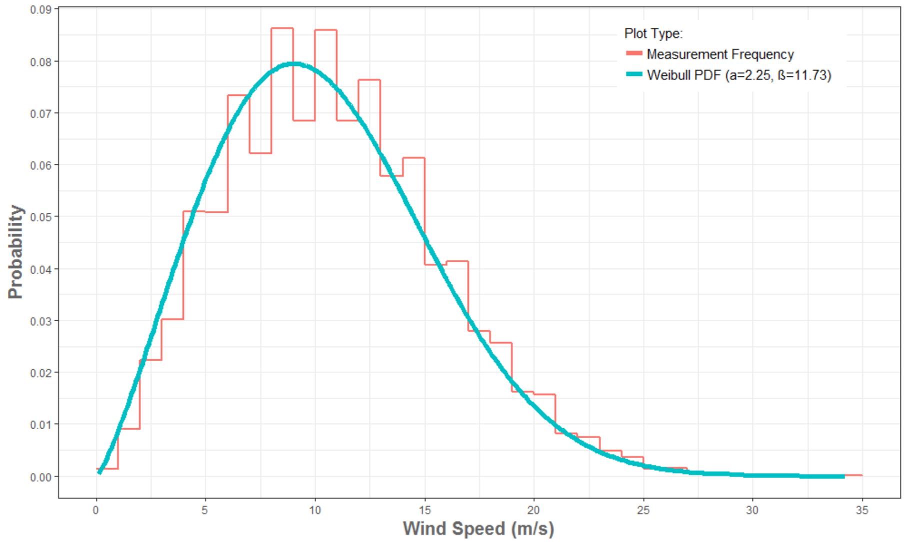


Figure 1-10 Historical wind condition at a reference offshore wind farm location

It is known that a two-parameter Weibull distribution generally can provide a close fit to wind speed measurements. As instance, the shape and scale parameters of fitted Weibull distribution to measurement frequencies plotted in Figure 1-10 are:

- Shape factor $\alpha = 2.25$
- Scale factor $\beta = 11.73$

By having the scale and shape factors, the Weibull Probability Density Function (PDF) can be calculated as followings (Bronshtein, Semendyayev, Musiol, & Mühlig, 2015):

$$f(v) = \frac{\alpha}{\beta}\left(\frac{v}{\beta}\right)^{\beta-1} exp[-\left(\frac{v}{\beta}\right)^{\beta}] \quad v \geq 0 \tag{1.6}$$

- v as wind speed bin
- $f(v)$ as Weibull PDF of wind speed bin v

In Figure 1-10, the Weibull PDF of this fit is visualized in blue. Therefore, about 32,000 measurement points can be summarized in two parameters of a Weibull distribution. If both scale and shape factors are known, then the mean wind speed for this location and measurement height can be calculated as (Bronshtein et al., 2015):

$$\mu = \beta\Gamma\left(1+\frac{1}{\alpha}\right) = 10.39\ {}^{m}/_{s} \tag{1.7}$$

The nominal AEP of a wind turbine can be calculated using the PV curve and historical wind condition. For instance, the nominal AEP of the 8 MW reference wind turbine plotted in Figure 1-9 with historical wind condition as plotted in Figure 1-10 can be estimated as:

$$AEP_{WT,Meas.} = \sum_{v=0}^{v=35} P_v \times 356 \times 24 \times f_v \ = \ 42.126\ GWh$$
$$AEP_{WT,Weib.} = \sum_{v=0}^{v=35} P_v \times 356 \times 24 \times f(v) = \ 42.000\ GWh \qquad (1.8)$$

- v as wind speed bin
- P_v as wind turbine warrantied power in wind speed bin v
- f_v as frequency of measurements in wind speed bin v
- $f(v)$ as Weibull PDF of wind speed bin v given in Equation (1.6)

From Equation (1.8) it can be seen that the nominal wind turbine AEP calculated based on Weibull parameters is very close to the AEP calculated based on actual measurement frequencies. Assuming a fixed electricity price such as 50 €/MWh, the nominal AEP of this reference wind turbine can be translated roughly into M€ 2.1 nominal revenue per year.

It is also possible to define a Weibull fit per season, meaning four set of Weibull parameters for the whole year, to calculate the nominal wind turbine AEP per season and reduce the uncertainty.

Now that the nominal AEP of each single turbine is known, the approximate nominal AEP of an 800 MW reference wind farm with 8 MW reference wind turbines based on the Weibull distribution shown in Figure 1-10 can be calculated:

$$AEP_{Nominal} = \ \sum_{n=1}^{n=N} AEP_{WT_n} = \sum_{1}^{100} 42\ GWh = 4.2\ TWh \qquad (1.9)$$

- $AEP_{Nominal}$ as nominal AEP of an offshore wind farm in Wh (without any losses)
- AEP_{WT_n} as nominal AEP of wind turbine n in Wh
- N as the total number of wind turbines in the offshore wind farm

Potential energy production

Now that the nominal AEP is known, the potential energy production can be estimated by deducting the lost production caused by the following reasons:

- Wake (wind speed deficit in downwind turbines)
- Performance (due to blade icing, blade degradation, turbine own consumption, yaw misalignment and pitch misalignment)
- Electrical (due to energy loss in subsea transmission cables)

Therefore, the potential AEP of an offshore wind farm by reducing the production losses will be:

$$AEP_{Potential} = AEP_{Nominal}(1 - \zeta_W - \zeta_P - \zeta_E) \quad (1.10)$$

- $AEP_{Potential}$ as the wind farm potential AEP by deducting wakes, underperformance and electrical losses in Wh
- ζ_W as production loss ratio due to wakes
- ζ_P as production loss ratio due to underperformance of turbines
- ζ_E as production loss ratio due to energy loss in subsea cables

As instance, the potential AEP of this reference offshore wind farm by assuming 3% wake loss, 2% underperformance loss and 0.5% electrical loss is:

$$AEP_{Potential} = AEP_{Nominal}(1 - \zeta_W - \zeta_P - \zeta_E) = 4.2\times(1 - 0.03 - 0.02 - 0.005) = 3.969\ TWh \quad (1.11)$$

Therefore, the potential AEP of an 800 MW reference offshore wind farm with considering production losses can be estimated as 3.969 TWh.

Unavailability production loss

As discussed earlier, the potential AEP is calculated assuming wind farm BoP electrical infrastructure and all wind turbines are 100% available throughout the year. However, due to faults or service of wind farm components occasionally wind turbines are shut down and/or BoP electrical infrastructure is not able to transmit the produced electricity onshore. This is known as unavailability production loss or OPEX production loss. As instance, the potential production loss by assuming unavailability production loss of 3% is:

$$AEP_{Loss} = \zeta_A AEP_{Potential} = 0.03\times3.969 = 0.119\ TWh \quad (1.12)$$

- ζ_A as the unavailability production loss ratio

The more accurate AEP of offshore wind farms is typically calculated using an AEP model such as WindPRO[3] developed by EMD, WindFarmer[4] developed by DNV GL or WAsP[5] developed by DTU.

[3] https://www.emd.dk/windpro/

[4] https://www.dnvgl.com/energy/generation/software/windfarmer/windfarmer-analyst.html

[5] http://www.wasp.dk

1.1.3.2 CAPEX

CAPEX also known as Installed Costs is the total cost of development, construction and decommissioning phases, which can include costs of project development, wind turbine supply, foundation supply, BoP supply, installation, commissioning, decommissioning and dismantling steps as discussed in the previous section of this chapter. In Figure 1-11 an approximate breakdown of CAPEX of a bottom-fixed offshore wind farm is visualized.

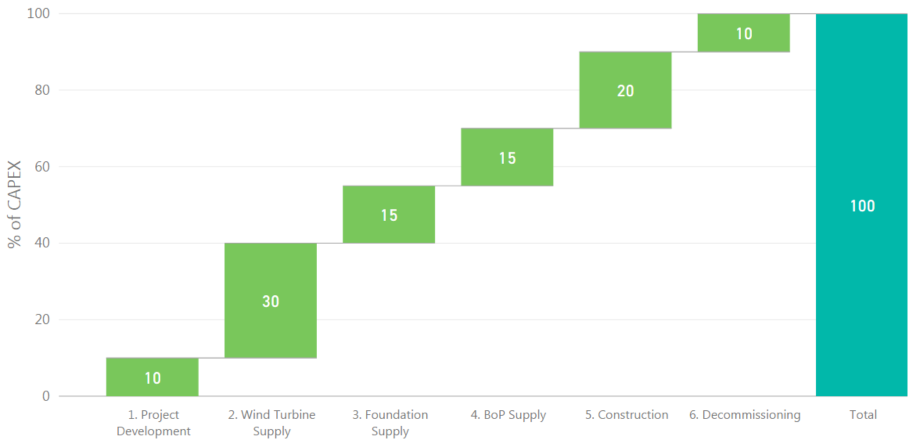


Figure 1-11 Breakdown of costs of a bottom-fixed offshore wind farm

In Figure 1-11 it can be seen that about 60% of CAPEX is due to supply of wind farm components, about 30% is due to construction, commissioning and decommissioning and about 10% is due to project development costs.

The CAPEX of offshore wind farms and its breakdown varies from one wind farm to another, depending on the country, offshore location, water depth, sea bed type and more factors. A simplified way to estimate CAPEX is based the average CAPEX per MW installed. In this thesis, it is assumed that CAPEX of offshore wind farms is about 4 M€/MW. Therefore, the CAPEX of an 800 MW reference wind farm will be:

$$CAPEX = CAPEX_{MW} \times P_{WF} = 4 \; {}^{M€}/_{MW} \times 800 \; MW = B€ \; 3.2 \qquad (1.13)$$

- $CAPEX_{MW}$ as CAPEX per MW turbine installed and commissioned in M€/MW
- P_{WF} as the total installed capacity of the wind farm in MW

Based on Equation (1.13), for an 800 MW reference offshore wind farm an initial investment of B€ 3.2 is required. It should be noted that this number doesn't represent actual CAPEX for an 800 MW offshore wind farm and it's only mentioned here to simply demonstrate the order of magnitude of investment required for development and construction of such an offshore wind farm.

1.1.3.3 OPEX

OPEX also known as Generation Costs is the average annual cost occurred during the generation phase of an offshore wind farm which can include warranty fee, direct operation and maintenance (O&M) costs and overhead costs. The OPEX of an offshore wind farm during in-house O&M step can be calculated as:

$$OPEX = C_{OM.Dir} + C_{OH} \tag{1.14}$$

- $C_{OM.Dir}$ as lifetime direct O&M costs such as vessels, technician and spares costs
- C_{OH} as lifetime overhead costs such as staff, facilities, legal, safety and insurance costs

The $C_{OM.Dir}$ or direct O&M costs is a significant part of OPEX and stands for costs of vessels, spares and technicians. As explained in section 1.1.3.1, during downtime of maintenance actions the wind farm suffers from production loss which can be translated into indirect O&M costs. Therefore, the total O&M costs can be calculated as: Figure 1-1

$$C_{OM} = C_{OM.Dir} + C_{OM.Ind} + C_{OH} \tag{1.15}$$

In Chapter 4, further breakdown of O&M costs of an 800 MW reference offshore wind farm is given in detail.

Similar to CAPEX, the OPEX of offshore wind farms varies from one wind farm to another, depending on the type of wind turbines, foundations, BoP, weather condition and maintenance strategy. A simplified way to estimate OPEX is based on the average OPEX per MWh potential AEP. Based on the real OPEX of similar operational offshore wind farms it can be assumed that the OPEX of this reference offshore wind farms is about 20 €/MWh. Therefore, the OPEX of an 800 MW reference offshore wind farm with 3.969 TWh potential AEP can be roughly estimated as:

$$OPEX = OPEX_{MWh} \times AEP_{Potential} = 20\,\frac{€}{MWh} \times 3.969\;TWh = M€\;79.38 \tag{1.16}$$

- $OPEX_{MWh}$ is assumed OPEX per MWh potential AEP in €/MWh

Based on Equation (1.16), total OPEX of an 800 MW offshore wind farm during its lifetime is about M€ 79.38. It should be noted that this number doesn’t represent actual OPEX for an 800 MW offshore wind farm with 8 MW wind turbines and it is just a presentation of order of magnitude of the OPEX of such a wind farm. In Chapter 4, OPEX estimation of offshore wind farms based on a baseline O&M strategy is explained further in detail.

Since for this reference offshore wind farm a rough estimation of CAPEX, CRF, OPEX and the AEP is available, using Equation (1.3) the LCoE produced by this reference offshore wind farm can be estimated:

$$LCoE = \frac{CAPEX \times CRF + OPEX}{AEP_{Potential} - AEP_{Loss}} = \frac{(3200 \times 0.064 + 79.38)\ M€}{3.969 - 0.119\ TWh} = 73.8\ {}^{€}/_{MWh} \qquad (1.17)$$

Therefore, the LCoE of the assumed 800 MW reference wind farm can roughly be estimated around 73.8 €/MWh. In Table 1-1, an overview of the LCoE elements of the assumed 800 MW reference wind farm and their percentage of the LCoE are shown.

LCoE Elements	Annual Estimation for 800 MW	% of LCoE
CAPEX x CRF	M€ 204.8	72%
OPEX	M€ 79.38	28%
AEP	3.85 TWh	---

Table 1-1 LCoE estimation of an 800 MW reference offshore wind farm

The LCoE of offshore wind farms can only be reduced if both CAPEX and OPEX are reduced and the AEP of the wind farm is increased. In general, the CAPEX and OPEX are connected, meaning that if more reliable and costly components are used then CAPEX and probably AEP get increased and OPEX gets decreased. The opposite holds true for less reliable components. The optimal reliability level of components can be estimated based on a balance between CAPEX, OPEX and AEP to minimize the LCoE.

This thesis is only focused on OPEX and lost AEP reduction of offshore wind farms, which both can be related to O&M costs. In the next section of this chapter, an introduction into O&M of offshore wind farms is given.

1.2. OFFSHORE WIND O&M

No doubt that offshore wind O&M has some similarities to the O&M of other power plants, however, in many cases offshore wind O&M is a totally different story. In the section, first the terminologies used in offshore wind O&M are specified and then, O&M resources required for the implementation of maintenance actions are discussed.

1.2.1. O&M TERMINOLOGY

When it comes to standard terminology, IEC 60050-191:1990 (Technical Committee IEC 1 & 56, 1990) is covering the majority of terms used in international and European standards. However, when it comes to maintenance terminology, EN 13306:2010 (Technical Committee CEN 319, 2010) provides a better definition by using IEC 60050-191:1990 (Technical Committee IEC 1 & 56, 1990) as basis. Hence, moving forward, EN 13306:2010 (Technical Committee CEN 319, 2010) is mainly used for definition of maintenance terms in this thesis.

1.2.1.1 Maintenance

The term "O&M" stands for all operation and maintenance activities intended to maintain failures, detect/predict/avoid faults and reduce degradation. In EN 13306:2010 (Technical Committee CEN 319, 2010), the term "maintenance" is defined as "*combination of all technical and administrative actions, including supervisory actions, intended to retain an item in, or restore it to, a state in which it can perform a required function*".

From this definition two type of maintenance can be derived. First, maintenance activities "intended to restore an item to a state in which it can perform a required function", this type of maintenance is known as "corrective maintenance". Second, maintenance activities "intended to retain an item in a state in which it can perform a required function", this type of maintenance is known as "preventive maintenance". In Figure 1-12, the maintenance categories according to EN 13306:2010 (Technical Committee CEN 319, 2010) are illustrated.

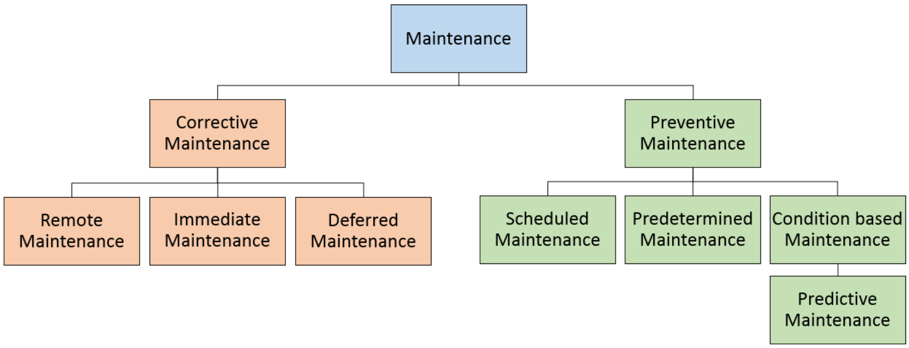


Figure 1-12 Maintenance categories according to EN 13306:2010 (Technical Committee CEN 319, 2010)

1.2.1.2 Corrective Maintenance

As illustrated in Figure 1-12, the EN 13306:2010 (Technical Committee CEN 319, 2010) defines corrective maintenance categories as followings:

- **Corrective Maintenance:** *"maintenance carried out after fault recognition and intended to put an item into a state in which it can perform a required function"*
- **Remote Maintenance:** *"maintenance of an item carried out without physical access by the personnel to the item"*
- **Immediate Maintenance:** *"corrective maintenance that is carried out without delay after a fault has been detected to avoid unacceptable consequences"*
- **Deferred Maintenance:** *"corrective maintenance which is not immediately carried out after a fault detection but is delayed in accordance with given rules"*

In other words, after occurrence of a failure, a corrective maintenance is done to repair or replace the failed component(s). The corrective maintenance can be done remotely (remote maintenance), or immediately after the failure (immediate maintenance) or at a later time (deferred maintenance).

The majority of maintenance actions nowadays in the wind industry are corrective. From failure statistics, it can be observed that each wind turbine on average experiences 10 corrective actions per year, of which 5 of them are immediate or deferred corrective actions and 5 of them are remote corrective actions. The remote corrective actions or remote resets require no resources and lead only to a few hours of downtime. However, immediate and deferred corrective actions require preparation, proper logistics, several inspections, repair or replacement together with significant downtime. In section 5.1 of this thesis corrective maintenance is discussed in more detail.

According to this assumption, the reference 800 MW offshore wind farm with 100 wind turbines defined earlier, on average experiences 500 remote corrective actions and 500 immediate or deferred corrective actions per year. It means that maintenance technicians on average repair 1.4 wind turbines per day during the whole 25 years lifetime of the wind farm, assuming the wind farm is accessible throughout the year. It shows that due to the current amount of corrective maintenance actions, the maintenance of such an offshore wind farm is a non-stop job. This challenge highlights the importance of preventive maintenance actions to reduce the amount of corrective actions to a much lower number.

1.2.1.3 Preventive Maintenance

Similarly as illustrated in Figure 1-12, EN 13306:2010 (Technical Committee CEN 319, 2010) defines preventive maintenance categories as followings:

- **Preventive Maintenance:** *“maintenance carried out at predetermined intervals or according to prescribed criteria and intended to reduce the probability of failure or the degradation of the functioning of an item”*
- **Scheduled Maintenance:** *“maintenance carried out in accordance with an established time schedule or established number of units of use”*
- **Predetermined Maintenance:** *“preventive maintenance carried out in accordance with established intervals of time or number of units of use but without previous condition investigation”* assuming *“Intervals of times or number of unit of use may be established from knowledge of the failure mechanisms of the item”*
- **Condition based Maintenance:** *“preventive maintenance which include a combination of condition monitoring and/or inspection and/or testing, analysis and the ensuing maintenance actions”*
- **Predictive Maintenance:** *“condition based maintenance carried out following a forecast derived from repeated analysis or known characteristics and evaluation of the significant parameters of the degradation of the item”*

In other words, preventive maintenance is intended to avoid faults and/or reduce degradation. The preventive maintenance can be time-based (scheduled maintenance), usage-based (predetermined maintenance), diagnosis-based (condition based maintenance) or prognosis-based (predictive maintenance). In section 5.2 condition based maintenance and in section 5.3 predictive maintenance is discussed further in detail.

Implementation of both corrective and preventive maintenance actions require proper O&M facilities and resources. These topics are discussed in the following sections.

1.2.2. O&M FACILITIES

The O&M consists of both operation related and maintenance related actions. The operation related activities of an offshore wind farm are typically handled by an operation hub and the maintenance related activities of an offshore wind farm are handled by a maintenance hub, both further explained in the followings.

1.2.2.1 Operation Hub

Offshore wind farms are typically monitored 24/7 by an operation hub, also known as control room or surveillance centre. An operation hub is responsible for monitoring of one or several offshore wind farms. The operation hub is not necessarily located in the vicinity of wind farms as all operations can be performed remotely. The main responsibility of an operation hub is to control and monitor offshore wind farms via a Supervisory Control and Data Acquisition (SCADA) system.

Control Activities

The control responsibilities of an operation hub are:

- **Remote Restart** of down turbines when it can be handled remotely (remote maintenance)
- **Remote Shutdown** of turbines in case of a severe fault detection
- **Remote Curtailment** of some turbines or the whole wind farm according to a defined production set point. Curtailments can be requested by the grid operator (to balance the grid), by the electricity traders (to optimize the sales) or by the maintenance hub (to delay a known failure).

Monitoring Activities

The monitoring responsibility of an operation hub is mainly information or error handling of the SCADA system. Each SCADA error consists of three parts:

- **Error Code:** a unique identifier number defined by the OEM for each specific turbine type
- **Error Description:** a short text to explain the error
- **Error Type:** the error type could be warning or alarm. Warning is when the SCADA system detects an anomaly (the wind turbine is still in operation) and alarm is when a turbine is not in operation due to failures or other reasons (the wind turbine is shut down).

Each wind turbine OEM has a different definition of errors for each specific turbine platform. This becomes problematic when a utility owns several different turbine types. A solution to this problem is to categories all different OEM errors into a limited number of error categories. Some utilities have their own defined error categorization, but majority of utilities nowadays use an adoption of the IEC 61400-26 information categories.

In order to classify error codes in the wind industry, IEC 61400-26-1:2011 (Technical Committee IEC 88, 2011) and IEC 61400-26-2:2014 (Technical Committee IEC 88, 2014) can be used for classification of wind turbine errors and IEC 61400-26-3:2016 (Technical Committee IEC 88, 2016) can be used for classification of wind farm errors. The IEC 61400-26-2:2014 (Technical Committee IEC 88, 2014) information categories for wind turbines are:

- **Operative**
    - In Service
        1. Full Performance
        2. Partial Performance (derated or degraded)
    - Out of Service
        3. Technical Standby
        4. Out of Environmental Specification (calm wind or other environmental)
        5. Requested Shutdown
        6. Out of Electrical Specification
- **Non-Operative**
    7. Scheduled Maintenance
    8. Planned Corrective Maintenance (retrofit, upgrade or other corrective actions)
    9. Forced Outage (response, diagnostic, logistic, failure repair)
    10. Suspended (scheduled maintenance, planned corrective maintenance, forced outage)
- 11. **Force Majeure**

There is also a 12th information category for when no information is available. The categories of IEC 61400-26-3:2016 (Technical Committee IEC 88, 2016) for wind farms are similar to wind turbines, except one additional in service category called “Ready Standby”. In Figure 1-13 the wind turbine information categories are also visualized.

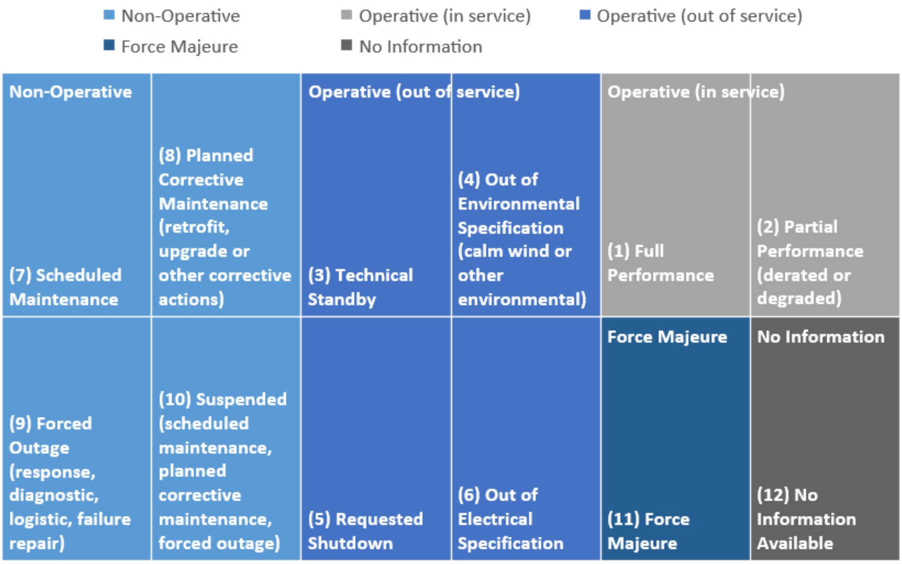


Figure 1-13 Wind turbine information categories according to IEC 61400-26-1:2011 (Technical Committee IEC 88, 2011) *and IEC 61400-26-2:2014* (Technical Committee IEC 88, 2014)

By using IEC information categories, thousands of the OEM define error codes can be categorized by the operation hub into a few IEC defined alarm categories. This allows a less complex dialogue between the wind farm owners and OEMs during the warranty period and facilitates the analysis of offshore wind farm errors.

When a wind turbine fails, an alarm is triggered via the SCADA system. Afterwards, the operators of the operation hub should investigate the alarm as soon as possible to minimize the downtime and lost revenue. If the alarm is not related to a component failure or a scheduled maintenance action, most likely the turbine can be restarted remotely.

If the alarm is related to a component failure, then a maintenance Work Order (WO) should be created in a Computerized Maintenance Management System (CMMS) such as SAP[6]. The WO created by the operation hub, will be added to back-log of maintenance activities of the maintenance hub technicians. In the next section, the maintenance hub and O&M work orders are described in more detail.

[6] https://www.sap.com/products/predictive-maintenance.html

1.2.2.2 Maintenance Hub

A maintenance hub, also known as service centre or service hub, is an onshore and/or offshore facility responsible for execution and logistics of O&M work orders. Offshore wind maintenance hubs are typically located in the closet harbour to a wind farm in which technicians are centralized, spare parts are stored and WOs are scheduled. In case of far offshore wind farms, it is beneficial to have also a secondary bottom-fixed or floating offshore maintenance hub to reduce the access time to the wind farm.

The main purpose of a maintenance hub is the execution of WOs as efficient as possible. As explained in the previous section, a WO is a maintenance task defined in a CMMS and typically created by an operation hub. When it comes to maintenance WOs, the maintenance categories defined in EN 13306:2010 (Technical Committee CEN 319, 2010) and visualized in Figure 1-12 can be translated directly into five different categories of maintenance WOs:

- **Corrective:** corrective unplanned WOs (immediate or deferred)
- **Scheduled:** preventive WOs for planned service of wind turbine components or BoP components (time based or usage based)
- **Condition based:** preventive WOs created when a fault is detected to avoid immediate failures (diagnosis based in which early sign of fault exists)
- **Predictive:** preventive WO created when a fault is predicted to decrease degradation rate and/or avoid future failures (prognosis based in which no sign of fault exists yet)
- **Upgrades:** upgrade WO to enhance the production of the wind turbines by means of aerodynamics upgrade (blade enhancements), rated power boost (controller update), extended cut-out (controller update) or blade de-icing.

The upgrade as the fifth WO category is not defined in EN 13306:2010 (Technical Committee CEN 319, 2010) since this standard is focused mainly on the maintenance and not enhancement of the production. In Figure 1-14, these five WO categories are illustrated.

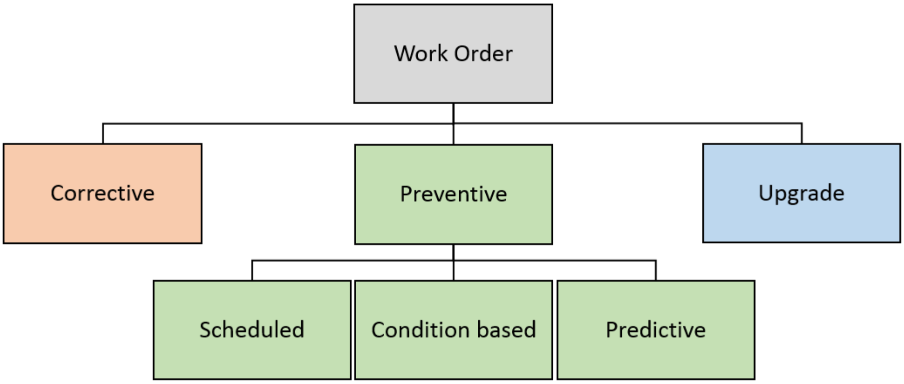


Figure 1-14 Categories of offshore wind maintenance work orders

A maintenance WO can only be successfully executed if the necessary O&M resources are available in the right time. In the next section, an overview of O&M resources is given.

1.2.3. O&M RESOURCES

Maintenance resources are all the necessary logistics that a maintenance hub requires to successfully execute maintenance WOs. In case of offshore wind, O&M resources are typically spares, vessels and technicians, all further explained in the followings.

1.2.3.1 Spare Parts

Spare part is an interchangeable component used for repair or replacement of failed units. According to EN 13306:2010 (Technical Committee CEN 319, 2010) spare part is an "*item intended to replace a corresponding item in order to retain or maintain the original required function of the item*". They are two type of spares, repairable components and consumables, both defined in EN 13306:2010 (Technical Committee CEN 319, 2010):

- **Repairable Item:** "*item which may be restored under given conditions, and after a failure to a state in which it can perform a required function*"
- **Consumable Item:** "*item or material which is expendable, may be regularly replaced and generally is not item specific*"

The repair cost of a repairable component is considerably higher than price of a new component (e.g. main bearing). However, consumables are not repairable or the repair cost is higher than the price of a new component (e.g. sensors).

When a component fails it is crucial to resolve the failure as soon as possible to reduce the downtime and revenue loss. Spare parts are an important part of every maintenance WO. Therefore, it is common to have an inventory of both critical repairable and consumable spare parts in the maintenance hub to reduce the waiting time when a component fails.

1.2.3.2 Vessels

Offshore wind vessels are mainly used for access to the wind farm components and/or support to specific maintenance activities. Offshore wind vessels can be categorized as access or support vessels.

Access Vessels

Access vessels are used for transfer of technicians and/or spare parts from maintenance hubs to offshore wind farms. Transfer of technicians and small spare parts is typically done using a Crew Transfer Vessel (CTV), a Service Operation Vessel (SOV) or a helicopter.

CTVs can be monohull or multihull vessels. The two most common offshore wind multihull CTV types are Catamaran and SWATH. They have both parallel hulls, but with different waterlines. The catamaran vessels have higher speeds, but less stability compared to SWATH vessels. Typically, CTVs have no dedicated access solution and after direct boat landing technicians must climb the support structure ladder to reach the turbine or BoP substation platforms. This is known as bump and jump, which is associated with high safety risk for technicians. A typical CTV can transfer around 10 technicians with 20-30 knots speed when wind speed is lower than 15 m/s and significant wave height is lower than 1.5 meters. An example of a CTV with boat landing access is shown in Figure 1-15.

Figure 1-15 Example of access vessels: CTV top left, helicopter top right and SOV in bottom (offshorewind.biz)

For far and/or large offshore wind farms Service Operation Vessels or SOVs are a more suitable option. A typical SOV can transfer around 40 technicians with 10-20 knots speed when wind speed is lower than 20 m/s and significant wave height is lower than 2 meters. SOVs normally have their own dedicated access gangway on the deck of the vessel. The access gangway acts as a bridge between the deck of the vessel and platform of the turbines or BoP substations. Using an access gangway technicians and sometimes spare parts up to 1 ton can be transferred safely to the platform. An example of a SOV with an access gang way is shown in Figure 1-15.

As explained above, both CTV and SOV are slow and can operate in low significant wave heights. Helicopters can be used to transfer around 5 technicians with 120 km/h speed when the wind speed is lower than 20 m/s with no significant wave height restriction. Helicopters can transfer technicians directly to the top of the nacelle of wind turbines or platforms of the BoP substations. Helicopters can also be used for rescue of injured technicians as the short transfer time becomes very crucial. In Figure 1-15, an example of a helicopter for transferring technicians to the wind turbine nacelle is shown.

It should be noted that helicopters can't transfer any heavy spare part, only tool boxes or very small spare parts. CTVs and SOVs both can transfer spare parts to a certain weight, limited to two lifting capacities. First, the spare part should be transferred from the vessel's deck to the turbine platform. This can be done using the turbine platform crane or using the vessel's crane (if available). Second, if failure has occurred in the nacelle then the spare part should be lifted to the nacelle. This can be done using the nacelle crane. Transport and lifting of heavier spare parts should be done using a support vessel.

Support Vessels

Support vessels are used for specific maintenance activities, such as transfer and lifting of heavy spares parts or major underwater maintenance actions. Support vessels are not typically owned by wind farms since their ownership costs are too high for a single offshore wind farm. Instead, support vessels are chartered once required, which is subject to long lead times.

If the weight of spare part is above the lifting capacity of turbine platform or nacelle cranes, then a jack-up barge is required. Nowadays, depending on the oil and gas market demand, on average it takes a few weeks to charter and mobilize a jack up barge for offshore wind and it costs around 100-200 K€ per day. Typically, the lifting of heavy spares can only be done if wind speed is lower than 10 m/s. In Figure 1-16 an example of a jack-up barge for offshore wind maintenance is shown.

Figure 1-16 Example of support vessels: jack-up barge in left and cable laying vessel in right (offshorewind.biz)

Minor maintenance of subsea cables and foundations can be done by divers, however major repair or replacement of subsea cables is typically done by a cable laying vessel equipped with an ROV. Nowadays, similar to jack up barges on average it takes a few weeks to charter and mobilize a cable laying vessel for offshore wind and it costs around 100-200 K€ per day. A cable laying vessel can typically operate when significant wave height is less than 1.5 meter. An example of a cable laying vessel for offshore wind is shown in Figure 1-16.

1.2.3.3 Technicians

Offshore wind technicians are the human factor side of the resources. Offshore wind technicians should pass at least two set of trainings, a basic safety training and a basic offshore wind maintenance training.

Global Wind Organization (GWO[7]) has developed a standard package for basic safety training. At least in Europe, all offshore wind technicians should be GWO certified, meaning they should pass the first aid, manual handling, fire awareness, working at heights and sea survival trainings. The GWO safety certificates are valid for maximum of two years and they should be renewed to ensure the highest level of safety at all time.

In addition to safety, offshore wind technicians should attend several maintenance trainings. Majority of known OEMs like Vestas[8] or Siemens[9] have developed their own maintenance training modules in which technicians get specialized in a specific turbine platform. There also several third-party trainings which technicians can get specialized in specific type of components (such as mechanical, electrical or structural) or specific access solution (such as rope access for blades or diving for foundations and subsea cables).

In contrary to installation technicians who work 24/7 in two or three working shifts, O&M technicians typically work in one working shift. The only exception to this is when an expensive support vessel is required for the maintenance. In such a scenario, O&M technicians work 24/7 in two or three working shifts to finalize the WO as soon as possible.

In the following section, an introduction into O&M planning of offshore wind farms is given.

[7] http://www.globalwindsafety.org/

[8] https://www.vestas.com/

[9] https://www.siemens.com/global/en/home/markets/wind.html

1.2.4. O&M PLANNING

The O&M planning of offshore wind farms can be long-term (e.g. yearly) or short-term (e.g. weekly or daily). The long-term O&M planning is used during both development and generation phases of an offshore wind farm:

- Development phase: for baseline O&M cost calculation used in the LCoE estimation of the tender bid based on an optimal O&M strategy
- Generation phase: for optimal EoW (to continue OEM warranty or to do the maintenance in-house) and EoL (to do lifetime extension, repowering or full dismantling) decision making and for optimization of shared O&M resources of the maintenance hub based on the available historical maintenance data

Within short-term planning, the scheduling, prioritization and estimated costs of outstanding WOs can be determined and optimal preventive WOs to reduce future corrective failures can be defined.

In Chapter 4 of this thesis long-term O&M planning and in Chapter 5 short-term O&M planning within several illustrative case studies are further explained.

1.3. THESIS STATEMENT

Now that a thorough introduction into current status of offshore wind O&M and its challenges is presented, the thesis statement can be defined. In the followings, first the objective of the thesis and thesis approach for achieving this objective are explained and then, a literature review on the state of the art of the thesis approach is given. In the last part, the outline of the following chapters of this thesis is briefly described.

1.3.1. OBJECTIVE

As explained in the introductory sections 1.1 and 1.2 of this chapter, the offshore wind can be a subsidy free and solid business case only if its LCoE is reduced to its minimum. The objective of this thesis is:

> “to define and demonstrate rational and applied solutions for reducing direct and indirect O&M costs of an offshore wind farm based on all available information and system criteria, given its reliability and performance”

It was discussed that LCoE can be optimized by balancing the CAPEX, OPEX and AEP. In other words, this thesis aims to provide applied methods for reducing OPEX (by reducing direct O&M costs) and increasing AEP (by reducing production loss due to unavailability or i.e. by reducing in-direct O&M costs) of an offshore wind farm, based on all available information, decision rules and targets, assuming more reliable offshore wind components cannot be used and power production performance of wind turbines cannot be increased.

1.3.2. APPROACH

The direct and indirect O&M costs of an offshore wind farm can be significantly reduced if both short-term and long-term O&M planning are optimized. As already discussed in 1.2.4, by optimized long-term O&M planning, optimal EoW and EoL decisions can be made and shared O&M resources of the maintenance hub can be optimized. Furthermore, by optimized short-term O&M planning, sufficient condition based and predictive WOs can be introduced to avoid future corrective failures and scheduling and prioritization models can be used to execute outstanding WOs as efficient as possible, leading to minimum direct and indirect O&M costs.

Optimization of long-term and short-term O&M planning can be done by modelling wind farm components based on their reliability and by making optimal decisions using risk based models. Therefore, the approach of this thesis for achieving its goal can be summarised into:

> “to optimize both long-term and short-term O&M planning of an offshore wind farm, using risk and reliability models based on all available information and system criteria”

In the past decades, O&M planning of offshore wind farms based on risk or reliability models is discussed in several academic studies. In the following section, a literature review on the past studies on this subject is given.

1.3.3. STATE OF THE ART

To date, the majority of offshore wind O&M literatures are focused on lifetime O&M cost estimation methods and/or theoretical O&M planning models, which are not applicable for large scale offshore wind farms with high level of complexity. On the other hands, only a handful of studies exist, in which an applied method for optimal O&M planning of complex offshore wind farms based on all available information and system criteria is introduced and uncertainties of unknown or stochastic variables are taken into account.

In (Shafiee & Sørensen, 2017) a systematic literature study on 246 publications focused in maintenance optimization of wind energy assets is given. The publication classification framework used in this study is based on the wind asset type, planning horizon, failure model, maintenance policy, solution technique and solution effectiveness of publications. The authors in (Shafiee & Sørensen, 2017) have concluded that for O&M planning of large wind farms a shift from theoretical research to applied research applicable for the industry is required, in which all available information regarding system reliability, failure mechanisms, methods of failure detection, and inspection and maintenance costs can be incorporated into one model.

As discussed in thesis approach, the optimal long-term and short-term solutions in this thesis are based on risk and reliability models. In (Welte & Wang, 2013), an overview on classical reliability models for lifetime estimation of wind turbine components is given. The authors in (Welte & Wang, 2013), have classified wind turbine reliability models into stochastic, physical, data-driven or combined models, all based on time to failure principle and applicable mainly for mechanical and electrical components of wind turbine drivetrain. In (Bagheri, Alizadeh, Nadarajah, & Deiri, 2016), (Gray & Watson, 2010) and (Guo, Watson, Tavner, & Xiang, 2009) stochastic reliability models based on Weibull distribution, Gamma distribution and Poisson process are discussed. In (Ber & Sørensen, 2016), (Escobet, Sanchez, Sankararaman, & Escobet, 2016), (J. J. Nielsen & Sørensen, 2011) and (Nijssen, 2006) the application of physics based reliability models based on Pars' law, S-N curves and fracture mechanics models is discussed. In (Le & Andrews, 2016) and (Garcia, Sanz-Bobi, & del Pico, 2006) examples of data-driven and artificial intelligence reliability models for wind turbine components are given. Furthermore, in (An, Choi, Kim, & Pattabhiraman, 2011), (J. J. Nielsen & Sørensen, 2011), (Straub, 2009) and (Shafaghi, 2008) Bayesian updating of stochastic and physics based reliability models based on inspection and monitoring data is discussed.

Similarly, several studies on probabilistic reliability modelling of offshore wind structural components are done, in which failure modes of structural components in terms of detailed limit state equations are defined and stochastic models for uncertain load and strength parameters are stablished. In (Stensgaard Toft, Branner, Nijssen, Lekou, & Pueyo, 2013) ultimate, fatigue, buckling and deflection limit states of wind turbine blades are defined and reliability estimation by structural reliability methods such as First Order Reliability Methods (FORM), Second Order Reliability Methods (SORM) and simulation techniques (e.g. Monte Carlo) is discussed. In (Sørensen, 2017) application of structural reliability models for O&M planning of offshore wind blades is presented. In (Thöns, 2012) a framework for probabilistic reliability assessment of offshore wind structures is defined and discussed in detail.

The cost estimation of offshore wind O&M is discussed within several academic studies, however, limited academic attention is paid into scheduling and prioritization of maintenance work orders. In (Asgarpour & Sørensen, 2015) and (Hofmann, 2011) an overview of existing offshore wind O&M cost models is given. In (Dinwoodie, Endrerud, Hofmann, Martin, & Sperstad, 2015) a comparison between different offshore wind O&M costs models based on several case studies is given.

The diagnostic, prognostic, condition based and predictive maintenance of offshore wind farms are also discussed within several studies. In (Coronado & Fischer, 2015) and (Tchakoua et al., 2014) an overview of the state of the art, new trends and future challenges of diagnostic techniques and condition monitoring of wind turbines is given. In (El-Thalji & Jantunen, 2012) requirements for development condition base maintenance strategies for offshore wind farms are discussed. In (Novaes, Leite, Maurício, André, & Rosas, 2018) a review on prognostic techniques applicable for maintenance of wind turbines is given. In (Canizo, Onieva, Conde, Charramendieta, & Trujillo, 2017) and (Yildirim, Gebraeel, & Sun, 2017) application of predictive maintenance for short-term O&M planning of offshore wind farms within case studies is discussed.

As briefly explained in section 1.3.2, in this thesis, Bayesian based reliability models and applied risk based decision models are used for optimal long-term and short-term O&M planning of offshore wind farms. In the next section, the outline of the thesis is briefly discussed.

1.3.4. OUTLINE

In Chapter 2 and Chapter 3 of this thesis several risk and reliability models are defined and then, in Chapter 4 and Chapter 5 the optimization of long-term and short-term O&M planning based on the developed risk and reliability models is explained. In Figure 1-17, an overview of the thesis' structure is given.

In Chapter 2, first failure and degradation mechanisms of offshore wind components are discussed then, applied failure, degradation and remaining useful lifetime models are developed. Additionally, several methods based on Bayes' rule for updating the initial reliability models using observations are proposed.

In Chapter 3, risk based cost, scheduling and prioritization models for optimization of long-term and short-term O&M planning are proposed. The scheduling model is based on resource and maintenance matrices and can be used to schedule any given list of maintenance work orders. The work order expected costs can be estimated using developed cost model. The prioritization model is based on defined time or cost targets and can be used to optimize the execution of a given list of outstanding work orders.

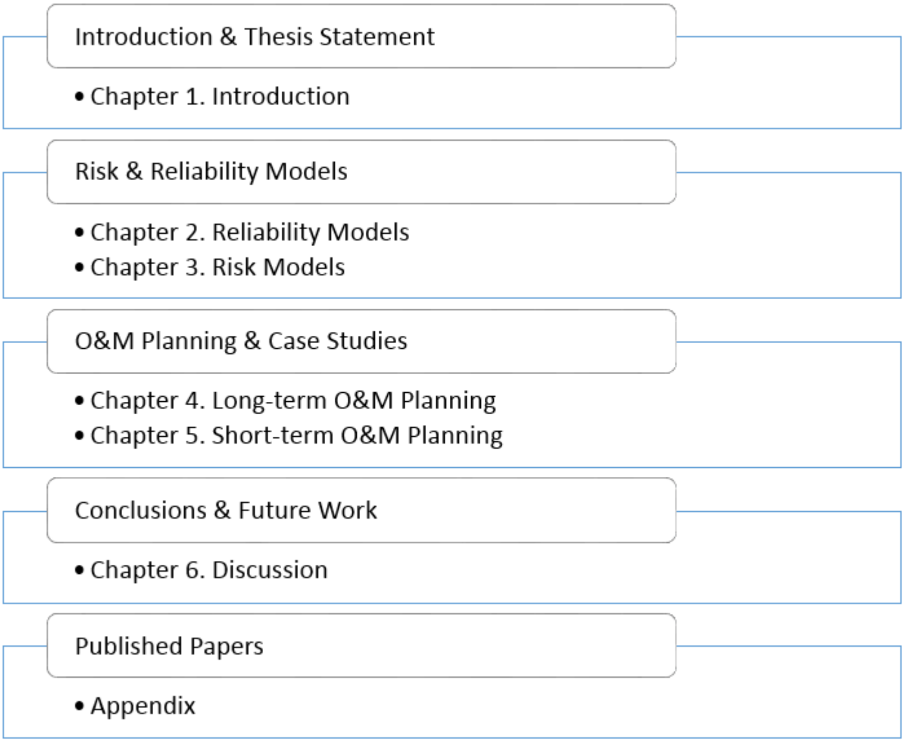


Figure 1-17 Outline of the thesis

In Chapter 4, first long-term O&M planning of offshore wind farms is further described and then, within a case study the baseline O&M strategy of a reference offshore wind farm is determined. Furthermore, updating the O&M strategy based on available maintenance history during operational years of an offshore wind farm is explained.

In Chapter 5, first short-term O&M planning is discussed in detail and then, short-term planning of corrective, condition based and predictive maintenance work orders within several illustrative examples is explained.

In Chapter 6, conclusions on the implemented approach for achieving the thesis' objective are given and several recommendations for future studies on this topic are proposed. In Appendix A, Appendix B, Appendix C and Appendix D the abstracts of papers enclosed to this thesis are given.

CHAPTER 2. RELIABILITY MODELS

In an O&M planning model, the offshore wind components are presented by their reliability. According to EN 13306:2010 (Technical Committee CEN 319, 2010) reliability is "*ability of an item to perform a required function under given conditions for a given time interval*". Reliability of wind farm components can be modelled using failure or degradation models. The failure models (also known as black box models) can only identify the probability of a component being in healthy or failed states, at a given time. However, the degradation models (also known as glass or white box models) can identify the degradation level of a component at any given time. Furthermore, once degradation of a component is known, the component lifetime and RUL can be estimated. In the followings, failure and degradation reliability models are discussed in detail.

2.1. FAILURE MODEL

According to EN 13306:2010 (Technical Committee CEN 319, 2010), failure is "termination of the ability of an item to perform a required function" and can be categorized based on its cause, mode, mechanism, severity or criticality:

- **Failure cause:** "*circumstances during specification, design, manufacture, installation, use or maintenance that result in failure*"
- **Failure mode:** "*manner in which the inability of an item to perform a required function occurs*"
- **Failure mechanism:** "*physical, chemical or other processes which may lead or have led to failure*"
- **Severity:** "*potential or actual detrimental consequences of a failure or a fault*". Also, it is noted that "*the severity of a failure may be related to safety, availability, costs, quality, environment, etc*"
- **Criticality:** "*numerical index of the severity of a failure or a fault combined with the probability or frequency of its occurrence*". Also, it is noted that "*the numerical index in this context may be defined, for example, as an area in the frequency of failure occurrence - severity matrix diagram*"

2.1.1. FAILURE MODELLING

The failure modelling of a component depends on the component type. Similar to spare part types discussed in section 1.2.3.1 of the previous chapter, main wind farm components can be categorized as non-repairable and repairable.

2.1.1.1 Non-repairable Components

Non-repairable components are components which cannot be repaired and are discarded upon a failure, such as sensors. In Figure 2-1, an example of failure of four identical non-repairable components is shown.

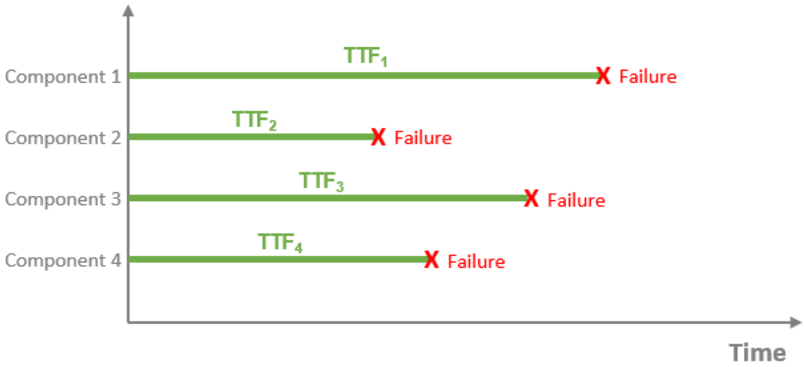


Figure 2-1 Example of failure of non-repairable components

In Figure 2-1 it can be seen that Time To Failure (TTF) or survival time of each component is a random variable. The Mean TTF or MTTF of a non-repairable component can be calculated by several run to failure tests on identical components. Then, the MTTF can be calculated as:

$$MTTF = \frac{1}{n}\sum_{i=1}^{i=n} TTF_i \tag{2.1}$$

- $MTTF(t)$ as the mean time to failure of a non-repairable component
- TTF_i as the survival time or time to failure of component i
- n as the total number of identical non-repairable components in the run to failure test

The average failure rate (λ) of non-repairable components is:

$$\lambda = {}^{1}/_{MTTF} \tag{2.2}$$

2.1.1.2 Repairable Components

Repairable components are components which can be repaired and reused upon a failure, such as a drivetrain bearing. In Figure 2-2, an example of failures of a repairable component is shown.

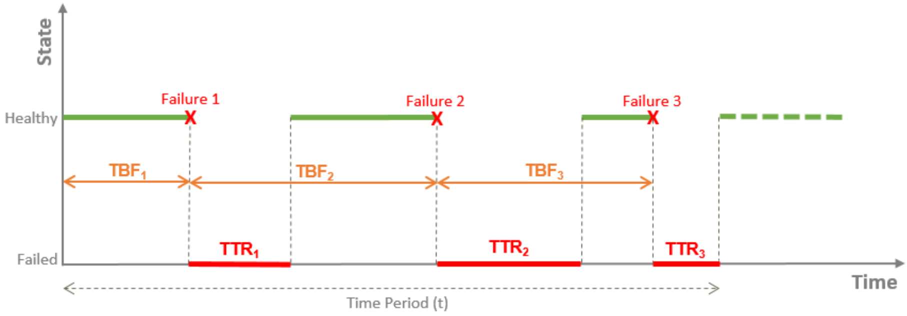


Figure 2-2 Example of failures of a repairable component

As shown in Figure 2-2, it can be seen that Time Between Failure (TBF) and Time To Repair (TTR) of failures of a repairable component is a random variable. The Mean TTR and Mean TBF of a repairable component can be calculated based on operational data of one or several identical components:

$$MTBF = \frac{1}{n}\sum_{i=1}^{i=n} TBF_i \tag{2.3}$$

- $MTBF$ as the mean time between failures of a repairable component
- TBF_i as the time between occurrence of failure i and previous failure (or beginning of lifetime)
- n as the total number of failures occurred in one or several identical repairable components

For repairable components, the average failure rate can be calculated as:

$$\lambda = {}^{1}\!/_{MTBF} \tag{2.4}$$

The wind farm components in this thesis are modelled as repairable components. The uncertainty of the failure rate of a repairable component can be modelled by a Weibull or Gamma distribution. As instance, the PDF of a Gamma distributed failure rate model is (Bronshtein et al., 2015):

$$f(\lambda) = \frac{\beta^\alpha}{\Gamma(\alpha)}\lambda^{\alpha-1}e^{-\beta\lambda} = \frac{\beta^\alpha}{\Gamma(\alpha)}\lambda^{\alpha-1}e^{-\beta\lambda} = \frac{\beta^\alpha}{(\alpha-1)!}\lambda^{\alpha-1}e^{-\beta\lambda} \tag{2.5}$$

- $f(\lambda)$ as PDF of Gamma distributed failure rate
- α as Gamma distribution shape factor
- β as Gamma distribution scale factor

Then, the mean and standard deviation of failure rate can be calculated as:

$$\mu_\lambda = {}^{\alpha}/_{\beta} = {}^{1}/_{MTBF}$$
$$\sigma_\lambda = {}^{\alpha}/_{\beta^2} \tag{2.6}$$

Now that the failure rate of wind farm component as a stochastic variable is defined, the probability of component failure at a given time can be calculated. The probability of a component failure can be modelled using several stochastic distributions such as exponential, Gamma or Weibull distributions. In (Welte & Wang, 2013), an overview of stochastic models for probability of failure modelling of wind turbine components is given.

In this thesis, probability of a component failure is modelled using Cumulative Distribution Function (CDF) of an exponential distribution (Bronshtein et al., 2015):

$$P(failure|t) = 1 - e^{-\lambda(\alpha,\beta)\times t} \tag{2.7}$$

- $P(failure|t)$ as probability of a component failure at time t
- $\lambda(\alpha, \beta)$ as the stochastic failure rate of the component modelled by a Gamma distribution with α and β as its shape and scale factors

In Figure 2-3, an example of the probability of failure at four different quantiles of a failure rate model of a component based on Equation (2.7) is illustrated.

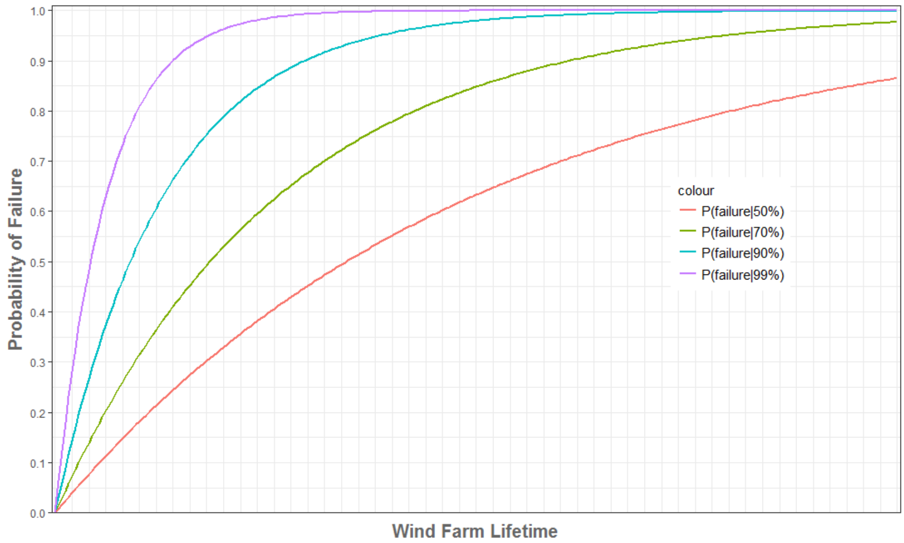


Figure 2-3 Example of probability of a component failure at four quantiles

The probability of failure of wind farm components varies from one failure type to another. According to EN 13306:2010 (Technical Committee CEN 319, 2010) they are three types of failures:

- **Wear-out failure:** "*failure whose probability of occurrence increases with the operating time or the number of operations of the item and the associated applied stresses*"
- **Ageing failure:** "*failure whose probability of occurrence increases with the passage of calendar time*". Also, it is noted that "*this time is independent of the operating time of the item*"
- **Sudden failure:** "*failure that could not be anticipated by prior examination or monitoring*"

In other words, probability of occurrence of a failure can increase with the operating time/level of a component (wear-out failure) and/or simply the age of a component (ageing failure) or without any relation to the age or operating time/level of a component (sudden failure).

Failures of wind farm components could be wear-out failures, sudden/random failures or infant mortality failures. The latter is not described in EN 13306:2010 (Technical Committee CEN 319, 2010). Infant mortality failures are typically caused by manufacturing or installation flaws and by time their failure rate gets decreased. In Figure 2-4, the three failure types of wind turbine components and variation of their probability of occurrence by time are illustrated.

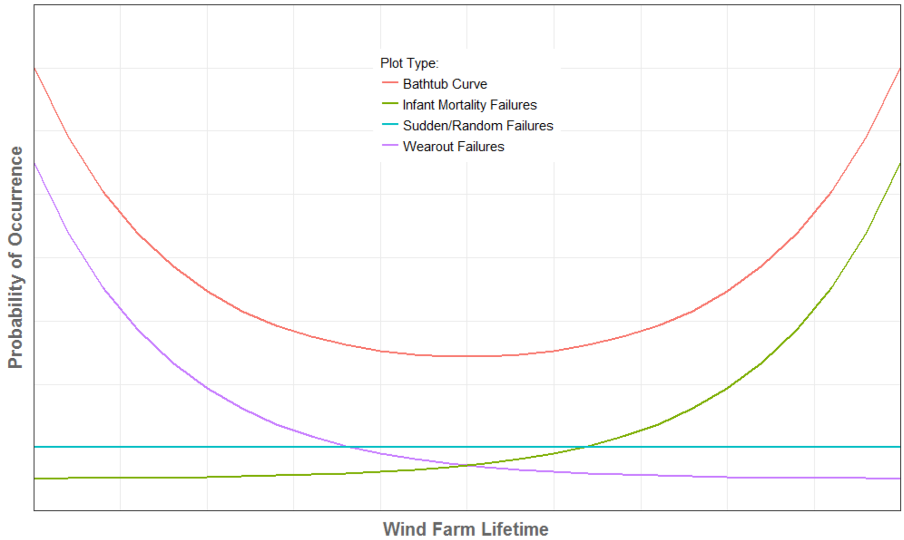


Figure 2-4 Failure types and their probability of occurrence of wind farm components

In Figure 2-4 also a fourth plot named “Bathtub Curve” is plotted in red. The bathtub curve is the summation of all average failure rates in any time stamp. The bathtub curve has a bathtub shape, meaning that during early years of a wind farm lifetime (e.g. first 5 years) the total averaged failure rate of wind farm components is decreasing, then during mid-years of a wind farm lifetime (years 5 to 20), the total averaged failure rate is almost constant and at last, during the last years of a wind farm lifetime (e.g. last 5 years), the total averaged failure rate of wind farm components is increasing.

2.1.2. UPDATING FAILURE MODEL

The failure rates of wind farm components initially are taken from O&M data of similar operational offshore wind farms. Once the offshore wind farm starts the operation and enough O&M data are gathered, the initial assumed failure rates can be updated.

The posterior failure rate model of a prior Gamma distributed failure rate model is also Gamma distributed. The shape and scale factors of the posterior failure rate model given some failure observation based on Bayes’ rule (Shafaghi, 2008) are:

$$\begin{aligned} \alpha_{posterior} &= \alpha_{prior} + n \\ \beta_{posterior} &= \beta_{prior} + t \end{aligned} \tag{2.8}$$

- $\alpha_{posterior}$ as shape factor of posterior Gamma distributed failure rate model
- α_{prior} as shape factor of prior Gamma distributed failure rate model
- n as number of failures observed in time period t
- $\beta_{posterior}$ as scale factor of posterior Gamma distributed failure rate model
- β_{prior} as shape factor of prior Gamma distributed failure rate model

Furthermore, based on Equation (2.6) the posterior mean and standard deviation of the failure rate model of a component is:

$$\begin{aligned} \mu_{\lambda_{posterior}} &= {\alpha_{posterior}}/{\beta_{posterior}} \\ \sigma_{\lambda_{posterior}} &= {\alpha_{posterior}}/{\beta_{posterior}^2} \end{aligned} \tag{2.9}$$

In Figure 2-5, an example of quantiles of the prior and posterior failure rate models of a component together with their average failure rates are visualized.

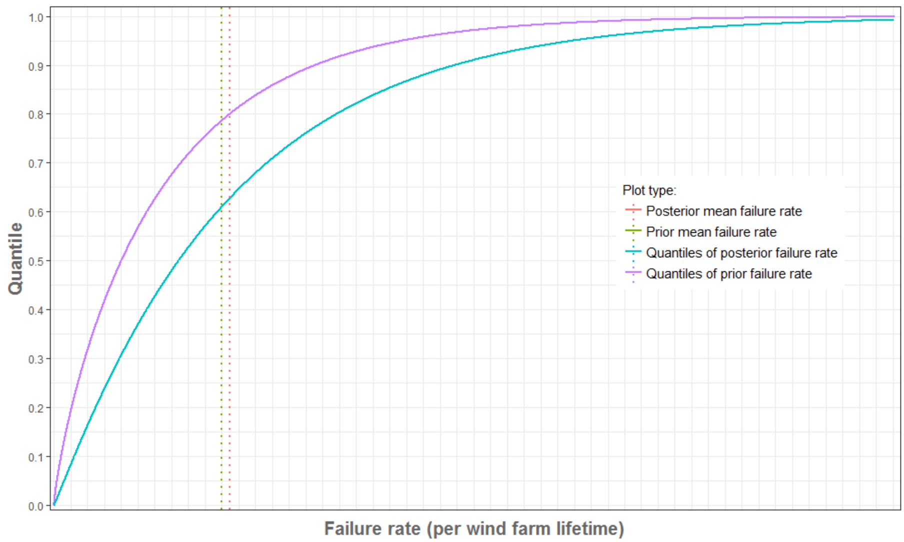


Figure 2-5 Example of prior and posterior Gamma distributed failure rate quantiles

2.1.3. FAILURE BASED RELIABILITY

Now that stochastic probability of a component failure at a given time is known, reliability of the component can be written as:

$$R(t) = 1 - P(failure|t) = e^{-\lambda(\alpha,\beta)\times t} \qquad (2.10)$$

- $R(t)$ as failure based reliability of a component at time t

In Figure 2-6, an example of failure based reliability of a wind farm component at four different quantiles is shown.

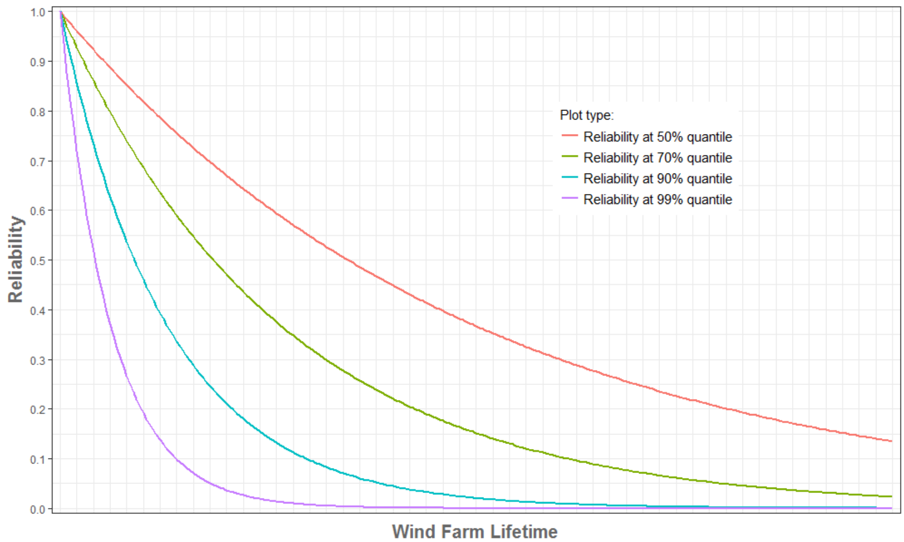


Figure 2-6 Example of failure based reliability of a component failure at three quantiles

In the following section, degradation modelling and degradation based reliability together with component lifetime and RUL estimations are discussed.

2.2. DEGRADATION MODEL

As discussed in the previous section, the failure based reliability models known as black box models can only determine the failure probability of a component at a given time. However, degradation based reliability models known as glass or white box models can determine discrete or continuous degradation level of a component at any given time. In the followings, first degradation modelling is discussed and then, a model for Bayesian updating of initial degradation model is proposed.

2.2.1. DEGRADATION MODELLING

According to EN 13306:2010 (Technical Committee CEN 319, 2010) degradation is "*detrimental change in physical condition, with time, use or external cause*". If a component's degradation is gradual, observable and measurable, then its reliability based on a degradation model can be determined. In (Welte & Wang, 2013), an overview of stochastic, physical and data-driven models for degradation modelling of wind turbine components is given. In this thesis, degradation of a component is modelled using an exponential function:

$$D(t) = \beta(\mu, \sigma) \times e^{\alpha t} \qquad (2.11)$$

- $D(t)$ as degradation level of a component at time t
- β as the stochastic scale factor modelled by a normal distribution $\beta(\mu, \sigma)$
- α as the shape factor

The initial shape factor of an exponential degradation model can be assumed. The shape factor of an exponential degradation model of a component determines how gradual the degradation of a component is and how much initial degradation due to manufacturing or installation flaws a new component has.

The smaller shape factors are associated with more gradual degradation process of a component and bigger shape factors are associated with less gradual degradation process. In Figure 2-7, an example of exponential degradation model of a component base on three different shape factors is shown.

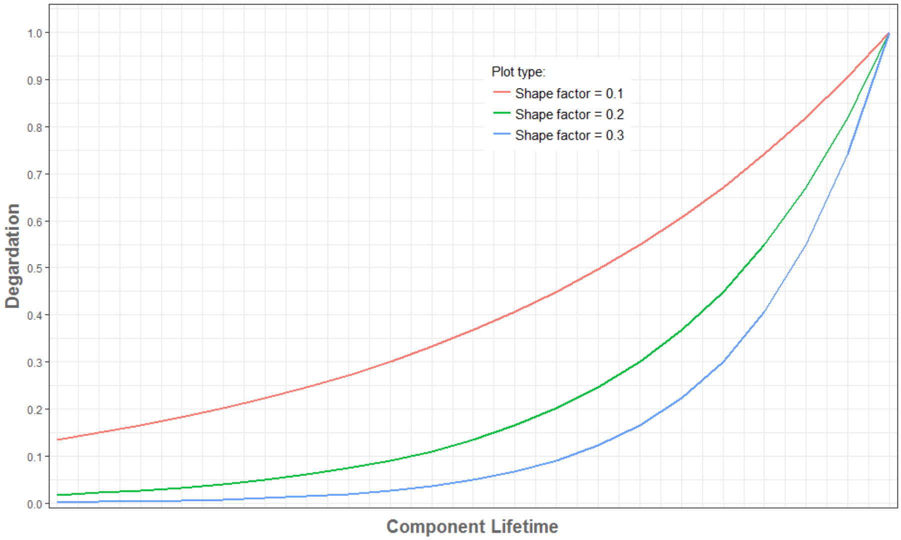


Figure 2-7 Example of degradation model of a component based on different shape factors

Now that initial shape factor is known, the mean and standard deviation of initial normal distributed scale factor can be calculated as:

$$D\left(t \approx {}^{1}/_{\lambda(\mu,\sigma)}\right) = 1 \xrightarrow{then} \beta(\mu,\sigma) = {}^{1}\Big/_{e^{\alpha/\lambda(\mu,\sigma)}} \longrightarrow$$

$$\mu_\beta = {}^{1}\Big/_{e^{\alpha/\mu_\lambda}} \qquad (2.12)$$

$$\sigma_\beta = {}^{1}\!/_{e^{\alpha/\sigma_\lambda}}$$

- λ as the Gamma distributed failure rate model of a component

Now that exponential degradation model of a component is known, the component lifetime and remaining useful lifetime based on the component degradation model can be estimated.

2.2.2. COMPONENT LIFETIME

By assuming degradation level of 1.0 once a component fails, the lifetime of a component based on its exponential degradation model is:

$$D(t) = \beta(\mu,\sigma)e^{\alpha t} = 1 \xrightarrow{then} LT = {}^{-ln\,\beta(\mu,\sigma)}\!/_{\alpha} \tag{2.13}$$

- LT as the component lifetime

2.2.3. COMPONENT RUL

Similarly, a component Remaining Useful Lifetime (RUL) based on its degradation model can be calculated as:

$$RUL(t) = LT - t = \left[{}^{-ln\,\beta(\mu,\sigma)}\!/_{\alpha}\right] - t \tag{2.14}$$

In (J. S. Nielsen & Sørensen, 2017), a more accurate Bayesian based model for RUL estimation of wind turbine blades is presented.

2.2.4. UPDATING DEGRADATION MODEL

The initial scale factor of exponential degradation model of a component can be updated once observations on degradation level or failures of that component are known. In the followings, updating of the shape and scale factors for each observation type is discussed in detail.

2.2.4.1 Observed Degradation

The degradation level of a component can be observed by using a Degradation Matrix to translate the inspection outcome into discrete degradation levels of that component. In Table 2-1, an example of such a degradation matrix for a wind turbine main bearing is given.

Component	Observed Damage	Estimated Degradation
Bearing		
	No damage	0 - 0.2
	Micro pitting	0.2 - 0.4
	Debris damage	0.4 - 0.6
	Edge loading	0.6 - 0.8
	Cage damage	0.8 - 1.0

Table 2-1 Example of degradation matrix for inspection of bearings (Asgarpour & Sørensen, 2017)

As instance, the degradation observation associated with edge loading of a main bearing reported by three individual technicians can be assumed as 0.65, 0.8 and 0.6. Then, assuming shape factor of 0.4 for main bearing degradation model, the mean observed scale factor associated with each observation is:

$$\begin{aligned} \mu_{\beta,observation\ 1} &= {}^{D}/_{e^{\alpha}} = {}^{0.65}/_{e^{0.4}} = 0.436 \\ \mu_{\beta,observation\ 2} &= {}^{D}/_{e^{\alpha}} = {}^{0.8}/_{e^{0.4}} = 0.536 \\ \mu_{\beta,observation\ 3} &= {}^{D}/_{e^{\alpha}} = {}^{0.6}/_{e^{0.4}} = 0.402 \end{aligned} \qquad (2.15)$$

Thus, the observed mean and standard deviation of these normal distributed scale factors can be determined as:

$$\beta(\mu_{observed}, \sigma_{observed}) = \beta(0.458, 0.0696) \qquad (2.16)$$

Now that the mean and standard deviation of the observed scale factor are known, using the Bayes' rule and Normal-Normal model (Jacobs, 2008), the posterior scale factor of the degradation model of this component can be calculated as:

$$ {}^{1}/_{\sigma^2_{posterior}} = {}^{1}/_{\sigma^2_{prior}} + {}^{1}/_{\sigma^2_{observed}} \qquad (2.17)$$

$$\mu_{posterior} = \frac{1/\sigma^2_{prior}}{1/\sigma^2_{posterior}} \times \mu_{Prior} + \frac{1/\sigma^2_{observed}}{1/\sigma^2_{posterior}} \times \mu_{observed}$$

- $\sigma_{\text{Posterior}}$ as the standard deviation of the posterior scale factor
- $\mu_{\text{Posterior}}$ as the mean of the posterior scale factor
- σ_{Prior} as the standard deviation of the prior scale factor given in Equation (2.12)
- μ_{Prior} as the mean of the prior scale factor shown in Equation (2.12)
- σ_{Observed} as the standard deviation of the observed scale factor given in Equation (2.16)
- μ_{Observed} as the mean of the observed scale factor given in Equation (2.16)

Now that posterior scale factor is known, the updated shape factor of this degradation model can be calculated as:

$$D\left(t \approx 1/\lambda(\mu,\sigma)\right) = \beta(\mu,\sigma)e^{\alpha t} = 1 \xrightarrow{then}$$
$$\alpha_{posterior} = -\mu_\lambda \, ln \, \mu_{\beta,posterior} \tag{2.18}$$

Therefore, the Bayesian updated posterior exponential degradation model of this component is formulated as:

$$\beta(\mu_{Posterior}, \sigma_{Posterior}) \times e^{\alpha_{posterior} t} \tag{2.19}$$

Instead of observed degradation, the observed failures of a component can be used to update its exponential degradation model.

2.2.4.2 Observed Failures

As discussed in section 2.1.2, once observations on component failures are available, the Gamma distributed failure rate model can be update. Then, using updated failure rate model given in Equation (2.9), the posterior mean and standard deviation of the scale factor based on Equation (2.12) becomes:

$$\mu_{\beta,posterior} = 1/e^{\alpha/\mu_{\lambda,posterior}}$$
$$\sigma_{\beta,posterior} = 1/e^{\alpha/\sigma_{\lambda,posterior}} \tag{2.20}$$

Similar to Equation (2.18), the updated shape factor of degradation model of this component becomes:

$$\alpha_{posterior} = -\mu_{\lambda,posterior} \ln \mu_{\beta,posterior} \tag{2.21}$$

2.2.5. DEGRADATION BASED RELIABILITY

Now that degradation of a component at a given time is known, reliability of that component can be written as:

$$R(t) = 1 - D(t) \tag{2.22}$$

- $R(t)$ as degradation based reliability of a component at time t

It should be noted in Equation (2.22) it is assumed that reliability of a component is directly related to its degradation, which is not entirely true for some component types.

In Paper IV (Asgarpour & Sørensen, 2017) of this thesis, within a case study the application of exponential degradation models for fault prediction of offshore wind components is discussed in detail.

CHAPTER 3. RISK MODELS

The associated risk of O&M planning models is presented by risk models. Relevant risk types associated with O&M planning of offshore wind farms are financial, environmental, health and safety risks. In this thesis, financial risks (e.g. O&M costs) are modelled using a cost model and other risk types are presented by user defined decision rules in scheduling and prioritization models (e.g. no wind turbine access if significant wave height is higher than 1.5 meter to reduce health and safety risks and no subsea cable maintenance in migration period of marine mammals to reduce environmental risk). In Figure 3-1, an overview of risk based cost, scheduling and prioritization models defined in this chapter is given.

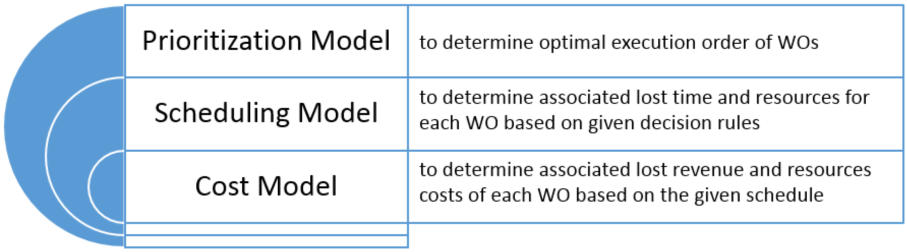


Figure 3-1 Overview of risk based models defined in this chapter

As shown in Figure 3-1, all three risk based models developed in this chapter are interconnected. The O&M cost model is used into the O&M scheduling model and the O&M scheduling model is used into the O&M prioritization model.

3.1. COST MODEL

During the development phase of an offshore wind farm it is required to estimate the lifetime O&M costs as part LCoE calculation. Moreover, during the generation phase of an offshore wind farm for scheduling and prioritization of maintenance WOs, the expected costs of each WO should be known. In Figure 3-2 framework of a risk based cost model is given, which can be used for estimation of both long-term O&M costs and short-term WO costs.

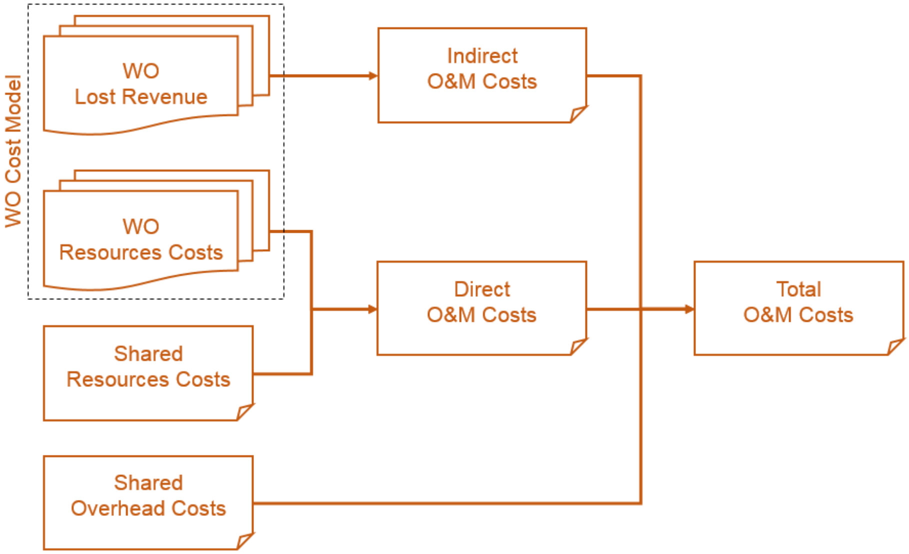


Figure 3-2 Framework of a risk based O&M cost model

In the followings first, WO costs are discussed and then, an overview into total long-term and short-term O&M costs of an offshore wind farm is given.

3.1.1. WO COSTS

The costs of a WO can be direct or indirect. The direct WO costs are associated with required resources of a WO and indirect WO costs are associated with its duration. Therefore, a WO costs can be formulated as:

$$C_{WO} = C_{WO.Dir} + C_{WO.Ind} \tag{3.1}$$

Once the estimated required resources and duration of a WO are known, the direct and indirect WO costs can be calculated.

3.1.1.1 Direct WO Costs

Besides spares and shared O&M resources available in the maintenance hub, each WO might require specific technicians or support vessels. The summation of WO spares cost and associated costs of WO specific resources is known as direct WO costs and can be calculated as:

$$C_{WO.Dir} = C_V + C_T + C_S \tag{3.2}$$

- C_V as cost of WO specific vessels such as jack up barge or cable laying vessel

- C_T as cost of WO specific technicians such as access or reliability specialists
- C_S as cost of spares used in a WO

3.1.1.2 Indirect WO Costs

Indirect WO cost is the revenue loss due to the production loss of wind turbine(s) affected by that WO. Indirect WO cost is the product of lost energy and cost of electricity during downtime period of a WO:

$$C_{WO.Ind} = E_{Loss} \times (C_E + S_E) \tag{3.3}$$

- E_{Loss} as energy loss during downtime period of a WO
- C_E as daily market electricity price during downtime period a WO in currency/Wh
- S_E as wind farm specific subsidy in currency/Wh to match a promised electricity price

Normally the governmental offshore wind subsidies are only paid out in early years of a wind farm's lifetime (e.g. first 5 years). After end of the subsidy scheme, the subsidy parameter in Equation (3.3) can be set to zero.

If a WO is wind turbine based then only power of one wind turbine is lost. However, if a WO is BoP based, then several or all wind turbines are shut down and therefore, the lost energy is much higher. If the wind speed measurements at hub height during the downtime of a WO is known, then using wind turbine PV curve (such as the one given in Figure 1-9) the WO lost power and subsequent WO lost energy can be simply calculated.

The main key to E_{Loss} calculation is to estimate the WO downtime as accurate as possible. From the moment that a wind turbine is shut down for maintenance (automated by alarms or manually by operation hub) until the moment that the WO is finalized the wind farm suffers from lost production. This time interval is known as downtime and can be calculated as:

$$T_{Downtime} = T_{Preparation} + T_{Resources} + T_{WorkingShift} + T_{Weather} + T_{Transfer} + T_{WO} \tag{3.4}$$

- $T_{Preparation}$ as the time required to identify the maintenance type and required resources
- $T_{Resources}$ as the waiting time for WO specific resources as defined by Equation (3.5)
- $T_{WorkingShift}$ as the waiting time for start of the next working shift

- $T_{Weather}$ as the waiting time for a suitable weather window when all vessels can operate and all exterior maintenance activities such as rope access can be performed
- $T_{Transfer}$ as the transfer time from the onshore or offshore maintenance hub to the WO location or vice versa
- T_{WO} as the WO duration which is the time spent to access and maintain a component

$$T_{Resources} = max(\,T_{WaitingVessel}, T_{WaitingSpares}, T_{WaitingTechnician}) \qquad (3.5)$$

- $T_{WaitingVessel}$ as the waiting time for required access and/or support vessels to become available
- $T_{WaitingSpares}$ as the waiting time for required spares to become available if they are not available in the inventory
- $T_{WaitingTechnician}$ as the waiting time for required number of technicians to become available if all technicians are occupied

In Figure 3-3, the downtime of a corrective maintenance WO based on Equation (3.4) is illustrated.

Figure 3-3 Downtime of a corrective maintenance work order

In Figure 3-3 it is assumed that the WO can be finalized in one attempt. However, if WO duration T_{WO} is bigger than the available weather window in a working shift, then the WO should be executed in parts within several different working shifts.

It should be noted that Equation (3.4) holds true only for corrective WOs and not for preventive or upgrade WOs. In case of preventive WOs, preparation, waiting for resources, waiting for suitable weather windows and transfer can be done in advance and the wind turbine is set off manually only when the technicians want to access the maintenance location. Therefore, the Equation (3.4) can be simplified to:

$$T_{Downtime} = T_{WO} \qquad (3.6)$$

In Figure 3-4, the downtime of a preventive maintenance WO based on Equation (3.6) is shown.

Figure 3-4 Downtime of a preventive maintenance work order

It can be easily seen that the overall costs of preventive WOs are considerably lower than corrective ones since the wind turbine downtime is much lower.

3.1.2. SHORT-TERM O&M COSTS

Now that WO costs are known, the short-term O&M costs for a given set of known maintenance WOs can be easily calculated. As discussed in section 1.1.3.3 and visualized in Figure 3-2, the total O&M cost is a summation of direct, indirect and overhead costs:

$$C_{OM} = C_{OM.Dir} + C_{OM.Ind} + C_{OH} \tag{3.7}$$

The direct O&M costs is the summation of direct WOs' costs and fixed costs of shared O&M resources:

$$C_{OM.Dir} = \sum_{i=1}^{i=N} C_{WO.Dir_i} + C_{OM.Res} \tag{3.8}$$

- $C_{WO.Dir_i}$ as direct WO costs of WO number i
- N as total number of executed WOs
- $C_{OM.Res}$ as fixed costs of shared O&M resources such as technicians, access vessels and spare part inventory

Similarly, the indirect O&M costs is equivalent to indirect WOs' costs:

$$C_{OM.Ind} = \sum_{i=1}^{i=N} C_{WO.Ind_i} \tag{3.9}$$

As explained before, overhead costs are staff, facilities, legal, safety and insurance costs of both operation and maintenance hubs.

3.1.3. LONG-TERM O&M COSTS

During the development phase of an offshore wind farm for LCoE estimation or during the generation phase for EoW or EoDL decisions, long-term O&M costs should be calculated. In order to calculate the long-term O&M costs first the occurrence of random unknown WOs should be modelled. The long-term O&M cost calculation is typically done using an O&M cost model.

During past decades, several O&M cost models for long-term O&M cost estimation of offshore wind farms have been developed. The main core of any offshore wind O&M cost model is the way that stochastic corrective maintenance WOs and their subsequent downtime are modelled, assuming the average failure rate or average number of corrective WOs per year for each wind farm component is known.

In Paper II (Asgarpour & Sørensen, 2015) an overview of existing models for long-term O&M cost estimation of offshore wind farms is given. In the followings of this section, the two most common O&M cost model types are explained.

3.1.3.1 Polynomial Cost Model

In a polynomial offshore wind cost model, instead of WO specific costs, the average O&M costs during the whole design lifetime of the wind farm is calculated. In polynomial models, the occurrence of corrective WOs or failures are not distributed randomly in the time domain. Instead, first a polynomial relation between the duration of a WO and the weather waiting time associated with that WO is found and then, O&M costs are simply calculated.

The most industry known polynomial offshore wind O&M cost model is ECN O&M Tool (Obdam & Braam, 2014), a Microsoft Excel based cost model developed by Energy Centre of the Netherlands. In ECN O&M Tool it is assumed that similar to Weibull approximation of wind speed condition for AEP calculation, there should be a similar approximation for weather waiting time and lost power of O&M work orders. In the ECN O&M Tool it is shown that a second or third order polynomial curve is the best fit for the average weather waiting time and lost power plotted against the WO duration.

As an example, in Figure 3-5 based on 11 years of wind speed and significant wave height measurements, the mean weather waiting time for various WO durations is plotted in red dots. The assumed weather restriction for this WO is maximum 15 m/s wind speed measured at 10 m height (equivalent to platform height of an offshore wind turbine) and maximum 1.5 significant wave height (equivalent to weather restriction of a CTV). It can be seen that based on this weather data and defined weather restrictions, on average only about 55% of the time or 200 days per a year technicians can access the turbine.

In Figure 3-5, the restriction caused by workings shift hours is not considered and it is assumed that technicians are ready to sail out at any time during the day. Clearly, applying working shift restriction will increase the mean weather waiting time for each WO duration.

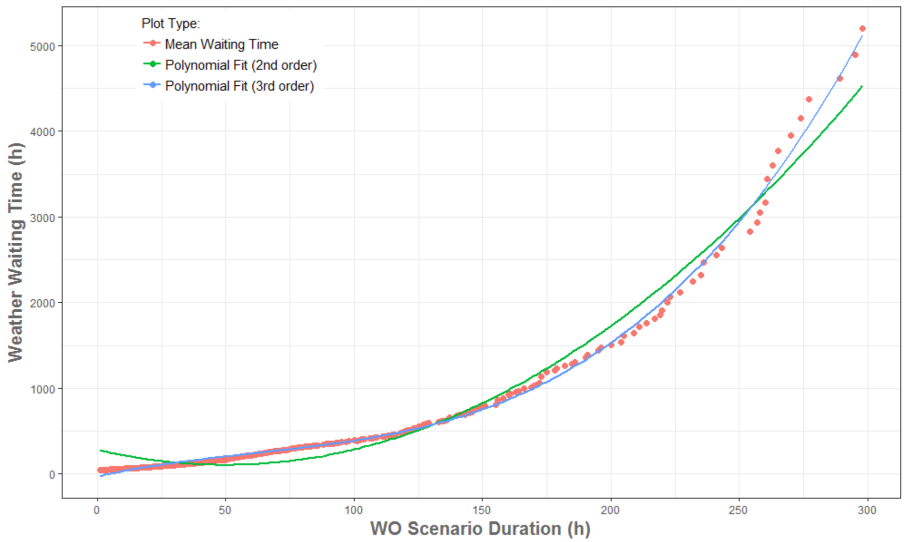


Figure 3-5 Mean weather waiting time and two polynomial fits for work order scenario durations with 15 m/s wind speed and 1.5 m significant wave height restrictions

In Figure 3-5, a second order and a third order polynomial curves are also plotted in green and blue lines. It can be seen that in this example, a third order polynomial curve is a better fit. The coefficients of this third order polynomial fit are:

$$f(t) = 0.0003068t^3 - 0.05588t^3 + 6.71t - 31.76 \tag{3.10}$$

- $f(t)$ as the mean weather waiting time of a WO with duration t (in hours) and 15 m/s wind speed and 1.5 m significant wave height weather restriction based on sample 11 years of measurement data

Therefore, similar to Weibull estimation for AEP calculation, it can be seen that by having the four coefficients of a third order polynomial curve, the mean weather waiting time for any WO duration can be estimated. As instance, based on Equation (3.10) for an 18-hour WO with the aforementioned weather restriction on average 72.7 hours weather waiting time should be expected. Similarly, a polynomial fit for lost power during waiting time and lost power during WO duration can be found.

For every given WO duration and weather restriction, similar polynomial fits for mean weather waiting time and lost power can found. Since now weather waiting time and lost power are known, energy loss for a WO according to the ECN O&M Tool can be calculated as:

$$E_{Loss} = \left(P_{Waiting} \times T_{Waiting}\right) + \left(P_{WO} \times T_{WO}\right) \tag{3.11}$$

- $P_{Waiting}$ as lost power during waiting time estimated from polynomial fits for T_{WO}
- $T_{Waiting}$ as weather and working shift waiting time according to Equation (3.5) estimated from polynomial fits for T_{WO}
- P_{WO} as lost power during the WO duration estimated from polynomial fits for T_{WO}

Now the energy loss during a work order is known, Equation (3.3) for indirect O&M costs of each WO can be rewritten as:

$$C_{OM.Ind} = \sum_{i=1}^{i=I} \left[\left(P_{Waiting} T_{Waiting} + P_{WO} T_{WO} \right)_i \times \left(C_{E,WO_i} + S_E \right) \right] \quad (3.12)$$

In order to simplify the Equation (3.12) for total O&M cost calculation, in the ECN O&M Tool work orders are categorized into a few limited scenarios, depending on their duration, required resources and maintenance types. By doing so, Equation (3.12) can be simply calculated, assuming component failure rate per each scenario is known.

In Paper I (Asgarpour & Sørensen, 2015) of this thesis, ECN O&M Tool is described further and a detailed case study for O&M cost calculation of an 800 MW reference offshore wind farm is presented.

3.1.3.2 Monte Carlo Cost Model

On the contrary to polynomial cost models discussed in the previous section, in Monte Carlo cost models component failures are distributed randomly in the time domain. The Monte Carlo method is based on repeated random sampling of stochastic variables. Based on the Monte Carlo simulation, the expected value of a function with random variable x is:

$$E[f(x)] = \frac{1}{n} \sum_{i=1}^{i=n} f(X_i) \quad (3.13)$$

- $E[f(x)]$ as the expected value of $f(x)$ function with random variable x
- $f(X_i)$ as the value of $f(x)$ based on random sampling X_i of variable x
- n as the total number of experiments or repetitions

The key stochastic variable of Monte Carlo based O&M cost models is the time stamp of a component's failures. The time to failure of offshore wind components can be modelled by a stochastic model such as Weibull distribution, Power law process, Gamma/Markov process or Poisson process. Since in Equation (2.7) of the previous chapter, probability of a failure is modelled using an exponential CDF model, a

Poisson process is the right choice for time to failure modelling of a Monte Carlo based O&M cost model.

In Figure 3-6 application of a Poisson process for modelling the occurrence of random failures is illustrated. The Poisson process is random occurrence of individual events with an average occurrence rate per unit of time. In this example, it is assumed that this wind turbine component has 0.25 failure rate or corrective WO per year, which means on average one failure every four years.

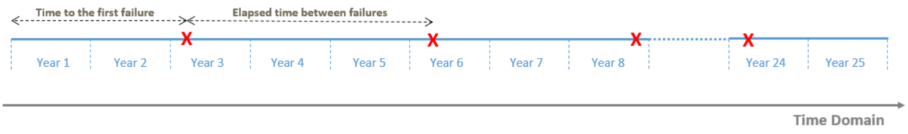


Figure 3-6 Poisson process to model occurrence of random failures

In order to distribute several component failures in a time domain, instead of probability of failure within a time period the elapsed time between failures should be calculated. The elapsed time between failures can be calculated using the inverse of Equation (2.7) for failure probability:

$$t = \frac{-\ln[1-P(t)]}{\lambda} \qquad (3.14)$$

- t as the elapsed time to the next failure as illustrated in Figure 3-6
- $P(t)$ as the probability of failure within time t, which can be substituted by a uniformed random variable between (0,1)

In order to test the accuracy of Equation (3.14), the average elapsed time for one million occurrences can be calculated. The results of the first five one-million trials are 3.995584, 4.000428, 3.997285, 4.003863 and 4.001004, all very close to our failure rate assumption of one failure every four years.

Using Equation (3.14) elapsed time between failures as stochastic variable of Monte Carlo simulations can be easily calculated. In each Monte Carlo simulation, first the occurrence of all failures of each component of each wind turbine or BoP system are randomly estimated and then, based on the O&M cost equations described in section 3.1.2 of this chapter the direct and indirect O&M costs are calculated. In Figure 3-7, an example of Monte Carlo simulations in the time domain for O&M cost calculation is illustrated.

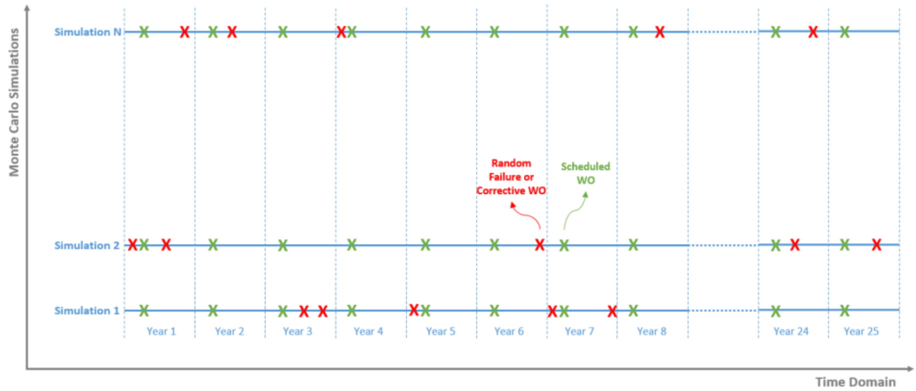


Figure 3-7 Monte Carlo simulations in the time domain for O&M cost calculation

As seen in Figure 3-7, beside random failures, scheduled WOs occurring at a fixed time every year (e.g. 1st of April) are also illustrated. Based on Equation (3.13), the total O&M costs of an offshore wind farm can be calculated as average of O&M costs of all simulations.

During the past decades, several Monte Carlo based cost models have been developed. In Paper II (Asgarpour & Sørensen, 2016) of this thesis, an overview of several Monte Carlo based offshore wind O&M cost models such as ECN O&M Calculator is given. The ECN O&M Calculator (Asgarpour & Pieterman, 2014) is a MATLAB based Monte Carlo simulation tool developed by Energy Centre of the Netherlands. In Paper II (Asgarpour & Sørensen, 2016) of this thesis, a case study for O&M cost calculation of a 400 MW reference offshore wind farm based on ECN O&M Calculator is demonstrated.

Now that risk based cost models for short-term and long-term O&M cost estimations are described, scheduling of the outstanding WOs of an offshore wind farm within a scheduling model can be discussed.

3.1. SCHEDULING MODEL

As discussed in section 1.2.1.2, an offshore wind farm with 100 wind turbines has about 500 corrective WOs per year, which can be translated into 10 WOs per week. The schedule, required resources and associated lost revenue of each outstanding WO can be estimated with a scheduling mode. In Figure 3-8, framework of a risk based O&M scheduling model is shown.

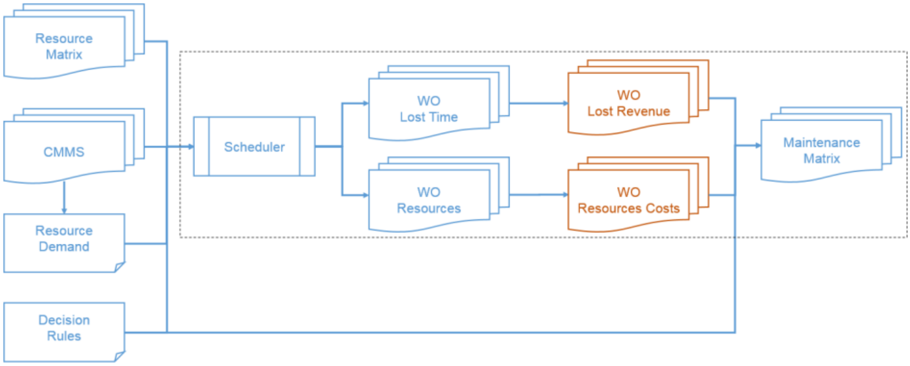


Figure 3-8 Framework for risk based O&M scheduling model

The outlined scheduling model requires inputs from CMMS, resource demand, resource matrix and decision rules. Then, based on all available information, the schedule of outstanding WOs in the CMMS is determined and using the cost model described in 3.1.1, the lost revenue and resources costs of each WO are calculated. At the end, all scheduling and cost results are given in a maintenance matrix. In the followings, first the inputs of the scheduling model are described and then, an example of the scheduling results in form of a maintenance matrix is given.

3.1.1. CMMS

As described in 1.2.2, CMMS is a maintenance management system to control the process and information flow of maintenance WOs. In Table 3-1, an example of a CMMS for an offshore wind farm is given.

ID	Alarm Date	Notification Date	Status	Asset	Component	Cat.
1	2017-11-01 12:10:00	2017-11-01 14:00:00	Finalized	WT01	Oil pump	Corr.
2	2017-11-02 04:30:00	2017-11-02 04:50:00	In-progress	WT04	Converter	Corr.
3	2017-11-04 23:00:00	2017-11-05 07:00:00	Out-standing	WT31	Transformer	Corr.
4	---	2017-11-06 07:00:00	Out-standing	WT12	Yaw drive	Sch.
5	---	2017-11-06 07:00:00	Out-standing	WT08	Pitch Motor	Pred.

Table 3-1 Example of CMMS of an offshore wind farm

As seen in Table 3-1, the corrective WOs are associated with an alarm date, however, preventive or upgrade WOs have only a notification date since turbines linked to these WOs are not stopped by an alarm.

3.1.2. RESOURCE DEMAND

The Resource Demand is estimated required resources for each WO type of each component. At beginning of lifetime, resource demand of WOs should be estimated. In Table 3-2, an example of assumed resource demand for two WO types of two components is shown.

Maintenance Type	Component	Duration (h)	Vessels	Technicians	Spares
Corrective					
	Converter	8	SOV	2	K€ 10
	Main shaft	30	Jack-up	4	K€ 500
Scheduled					
	Converter	4	SOV	2	K€ 1
	Main shaft	8	SOV	2	K€ 20

Table 3-2 Example of resource demand for execution of outstanding WOs of an offshore wind farm

Once sufficient O&M history is available, the resource demand of outstanding WOs can be taken from average resource demand of similar finalized WOs in the CMMS.

3.1.3. RESOURCES MATRIX

The Resources Matrix is intended to keep track of usage of O&M resources such as vessels or technicians. Furthermore, the resources matrix contains the weather data, which can be used for possible power estimation of wind turbines or accessibility check of access vessels. In Table 3-3, an example of resource matrix for O&M of an offshore wind farm is given.

Date Time	WS (m/s)	WH (m)	Power (kW)	Access SOV	Avail. SOV	No. Technicians
2017-11-01 10:00:00	10.8	2.1	7940	False	Ture	12
2017-11-01 10:030:00	9.8	1.9	7860	True	False	9
2017-11-01 11:00:00	8.5	1.8	7450	True	False	9

Table 3-3 Example of resource matrix for an offshore wind farm

The weather data used in the resource matrix can be based on short-term weather forecast or long-term averaged historical weather data. As seen in Table 3-3, at the first time slot the significant wave height is higher than weather restriction of the SOV and for that reason, the accessibility of SOV is set to false. In the next time stamp, once the significant wave height goes below 2 meters, the SOV becomes accessible and can be used for execution of WOs. Once the SOV is used to transfer three technicians to a WO location, its availability becomes false and number of technicians is reduced by three.

3.1.4. DECISION RULES

Decision rules can be used to reflect wind farm owner's targets on the O&M planning or to reduce or mitigate risks. As instance, the following decision rules can be applied for scheduling of outstanding WOs:

- The costs of preventive WOs shouldn't exceed K€ 10 (financial risk)
- The condition based or predictive WOs should be done at least one week prior to their estimated failure date (financial risk)
- The maintenance of subsea cables shouldn't be done in month of June (environmental risk)
- The access from CTVs to the wind turbine platform should be done only if significant wave height is lower than 1.5 meters (health and safety risk)

The defined decision rules can be stationary or time dependent, as the scheduling model is able to incorporate both types.

3.1.5. MAINTENANCE MATRIX

Once all inputs are given and the decision rules are defined, the scheduling of outstanding WOs can be done. As result of scheduling, the schedule (start and end time) and costs (spares, specific technician or support vessel and lost revenue) of each outstanding WO is determined. In Table 3-4, an example of scheduled maintenance matrix of the outstanding WOs of the CMMS shown in Table 3-1 is given.

ID	Start Date	End Date	Res. Costs	Duration	Lost Time	Lost Revenue
2	2017-11-06 07:30:00	2017-11-06 15:30:00	K€ 10	8	59	K€ 23.6
3	2017-11-06 08:00:00	2017-11-08 13:00:00	K€ 40	14.5	38	K€ 15.2
4	2017-11-08 13:00:00	2017-11-08 17:00:00	K€ 1	4	4	K€ 1.6
5	2017-11-08 13:30:00	2017-11-08 15:30:00	K€ 5	2	2	K€ 0.8

Table 3-4 Example of maintenance matrix based on scheduling of the CMMS shown in Table 3-1

In Table 3-4 it can be seen that lost time of preventive WOs based on Equation (3.6) is equal to their WO duration. Now the total direct and indirect WO costs of these four WOs can be easily calculated:

$$C_{WO.Dir} = \sum_{i=1}^{i=4} C_{WO.Dir_i} = K€\ 56$$

$$C_{WO.Ind} = \sum_{i=1}^{i=4} C_{WO.Ind_i} = K€\ 41.1 \tag{3.15}$$

$$C_{WO} = C_{WO.Dir} + C_{WO.Ind} = 56 + 41.1 = K€\ 97.1$$

The calculated K€ 97.1 of WO costs is associated with scheduling of outstanding WOs in order of their ID. A different order of WO execution will result into a different total WO costs. The optimal (minimum) WO costs can be achieved by scheduling outstanding WOs in their optimal order. The optimal prioritization order of outstanding WOs is discussed in the following section within a prioritization model.

3.2. PRIORITIZATION MODEL

Nowadays WO scheduling is typically done by a “scheduler”. The scheduler engineer normally every day looks at several availability and forecast charts and then, select and prioritize a list of WOs for the next working shift. Depending of the size and complexity of a wind farm this task can be very challenging since it is very cumbersome to digest all this information quickly and come up with an optimal schedule.

As an alternative, optimal prioritization of any given outstanding WOs can be calculated. In Figure 3-9, a framework for risk based prioritization of outstanding WOs is shown.

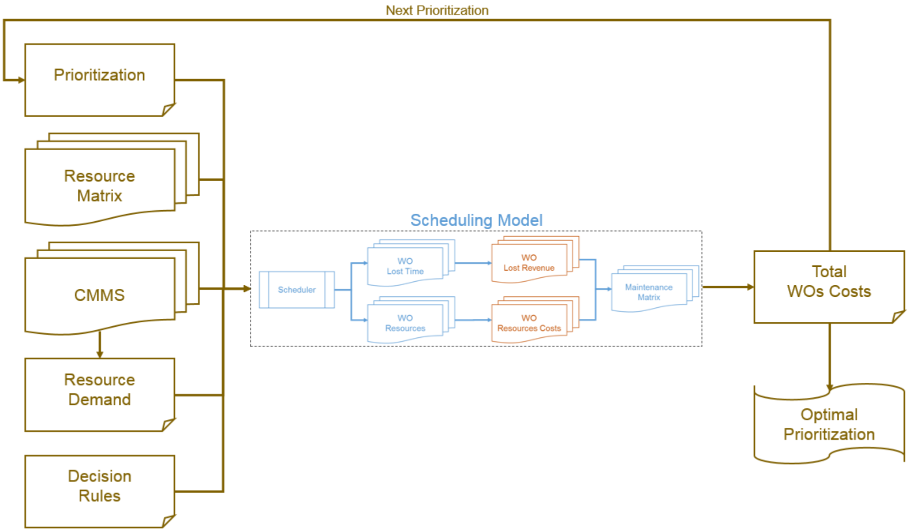


Figure 3-9 Framework of a risk based O&M prioritization model

In Figure 3-9, it can be seen that the cost and scheduling models discussed in the previous sections are incorporated into this O&M prioritization model. The inputs of this prioritization model are similar to the scheduling model, with addition of a prioritization input, which is the execution order of outstanding WOs.

Within this model, based on the all available information and defined decision rules, the WO costs based on every possible prioritization of WOs are calculated and then, the prioritization order associated with minimum WO costs is reported back as the optimal prioritization order, which maintenance hub technicians should follow in their next working shift.

The risk and reliability based models developed in this and previous chapter are coded using R[10], which is a free software environment for statistical computing and graphics. Based on the developed reliability and risk models, in Chapter 4 long-term O&M planning and in Chapter 5 short-term O&M planning of offshore wind farms within several illustrative case studies are discussed.

[10] https://cran.r-project.org

CHAPTER 4. LONG-TERM O&M PLANNING

As discussed briefly in Chapter 1, at the beginning of the wind farm lifetime the long-term O&M planning can be used to determine the baseline O&M costs and optimal shared O&M resources. Furthermore, during the operational years of the wind farm lifetime, the long-term O&M planning can be used to update the baseline O&M costs and assumed shared O&M resources. In Figure 4-1, a framework of optimal long-term O&M planning of offshore wind farms is shown.

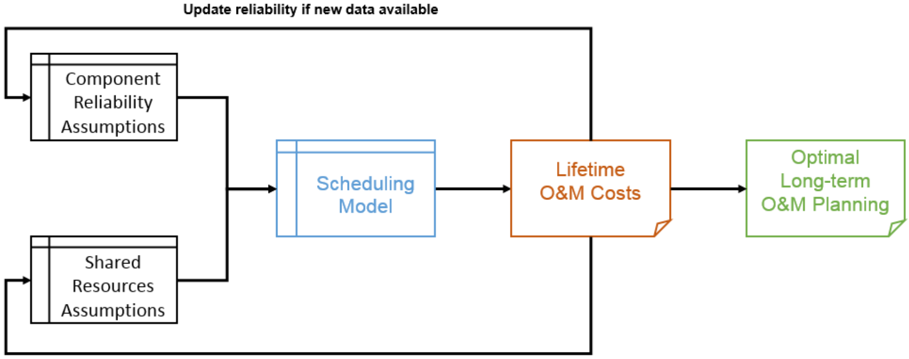


Figure 4-1 Framework for optimal long-term O&M planning of offshore wind farms

As seen in Figure 4-1, reliability models discussed in Chapter 2 and scheduling and cost models discussed in Chapter 3 are incorporated into this long-term O&M planning framework. In the followings, first baseline and updated long-term O&M strategies are discussed further and then, a case study for long-term O&M planning of a reference offshore wind farm is given.

4.1. BASELINE STRATEGY

During development phase of an offshore wind farm, long-term O&M planning is used to determine a baseline O&M strategy. Within a baseline O&M strategy firs several scenarios for shared O&M resources are defined and then, lifetime O&M costs for each scenario is determined. Then, the shared O&M resources scenario leading to minimum lifetime O&M costs is selected as the baseline O&M strategy.

In section 4.3 of this chapter, baseline O&M strategy is further explained within a case study. Furthermore, in Paper I (Asgarpour & Sørensen, 2016) and Paper II

(Asgarpour & Sørensen, 2015) within several illustrative examples, long-term O&M planning and baseline O&M strategy are discussed.

4.2. UPDATED STRATEGY

Once an offshore wind farm is in operation for some years, the existing operational data can be used to update the assumptions made for baseline O&M strategy. In the followings, two use cases of the updated O&M strategy are explained.

4.2.1. UPDATED O&M COSTS

For several decisions during the generation phase of an offshore wind farm, the long-term O&M costs should be recalculated. As instance, when an offshore wind farm reaches its end of warranty, based on the existing operational data, the reliability assumptions shown in Figure 4-1 should be updated and then, updated long-term O&M costs for post end of warranty period should be calculated. Once updated long-term O&M costs are known, an informed decision on extension of warranty contract can be made.

Similarly, once an offshore wind farm reaches its end of design lifetime, using all historical operational data the reliability assumptions should be updated and then, long-term O&M costs for post end of design lifetime should be calculated. Once, remaining useful lifetime of structural components and updated long-term O&M costs are known, an informed decision on lifetime extension can be made.

4.2.2. UPDATED O&M RESOURCES

The shared O&M resources of an offshore wind farm influence direct and indirect O&M costs. Therefore, it is advised that every five years, based on the experience gained so far, a new set of scenarios for shared O&M resources be defined and then, long-term O&M costs for each scenario be calculated. Then, the shared O&M resources scenario with minimum long-term O&M costs can replace the existing shared O&M resource strategy of the wind farm.

4.3. CASE STUDY

In the followings, first the layout of a reference offshore wind farm and then, based on the framework shown in Figure 4-1, baseline O&M costs of this reference offshore wind farm are calculated.

4.3.1. REFERENCE WIND FARM

The reference offshore wind farm defined in this thesis is an adaption of 800 MW NORCOWE reference wind farm (Bak et al., 2017), but with hundred 8 MW wind turbines installed on monopile foundations in 30 m water depth. The power curve of 8 MW reference turbines is given in Figure 1-9.

As discussed in section 1.1.3.1, assuming 3% production loss due to wakes, 2% production loss due to underperformance and 0.5% production loss due to electrical cables, the potential AEP of this wind farm is estimated as 3.969 TWh. The production loss due to unavailability is calculated more accurately in this case study. Furthermore, as discussed in Chapter 1, the installed cost or CAPEX of this wind farm is assumed to be 4 M€/MW or B€ 3.2 in total. The O&M overhead costs are assumed to be M€ 10 per year.

This reference offshore wind farm is assumed to be commissioned on 1st January 2020 and to operate for 25 years until 31st of December 2044. It is assumed that this wind farm is subsidy free meaning that no governmental subsidy is provided for produced electricity.

In Figure 4-2, the layout of the described reference offshore wind farm is illustrated. The wind farm consists of two 400 MW sections. Each wind farm section consists of 50 wind turbines, 5 array cables and one offshore transformer station. The two sections of this reference offshore wind farm can also be considered as two neighbour wind farms operated by the same maintenance hub.

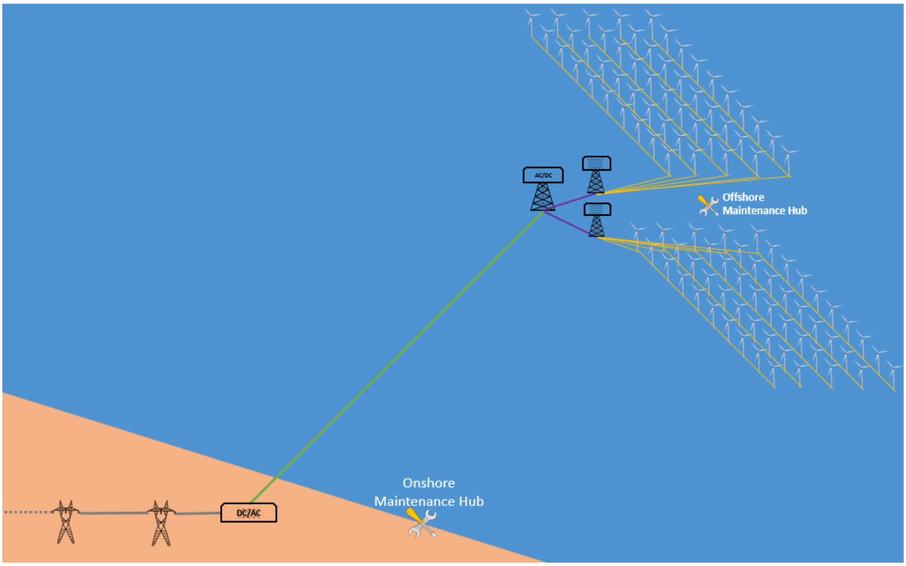


Figure 4-2 Layout of an 800 MW reference offshore wind farm with two 400 MW sections

Each string of subsea array cable is designed to collect power from 10 wind turbines with maximum load capacity of 80 MW. The high voltage electricity power from two offshore transformer stations is transmitted to an offshore converter station to convert it from AC to DC for long distance offshore transmission.

It is assumed that this wind farm has no warranty period and the wind farm is maintained by its maintenance hubs. As shown in Figure 4-2, it is assumed that the wind farm has two maintenance hubs, one onshore maintenance hub located in the closet harbour and one offshore maintenance hub placed between two wind farm sections on a jacket foundation. The onshore maintenance hub is 80 km far from the onshore maintenance hub.

4.3.1.1 O&M Resources

As discussed in section 3.1.2, besides shared O&M resources some WOs require specific resources to finalize. In the followings assumed O&M resources for this reference offshore wind farm are described.

O&M Spares

In an offshore wind farm several different types of spare parts are used. However, for this reference wind farm spare parts are categorized based on their costs and lead time. The costs of spare parts are assumed as a percentage (0.01%, 0.1%, 0.5% or 10%) of one wind turbine supply cost. Similar to Chapter 1, it is assumed that wind turbine supply cost is 30% of total CAPEX, which can be translated into M€ 9.6 as supply cost of one 8 MW reference offshore wind turbine.

For less expansive spare parts (costing equal or less than 0.5% of wind turbine price) it is assumed that the spare part is available in the inventory. The inventory costs per year it is assumed to be equal to 1% of one wind turbine supply cost (K€ 96 per year).

For more expensive spare parts (10% of one wind turbine supply cost) a lead time of two weeks is assumed. The lead time of a spare part is the waiting time between the spare part request and spare part delivery.

O&M Vessels

As explained in section 1.2.3.2, CTVs, SOVs or helicopters can be used as access vessel. For this reference offshore wind farm, it is assumed that one SOV and one helicopter are available throughout the lifetime of the wind farm. The ownership of the SOV costs M€ 5 per year and the ownership of the helicopter costs M€ 1 per year.

The SOV transfers technicians from the offshore maintenance hub to WO locations and vice versa. It is assumed that each transfer of this SOV takes 30 minutes. The SOV only leaves the offshore maintenance hub if a minimum one hour suitable weather window is forecasted.

The helicopter is only used for emergency rescues or if the SOV is not available to pick up technicians at the end of their working shift. Furthermore, transfer of technicians between onshore and offshore maintenance hubs is done by the helicopter.

If the weight of a component is higher than the lifting capacity of the turbine or SOV, then a jack-up barge should be chartered for replacement of that component. Similarly, for major underwater maintenance of subsea cables a cable laying vessel should be chartered.

The weather restrictions defined in section 1.2.3.2 holds true for vessels of this reference wind farm. Both jack up barge and cable laying vessel costs K€ 120 per day, with K€ 200 mobilization and demobilization costs and two weeks lead time once chartered.

O&M Technicians

This reference wind farm employs 40 technicians with averaged K€ 100 yearly salary, ranging from GWO certified technicians to component or access specialists. Technicians of this reference wind farm work two weeks at the offshore maintenance hub and have two weeks off. Therefore, only 20 technicians are available for execution of maintenance activities in one 12 hour working shift from 07:00 until 19:00.

The duration of a work order is the time that technicians spend in the WO location to inspect, repair or replace a wind farm component. The WO duration can vary from a few hours to a few days. For this reference wind farm, it is assumed that minimum WO duration is 4 hours and maximum WO duration is 40 hours.

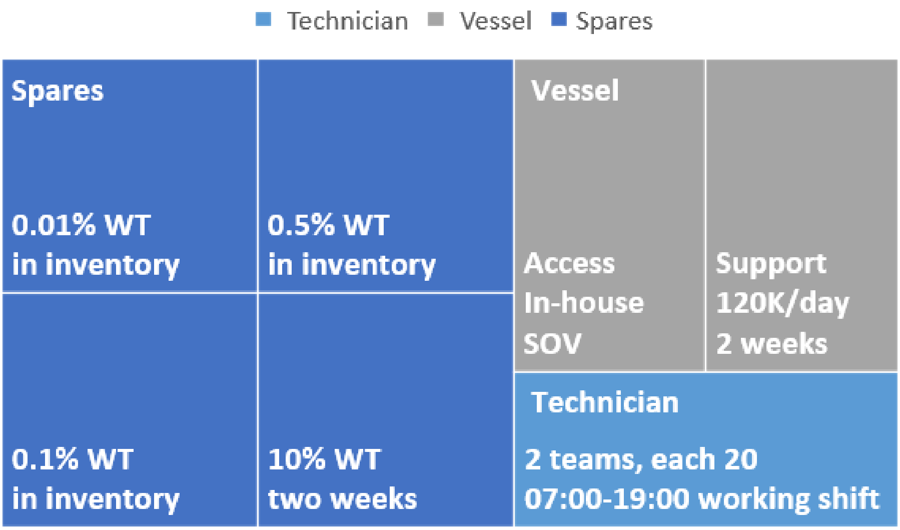


Figure 4-3 Maintenance resources for baseline O&M strategy of the reference wind farm

The described maintenance resources for the baseline O&M strategy of the reference offshore wind farm are translated into several decision rules for the scheduling model of the framework shown in Figure 4-1. An overview of the assumed O&M resources for this reference offshore wind farm is also given in Figure 4-3.

In order to simplify the baseline O&M strategy, condition based and predictive maintenance are skipped. Therefore, in the baseline model only corrective and mandatory scheduled maintenance WOs are considered.

Furthermore, based on the discussed O&M resources in the previous section, corrective and scheduled maintenance are categorized in 6 different scenarios. In Table 4-1, depending on the maintenance category, the resource demand of 6 different maintenance scenarios are defined.

Maintenance	#	Duration (h)	Vessels	Technicians	Spares
Corrective					
	1	4	SOV	2	0.01%
	2	8	SOV	2	0.1%
	3	12	SOV	3	0.5%
	4	40	Jack up Barge	0	10%
	5	40	Cable Laying	0	10%
Scheduled					
	6	8	SOV	2	0.1%

Table 4-1 Resource demand for execution of WOs of the reference offshore wind farm

In resource demand of Table 4-1, it is assumed that corrective WOs take from 4 to 40 hours and scheduled WOs take 8 hours to finalize. All maintenance scenarios except 40 hours corrective maintenance can be carried out using the in-house SOV and helicopter.

In case of 40 hours corrective scenarios using a support vessel (scenarios 5 and 6), no SOV or wind farm technician is required as it is assumed that the support vessel crew are responsible for the whole maintenance process.

4.3.1.2 Component Reliability

Now that shared O&M resources and resource demand of maintenance scenarios of the reference wind farm are known, it is necessary to define the wind farm components and their reliability.

For purpose of O&M modelling of this reference offshore wind farm only 13 first level components of the wind farm are considered. In Table 4-2, eleven first level wind turbine components and two BoP components are shown. Each of these components consist of several other component levels which are skipped here. In Table 4-2, the BoP transformer and converter stations are considered alike and categorized as substation.

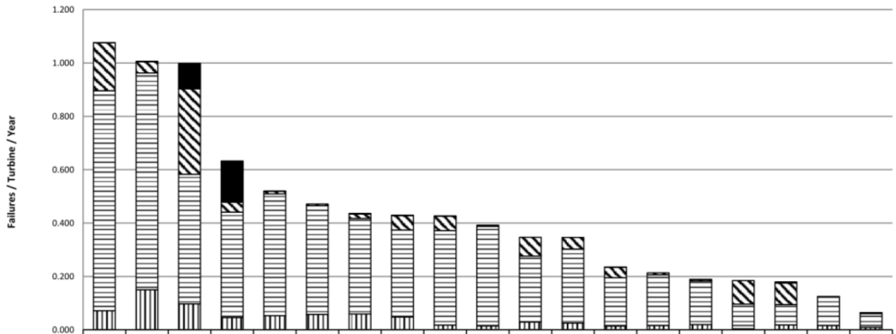
Main System	Components	RDS-PP Code
Wind Turbine		**MD**
	Rotor System	MDA
	Drivetrain System	MDK
	Yaw System	MDL
	Hydraulic System	MDX
	Control System	MDY
	Generation System	MKA
	Converter System	MSE
	Transformer System	MST
	Cooling System	MUR
	Nacelle System	MUD
	Tower System	UMD
Balance of Plant		
	Subsea Cables	W
	Substations	ATA

Table 4-2 Components of the reference offshore wind farm

In the past couple of years, the wind industry has aimed to define a naming convention for wind farm components to avoid random naming conventions across different OEMs and utilities. The most successful initiative is RDS-PP classification code coordinated by VGB (VGB PowerTech Service GmbH, 2013). As instance, in the last column of Table 4-2, the RDS-PP classification codes of wind farm components are given.

During the development phase of an offshore wind farm very few information on the reliability level of wind farm components is known. Therefore, failure frequencies of similar operational components are typically taken as reliability model of baseline

O&M strategies. If the turbine platform is new and no operational data exists, then operational data of similar turbine platforms should be used. As instance, in (Carroll, McDonald, & McMillan, 2016) a study on observed failure rates of offshore wind turbine components is given. In Figure 4-4, based on this study an overview of failure rates of offshore wind turbines is shown.



	Pitch / Hyd	Other Components	Generator	Gearbox	Blades	Grease / Oil / Cooling Liq.	Electrical Components	Contactor / Circuit Breaker / Relay	Controls	Safety	Sensors	Pumps/ Motors	Hub	Heaters / Coolers	Yaw System	Tower / Foundation	Power Supply / Converter	Service Items	Transformer
Major Replacement	0.001	0.001	0.095	0.154	0.001	0.000	0.002	0.002	0.001	0.000	0.000	0.000	0.001	0.000	0.001	0.000	0.005	0.000	0.001
Major Repair	0.179	0.042	0.321	0.038	0.010	0.006	0.016	0.054	0.054	0.004	0.070	0.043	0.038	0.007	0.006	0.089	0.081	0.001	0.003
Minor Repair	0.824	0.812	0.485	0.395	0.456	0.407	0.358	0.326	0.355	0.373	0.247	0.278	0.182	0.190	0.162	0.092	0.076	0.108	0.052
No Cost Data	0.072	0.150	0.098	0.046	0.053	0.058	0.059	0.048	0.018	0.015	0.029	0.025	0.014	0.016	0.020	0.004	0.018	0.016	0.009

Figure 4-4 Failure frequency of offshore wind turbine components (Carroll et al., 2016)

In Table 4-3, a summary of assumed WO frequencies of this reference offshore wind farm is given.

Main System	Maintenance	WO/year/System
MD		**5.0**
	Corrective	4.0
	Scheduled	1.0
ATA		**1.0**
	Scheduled	1.0
W		**0.1**
	Corrective	0.1

Table 4-3 Assumed WO frequency for corrective and scheduled maintenance of the reference offshore wind farm

According to Table 4-3, each wind turbine has 5 WOs per year (4 corrective and 1 scheduled), each substation has one scheduled WO per year and each string of array cable has 0.1 corrective WO per year. During the scheduled maintenance of wind turbines, it is assumed that wind turbines are shut down, which results into lost power. However, during the scheduled maintenance of substations it is assumed that they are in operation. In case of array cable failure, it is assumed that half of the wind turbines connected to that cable string are affected.

The four wind turbine failures and 0.1 subsea cable failure given in Table 4-3 can be broken down into individual components and maintenance scenarios. In Table 4-4, failure rate of each wind farm component per each corrective maintenance scenario is given.

Components	WO/year/Component (λ)	Maintenance Scenario	Probability
MDA	0.4		
		Corrective (1)	30%
		Corrective (2)	40%
		Corrective (3)	30%
MDK	0.2		
		Corrective (3)	90%
		Corrective (4)	10%
MDL	0.4		
		Corrective (1)	20%
		Corrective (2)	40%
		Corrective (3)	40%
MDX	0.5		
		Corrective (1)	40%
		Corrective (2)	60%
MDY	0.6		
		Corrective (1)	70%
		Corrective (2)	30%
MKA	0.4		
		Corrective (2)	40%
		Corrective (3)	60%
MSE	0.8		
		Corrective (1)	80%
		Corrective (2)	20%
MST	0.2		
		Corrective (2)	40%
		Corrective (3)	60%
MUR	0.3		
		Corrective (1)	70%
		Corrective (2)	30%
MUD	0.1		
		Corrective (1)	80%
		Corrective (2)	20%
UMD	0.1		
		Corrective (1)	70%
		Corrective (2)	30%
W	0.1		
		Corrective (5)	100%

Table 4-4 Summary of work order frequencies per component and corrective scenario

The failure rates given in Table 4-4 can be summarized for each wind farm main system and maintenance scenario. In Table 4-5, summary of WO frequencies per main system and maintenance scenario is shown.

Main System	Number	Maintenance Scenario	WO/year/System	WO/year
MD	**100**		**5.0**	**500**
		Corrective (1)	1.82	182
		Corrective (2)	1.34	134
		Corrective (3)	0.82	82
		Corrective (4)	0.02	2
		Preventive (6)	1.00	100
ATA	**3**		**1.0**	**3**
		Preventive (6)	1.00	3
W	**10**		**0.1**	**1**
		Corrective (5)	0.10	1

Table 4-5 Summary of work order frequencies per main system and maintenance scenario

As shown in Table 4-5, this reference wind farm on average every year experiences 401 corrective and 103 scheduled WOs, which sums up to 504 WOs in total. This number can be translated into approximately one and half WOs per day during the wind farm lifetime, which demonstrates the challenging nature of maintenance of large offshore wind farms.

In the followings, based on the assumptions given in this section, lifetime O&M costs of the reference offshore wind farm using the framework shown in Figure 4-1 are calculated.

4.3.2. BASELINE O&M COSTS

Now that O&M resources and reliability assumptions of this reference offshore wind farm are known, based on the framework shown in Figure 4-1, the baseline lifetime O&M costs of this reference offshore wind farm can be calculated. In the followings, first resource and maintenance matrices of the scheduling model are defined and then, the scheduling model is used to estimate the lifetime O&M costs.

4.3.2.1 Resource Matrix

As discussed in 3.1.3, the baseline O&M resources can be summarized into a resource matrix. The resource matrix of this reference offshore wind farm contains the following information in each row:

- Date and time with 30 minutes resolution
- Vessel's weather window based on defined weather restriction of the vessels and historical weather data (e.g. 48 ½ hours meaning that for the next 48 ½ hours a suitable weather window for SOV operation exists)
- Vessel's availability defined as logical true if the vessel is available or false if the vessel is occupied for another WO
- Technicians' availability as number of available technicians out of total 20
- Power possible to be produced by one offshore wind turbine in that time period in kW

DateTime	WS	HS	Power	AccessSOV	AccessHeli	AccessJackup	AccessCable	WindowSOV	WindowHeli	WindowJackup	WindowCable	VesselSOV	VesselHeli	VesselJackup	VesselCable	Technician
2020-01-01 00:00:00	10.20	1.30	7590	TRUE	TRUE	FALSE	TRUE	29.5	413.5	6.5	2.5	TRUE	TRUE	TRUE	TRUE	20
2020-01-01 00:30:00	10.35	1.35	7730	TRUE	TRUE	FALSE	TRUE	29.0	413.0	6.0	2.0	TRUE	TRUE	TRUE	TRUE	20
2020-01-01 01:00:00	10.50	1.40	7840	TRUE	TRUE	FALSE	TRUE	28.5	412.5	5.5	1.5	TRUE	TRUE	TRUE	TRUE	20
2020-01-01 01:30:00	10.65	1.45	7880	TRUE	TRUE	FALSE	TRUE	28.0	412.0	5.0	1.0	TRUE	TRUE	TRUE	TRUE	20
2020-01-01 02:00:00	10.80	1.50	7940	TRUE	TRUE	FALSE	TRUE	27.5	411.5	4.5	0.5	TRUE	TRUE	TRUE	TRUE	20
2020-01-01 02:30:00	10.95	1.55	7980	TRUE	TRUE	FALSE	FALSE	27.0	411.0	4.0	9.5	TRUE	TRUE	TRUE	TRUE	20
2020-01-01 03:00:00	11.10	1.60	8000	TRUE	TRUE	FALSE	FALSE	26.5	410.5	3.5	9.0	TRUE	TRUE	TRUE	TRUE	20
2020-01-01 03:30:00	10.97	1.63	8000	TRUE	TRUE	FALSE	FALSE	26.0	410.0	3.0	8.5	TRUE	TRUE	TRUE	TRUE	20
2020-01-01 04:00:00	10.83	1.67	8000	TRUE	TRUE	FALSE	FALSE	25.5	409.5	2.5	8.0	TRUE	TRUE	TRUE	TRUE	20
2020-01-01 04:30:00	10.70	1.70	8000	TRUE	TRUE	FALSE	FALSE	25.0	409.0	2.0	7.5	TRUE	TRUE	TRUE	TRUE	20
2020-01-01 05:00:00	10.57	1.73	8000	TRUE	TRUE	FALSE	FALSE	24.5	408.5	1.5	7.0	TRUE	TRUE	TRUE	TRUE	20
2020-01-01 05:30:00	10.43	1.77	7980	TRUE	TRUE	FALSE	FALSE	24.0	408.0	1.0	6.5	TRUE	TRUE	TRUE	TRUE	20
2020-01-01 06:00:00	10.30	1.80	7980	TRUE	TRUE	FALSE	FALSE	23.5	407.5	0.5	6.0	TRUE	TRUE	TRUE	TRUE	20
2020-01-01 06:30:00	9.85	1.77	7920	TRUE	TRUE	TRUE	FALSE	23.0	407.0	19.0	5.5	TRUE	TRUE	TRUE	TRUE	20
2020-01-01 07:00:00	9.40	1.73	7840	TRUE	TRUE	TRUE	FALSE	22.5	406.5	18.5	5.0	TRUE	TRUE	TRUE	TRUE	20
2020-01-01 07:30:00	8.95	1.70	7730	TRUE	TRUE	TRUE	FALSE	22.0	406.0	18.0	4.5	TRUE	TRUE	TRUE	TRUE	20
2020-01-01 08:00:00	8.50	1.67	7450	TRUE	TRUE	TRUE	FALSE	21.5	405.5	17.5	4.0	TRUE	TRUE	TRUE	TRUE	20
2020-01-01 08:30:00	8.05	1.63	7240	TRUE	TRUE	TRUE	FALSE	21.0	405.0	17.0	3.5	TRUE	TRUE	TRUE	TRUE	20
2020-01-01 09:00:00	7.60	1.60	6780	TRUE	TRUE	TRUE	FALSE	20.5	404.5	16.5	3.0	TRUE	TRUE	TRUE	TRUE	20
2020-01-01 09:30:00	7.73	1.58	6940	TRUE	TRUE	TRUE	FALSE	20.0	404.0	16.0	2.5	TRUE	TRUE	TRUE	TRUE	20

Figure 4-5 Resource matrix for scheduling model of the reference offshore wind farm

The generated resource matrix can be used to keep track of availability and usage of resources during the lifetime of the wind farm. In Figure 4-5, the first rows of such a resources matrix is shown.

4.3.2.2 CMMS

As described in 3.1.3.2, a Poisson process is used to translate the component reliability assumptions of this reference offshore wind farm (given in Table 4-5) into outstanding corrective WOs. In Figure 4-6, notification dates of 401 corrective WOs generated randomly by the Poisson process and 103 scheduled WOs for 100 wind turbines (MD), 10 subsea array cables (W) and 3 substations (ATA) are shown.

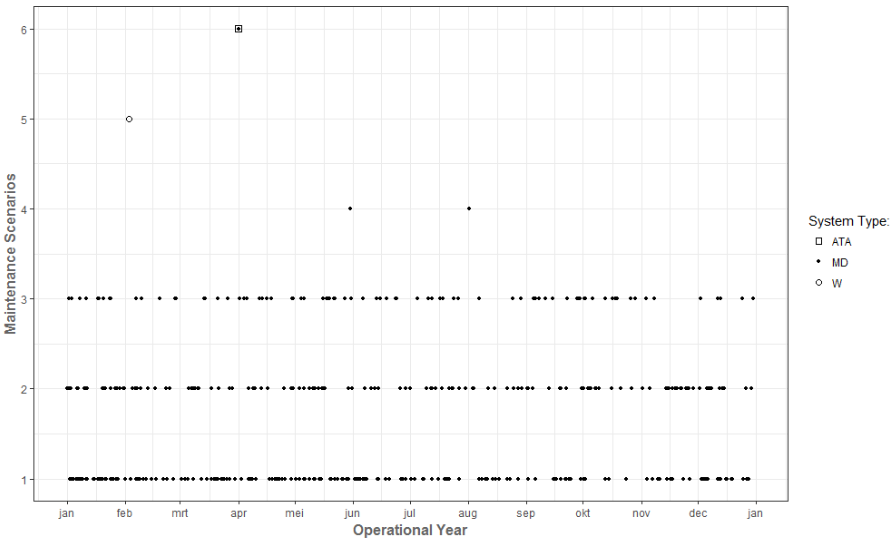


Figure 4-6 Example of yearly randomly generated WOs in the CMMS

In Figure 4-6 it can be seen that every year the defined reference wind farm experiences 401 corrective WOs (scenarios 1 to 5) and 103 scheduled WOs (scenario 6, all initiated on 1st of April). Furthermore, in Figure 4-6 two wind turbine drivetrain failures (scenario 4) and one subsea array cable failure (scenario 5) can be easily spotted.

4.3.2.3 Maintenance Matrix

The discussed CMMS matrix of this reference offshore wind farm is directly incorporated into its maintenance matrix. The maintenance matrix of this reference offshore wind farm contains the following information:

- Work order ID, which is an auto generated number for each maintenance WO. As shown in Table 4-5 for the reference offshore wind farm 504 WOs per year should be generated.
- Alarm date, generated randomly based on Equation (3.14) for corrective maintenance actions. For preventive scheduled actions, no alarm date is necessary.
- Notification date is the time that a WO is added to the CMMS backlog of outstanding WOs. In case of corrective WOs, an average alarm processing time of 3 hours is assumed (done by operation hub as explained in section 1.2.2.1). In case of scheduled WOs, notification date is set automatically to 1st of April of each year.

- Status of WO, which is by default *outstanding* for new WOs. The status later on can be changed to *ongoing* or *complete* once the WO is processed and finalized.
- System that a WO is intended for defined by its RDS-PP code
- Category of a WO defined based on the maintenance scenarios given in Table 4-1
- Duration of a WO in hours based on Table 4-1
- Number of technicians required for a WO based on Table 4-1
- Spares required for the WO based on Table 4-1 in Euro
- Start date of a WO, which the first moment that resources become available or the first moment that a suitable weather window is found
- End date of a WO is when the WO is finalized and the component can be set back to operation
- Lost time is the downtime associated with a WO in hours
- Lost energy is the electricity lost during the downtime of a WO in kWh, taken from calculated power in the Resources Matrix

In Figure 4-7, a few rows of such a randomly generated maintenance matrix is shown. It can be seen that the notification date of scheduled WOs is set as 1st of April and notification date of the corrective WOs is three hours after their alarm date and time.

	AlarmDate	NotificationDate	Status	System	Component	Category	Duration	Technician	Spares	StartDate	EndDate	LostTime	LostEnergy
116	2020-03-19 19:00:00	2020-03-19 22:00:00	Outstanding	MD	MD	1	4	2	960	NA	NA	NA	NA
117	2020-03-20 06:00:00	2020-03-20 09:00:00	Outstanding	MD	MD	1	4	2	960	NA	NA	NA	NA
118	2020-03-20 19:00:00	2020-03-20 22:00:00	Outstanding	MD	MD	3	12	3	48000	NA	NA	NA	NA
119	2020-03-20 21:00:00	2020-03-21 00:00:00	Outstanding	MD	MD	1	4	2	960	NA	NA	NA	NA
120	2020-03-21 11:00:00	2020-03-21 14:00:00	Outstanding	MD	MD	2	8	2	9600	NA	NA	NA	NA
121	2020-03-21 13:00:00	2020-03-21 16:00:00	Outstanding	MD	MD	2	8	2	9600	NA	NA	NA	NA
122	2020-03-22 22:00:00	2020-03-23 01:00:00	Outstanding	MD	MD	1	4	2	960	NA	NA	NA	NA
123	2020-03-23 23:00:00	2020-03-24 02:00:00	Outstanding	MD	MD	1	4	2	960	NA	NA	NA	NA
124	2020-03-24 09:00:00	2020-03-24 12:00:00	Outstanding	MD	MD	1	4	2	960	NA	NA	NA	NA
125	2020-03-25 17:00:00	2020-03-25 20:00:00	Outstanding	MD	MD	1	4	2	960	NA	NA	NA	NA
126	2020-03-26 04:00:00	2020-03-26 07:00:00	Outstanding	MD	MD	3	12	3	48000	NA	NA	NA	NA
127	2020-03-27 05:00:00	2020-03-27 08:00:00	Outstanding	MD	MD	2	8	2	9600	NA	NA	NA	NA
128	2020-03-27 08:00:00	2020-03-27 11:00:00	Outstanding	MD	MD	1	4	2	960	NA	NA	NA	NA
129	2020-03-28 19:00:00	2020-03-28 22:00:00	Outstanding	MD	MD	2	8	2	9600	NA	NA	NA	NA
130	2020-03-30 08:00:00	2020-03-30 11:00:00	Outstanding	MD	MD	1	4	2	960	NA	NA	NA	NA
131	NA	2020-04-01 00:00:00	Outstanding	ATA	ATA	6	8	2	9600	NA	NA	NA	NA
132	NA	2020-04-01 00:00:00	Outstanding	ATA	ATA	6	8	2	9600	NA	NA	NA	NA
133	NA	2020-04-01 00:00:00	Outstanding	ATA	ATA	6	8	2	9600	NA	NA	NA	NA
134	NA	2020-04-01 00:00:00	Outstanding	MD	MD	6	8	2	9600	NA	NA	NA	NA
135	NA	2020-04-01 00:00:00	Outstanding	MD	MD	6	8	2	9600	NA	NA	NA	NA
136	NA	2020-04-01 00:00:00	Outstanding	MD	MD	6	8	2	9600	NA	NA	NA	NA

Showing 115 to 136 of 504 entries

Figure 4-7 Example of maintenance matrix used in the scheduling model

4.3.2.4 WO Scheduling

As illustrated in Figure 3-8, both resources and maintenance matrices are used into a scheduler. Based on the defined baseline O&M strategy rules in section 4.3.1of this chapter, the scheduling model processes the outstanding WOs in the maintenance matrix one by one and calculates their start date, end time, lost time and lost energy. In Figure 4-8 the scheduling results for the WOs shown in Figure 4-6 are given.

	AlarmDate	NotificationDate	Status	System	Component	Category	Duration	Technician	Spares	StartDate	EndDate	LostTime	LostEnergy
116	2020-03-19 19:00:00	2020-03-19 22:00:00	Outstanding	MD	MD	1	4	2	960	2020-03-21 08:00:00	2020-03-21 12:00:00	41.0	193132.5
117	2020-03-20 06:00:00	2020-03-20 09:00:00	Outstanding	MD	MD	1	4	2	960	2020-03-21 08:30:00	2020-03-21 12:30:00	30.5	110017.5
118	2020-03-20 19:00:00	2020-03-20 22:00:00	Outstanding	MD	MD	3	12	3	48000	2020-03-21 09:00:00	2020-03-22 10:00:00	39.0	79917.5
119	2020-03-20 21:00:00	2020-03-21 00:00:00	Outstanding	MD	MD	1	4	2	960	2020-03-21 09:30:00	2020-03-21 13:30:00	16.5	14177.5
120	2020-03-21 11:00:00	2020-03-21 14:00:00	Outstanding	MD	MD	2	8	2	9600	2020-03-21 15:00:00	2020-03-22 13:00:00	26.0	70390.0
121	2020-03-21 13:00:00	2020-03-21 16:00:00	Outstanding	MD	MD	2	8	2	9600	2020-03-21 17:00:00	2020-03-22 16:00:00	27.0	74975.0
122	2020-03-22 22:00:00	2020-03-23 01:00:00	Outstanding	MD	MD	1	4	2	960	2020-03-23 07:30:00	2020-03-23 11:30:00	13.5	21975.0
123	2020-03-23 23:00:00	2020-03-24 02:00:00	Outstanding	MD	MD	1	4	2	960	2020-03-24 07:30:00	2020-03-24 11:30:00	12.5	21120.0
124	2020-03-24 09:00:00	2020-03-24 12:00:00	Outstanding	MD	MD	1	4	2	960	2020-03-24 13:00:00	2020-03-24 17:00:00	8.0	9780.0
125	2020-03-25 17:00:00	2020-03-25 20:00:00	Outstanding	MD	MD	1	4	2	960	2020-03-26 07:30:00	2020-03-26 11:30:00	18.5	97032.5
126	2020-03-26 04:00:00	2020-03-26 07:00:00	Outstanding	MD	MD	3	12	3	48000	2020-03-26 08:00:00	2020-03-27 09:00:00	29.0	166325.0
127	2020-03-27 05:00:00	2020-03-27 08:00:00	Outstanding	MD	MD	2	8	2	9600	2020-03-27 09:00:00	2020-03-27 17:00:00	12.0	19695.0
128	2020-03-27 08:00:00	2020-03-27 11:00:00	Outstanding	MD	MD	1	4	2	960	2020-03-27 12:00:00	2020-03-27 16:00:00	8.0	13205.0
129	2020-03-28 19:00:00	2020-03-28 22:00:00	Outstanding	MD	MD	2	8	2	9600	2020-03-29 07:30:00	2020-03-29 15:30:00	19.5	44455.0
130	2020-03-30 08:00:00	2020-03-30 11:00:00	Outstanding	MD	MD	1	4	2	960	2020-03-30 17:00:00	2020-03-31 10:00:00	26.0	170015.0
131	NA	2020-04-01 00:00:00	Outstanding	ATA	ATA	6	8	2	9600	2020-04-01 07:30:00	2020-04-01 15:30:00	0.0	0.0
132	NA	2020-04-01 00:00:00	Outstanding	ATA	ATA	6	8	2	9600	2020-04-01 08:00:00	2020-04-01 16:00:00	0.0	0.0
133	NA	2020-04-01 00:00:00	Outstanding	ATA	ATA	6	8	2	9600	2020-04-01 08:30:00	2020-04-01 16:30:00	0.0	0.0
134	NA	2020-04-01 00:00:00	Outstanding	MD	MD	6	8	2	9600	2020-04-01 09:00:00	2020-04-01 17:00:00	8.0	14685.0
135	NA	2020-04-01 00:00:00	Outstanding	MD	MD	6	8	2	9600	2020-04-01 09:30:00	2020-04-01 17:30:00	8.0	14545.0
136	NA	2020-04-01 00:00:00	Outstanding	MD	MD	6	8	2	9600	2020-04-01 10:00:00	2020-04-01 18:00:00	8.0	14965.0

Showing 115 to 136 of 504 entries

Figure 4-8 Scheduling results of the maintenance matrix given in Figure 4-7

In Figure 4-8 it can be seen that according to Equation (3.6), the lost time of scheduled WOs of wind turbines (system MD, scenario 6) is equal to their WO duration. However, the lost time and lost energy of scheduled WOs of substations (System ATA, scenario 1) is zero, since in the baseline O&M strategy of this reference wind farm it is assumed that during the scheduled maintenance of substations wind turbines can be in operation.

In Figure 4-8 it can also be seen that the lost time of corrective WOs is way beyond their WO duration due to the waiting time for weather and/or resources. For example, 4 hours duration of the WO 140 in Figure 4-8 has led to 26 hours of lost time and approximately 170 MWh of lost energy. In Figure 4-9, the resource matrix at the time of WO 130 is shown.

DateTime	WS	HS	Power	AccessSOV	AccessHeli	AccessJackup	AccessCable	WindowSOV	WindowHeli	WindowJackup	WindowCable	VesselSOV	VesselHeli	VesselJackup	VesselCable	Technician
2020-03-30 11:00:00	12.30	2.43	8000	FALSE	TRUE	FALSE	FALSE	5.5	4798.0	7.0	14.5	TRUE	TRUE	TRUE	TRUE	20
2020-03-30 11:30:00	11.90	2.37	8000	FALSE	TRUE	FALSE	FALSE	5.0	4797.5	6.5	14.0	TRUE	TRUE	TRUE	TRUE	20
2020-03-30 12:00:00	11.50	2.30	8000	FALSE	TRUE	FALSE	FALSE	4.5	4797.0	6.0	13.5	TRUE	TRUE	TRUE	TRUE	20
2020-03-30 12:30:00	11.50	2.27	8000	FALSE	TRUE	FALSE	FALSE	4.0	4796.5	5.5	13.0	TRUE	TRUE	TRUE	TRUE	20
2020-03-30 13:00:00	11.50	2.23	8000	FALSE	TRUE	FALSE	FALSE	3.5	4796.0	5.0	12.5	TRUE	TRUE	TRUE	TRUE	20
2020-03-30 13:30:00	11.50	2.20	8000	FALSE	TRUE	FALSE	FALSE	3.0	4795.5	4.5	12.0	TRUE	TRUE	TRUE	TRUE	20
2020-03-30 14:00:00	11.50	2.17	8000	FALSE	TRUE	FALSE	FALSE	2.5	4795.0	4.0	11.5	TRUE	TRUE	TRUE	TRUE	20
2020-03-30 14:30:00	11.50	2.13	8000	FALSE	TRUE	FALSE	FALSE	2.0	4794.5	3.5	11.0	TRUE	TRUE	TRUE	TRUE	20
2020-03-30 15:00:00	11.50	2.10	8000	FALSE	TRUE	FALSE	FALSE	1.5	4794.0	3.0	10.5	TRUE	TRUE	TRUE	TRUE	20
2020-03-30 15:30:00	11.23	2.07	8000	FALSE	TRUE	FALSE	FALSE	1.0	4793.5	2.5	10.0	TRUE	TRUE	TRUE	TRUE	20
2020-03-30 16:00:00	10.97	2.03	8000	FALSE	TRUE	FALSE	FALSE	0.5	4793.0	2.0	9.5	TRUE	TRUE	TRUE	TRUE	20
2020-03-30 16:30:00	10.70	2.00	7960	TRUE	TRUE	FALSE	FALSE	161.0	4792.5	1.5	9.0	TRUE	TRUE	TRUE	TRUE	20
2020-03-30 17:00:00	10.43	1.97	7920	TRUE	TRUE	FALSE	FALSE	160.5	4792.0	1.0	8.5	TRUE	TRUE	TRUE	TRUE	20
2020-03-30 17:30:00	10.17	1.93	7880	TRUE	TRUE	FALSE	FALSE	160.0	4791.5	0.5	8.0	TRUE	TRUE	TRUE	TRUE	20
2020-03-30 18:00:00	9.90	1.90	7840	TRUE	TRUE	TRUE	FALSE	159.5	4791.0	1.0	7.5	TRUE	TRUE	TRUE	TRUE	20
2020-03-30 18:30:00	9.97	1.87	7820	TRUE	TRUE	TRUE	FALSE	159.0	4790.5	0.5	7.0	TRUE	TRUE	TRUE	TRUE	20
2020-03-30 19:00:00	10.03	1.83	7800	TRUE	TRUE	FALSE	FALSE	158.5	4790.0	6.0	6.5	TRUE	TRUE	TRUE	TRUE	20
2020-03-30 19:30:00	10.10	1.80	7730	TRUE	TRUE	FALSE	FALSE	158.0	4789.5	5.5	6.0	TRUE	TRUE	TRUE	TRUE	20
2020-03-30 20:00:00	10.17	1.77	7660	TRUE	TRUE	FALSE	FALSE	157.5	4789.0	5.0	5.5	TRUE	TRUE	TRUE	TRUE	20
2020-03-30 20:30:00	10.23	1.73	7590	TRUE	TRUE	FALSE	FALSE	157.0	4788.5	4.5	5.0	TRUE	TRUE	TRUE	TRUE	20

Figure 4-9 Status of the resource matrix at the time of WO 130 of the maintenance matrix given in Figure 4-8

In Figure 4-9 it can be seen that at the time of WO 130 notification (2020-03-30 11:00:00) the significant wave height is higher than 2 meters and the SOV cannot access the wind turbines. It goes the same until 6.5 hours after (2020-03-30 16:30:00) once the wave height goes equal or below 2 meters and technicians can be transferred to the wind turbine to start this WO, just for one and half hour of work. In Figure 4-10, the breakdown of WO 130 from the alarm date until the finalization of the WO (2020-03-31 10:00:00) is illustrated.

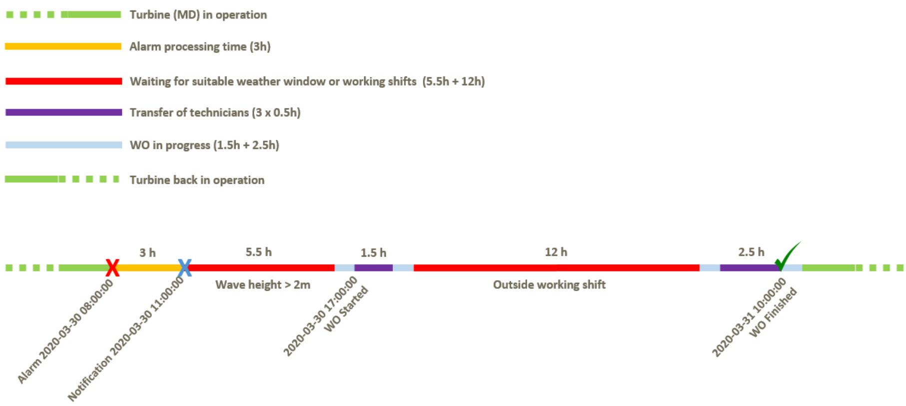


Figure 4-10 Breakdown of WO 127 of the maintenance matrix given in Figure 4-8

In Figure 4-10, it can be seen that this 4 hours long WO is executed within two steps, with 17.5 hours of weather and working shift waiting time in between.

Besides updating the maintenance matrix with start date, end time, lost time and lost revenue of WOs, the scheduler also updates the resource matrix with usage history of technicians and vessels. In Figure 4-11, the usage history of O&M vessels for WOs given in Figure 4-6 is illustrated.

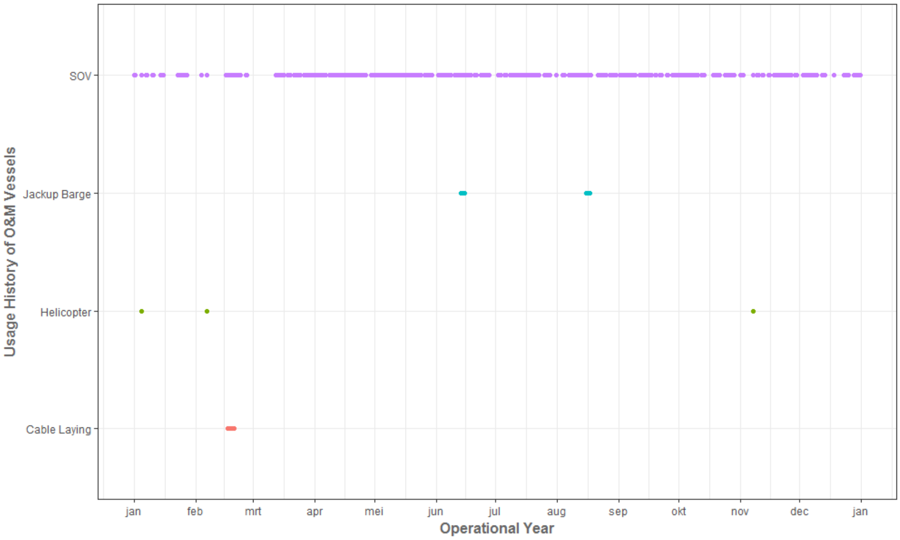


Figure 4-11 Usage history of O&M vessels for WOs given in Figure 4-6

As shown in Figure 4-11, the SOV is actively used, especially around the spring and summer seasons once scheduled WOs are initiated. The helicopter is used only in three occasions when the SOV hasn't been available to pick up the technicians at the end of their working shift (also for bi-weekly transfer of technicians from the onshore maintenance hub to offshore maintenance hub.

In Figure 4-11 it can also be seen that the jack up barge is chartered two times for two drivetrain replacements (scenario 4). It can also be seen that the cable laying vessel is only chartered once in mid-February for a subsea cable replacement (scenario 5).

Similarly, in Figure 4-12 the usage history of technicians for WOs given in Figure 4-6 is illustrated.

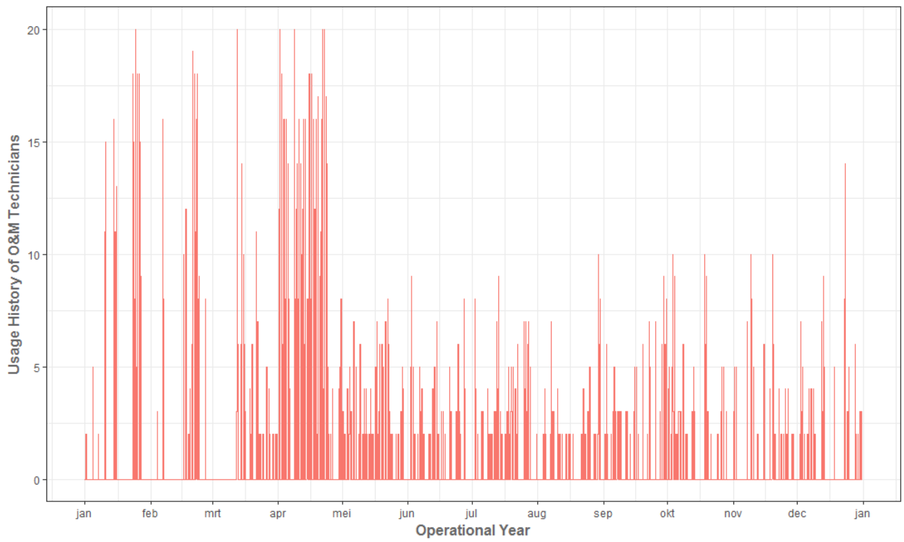


Figure 4-12 Usage history of O&M technicians for WOs given in Figure 4-6

As illustrated in Figure 4-12, only in 13 occasions all 20 offshore based technicians are occupied. Once all technicians are occupied, the remaining WOs get delayed until required technicians become available again.

4.3.2.5 O&M Costs

Once all WOs are scheduled, according to the equations given in 1.1.3 and 3.1.2 the total O&M costs for WOs shown in Figure 4-6 can be calculated as:

$$C_{OM.Dir} = \sum_{i=1}^{i=N} C_{WO.Dir_i} + C_{OM.Res} = C_V + C_T + C_S = (7.4 + 4 + 9.4) = M€\ 20.8 \tag{4.1}$$

- C_V = ownership costs of the SOV (M€ 5) and helicopter (M€ 1) plus WO specific support vessels costs (M€ 1.4) according to the scheduling results
- C_T = salaries for 40 technicians (M€ 4)
- C_S = spare part inventory costs (K€ 96) and cost of WO specific spares (M€ 9.3) according to the scheduling results

$$OPEX = C_{OM.Dir} + C_{OH} = 20.8 + 10 = M€\ 30.8 \tag{4.2}$$

Moreover, according to the scheduling results the energy loss for all WOs is:

$$E_{Loss} = 284.5\ GWh \tag{4.3}$$

Now that both OPEX and energy loss due to WOs are known, the LCoE can be calculated:

$$LCoE = \frac{CAPEX \times CRF + OPEX}{AEP_{Potential} - AEP_{Loss}} = \frac{(3200 \times 0.064 + 30.8)\ M€}{3.969 - 0.284\ TWh} = 63.9\ {€}/_{MWh} \qquad (4.4)$$

Now the calculated LCoE can be used as averaged market electricity price for calculation of indirect O&M costs:

$$C_{OM.Ind} = E_{Loss} \times (C_E + S_E) = 284.5\ GWh \times \left(63.9\ {€}/_{MWh} + 0\right) = M€\ 18.2 \qquad (4.5)$$

At last, the total O&M costs is:

$$C_{OM} = C_{OM.Dir} + C_{OM.Ind} + C_{OH} = (20.8 + 18.2 + 10) = M€\ 49 \qquad (4.6)$$

In Table 4-6, the yearly and lifetime O&M costs of the reference offshore wind farm based WOs shown in Figure 4-6 are shown.

O&M Costs	Cost Element	Yearly Costs (M€)	Lifetime Costs (B€)
Direct costs		**20.8**	**0.520**
	Vessels	7.4	0.185
	Spares	9.4	0.235
	Technicians	4.0	0.100
Indirect costs		**18.2**	**0.454**
Overhead costs		**10.0**	**0.25**
Total		**49.0**	**1.22**

Table 4-6 O&M costs of the reference wind farm based on distribution of WOs given in Figure 4-6

Furthermore, in Table 4-7 a summary of the calculated LCoE elements based on WOs given in Figure 4-6 is given.

LCoE Elements	Annual Estimation	% of LCoE
CAPEX x CRF	M€ 204.8	87%
OPEX	M€ 30.8	13%
AEP	3.684 TWh	---

Table 4-7 LCoE of the reference wind farm based on WOs given in Figure 4-6

Moreover, it can be seen that 19.3% of total LCoE is due to M€ 49 yearly O&M costs as shown in Figure 4-6 (part of it as OPEX and part of it as lost energy).

The O&M costs and LCoE elements given in Table 4-6 and Table 4-7 are heavily influenced by the assumed distribution of WOs as shown in Figure 4-6. Repeating the O&M cost calculation based on another WO distribution will result most likely into different O&M costs and LCoE estimation. In order to reduce this uncertainty, as described in 3.1.3.2 the aforementioned process should be repeated for several Monte Carlo simulations and then, average O&M costs of all simulations should be taken as the O&M costs of this reference offshore wind farm. As an example, in Figure 4-13 the convergence of averaged O&M costs based on repeated Monte Carlo simulations is shown.

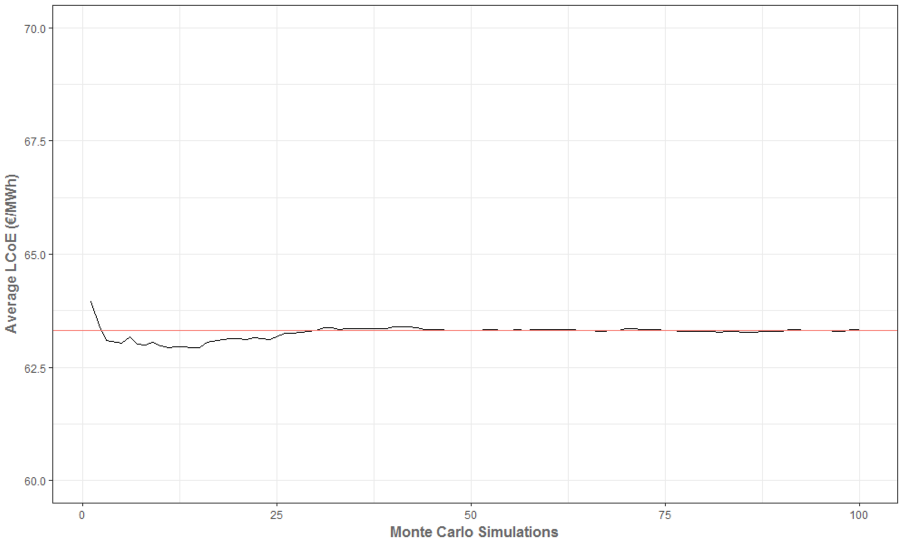


Figure 4-13 Convergence of LCoE based on 100 Monte Carlo simulations

In Figure 4-13 it can be seen that just after 50 simulations the averaged LCoE is 99% converged. Now that the O&M costs are no longer influenced by the occurrence time of WOs, the O&M costs can be recalculated. In Table 4-8, the average yearly and lifetime O&M costs of the reference offshore wind farm are shown.

O&M Costs	Cost Element	Yearly Costs (M€)	Lifetime Costs (B€)
Direct Costs		**22.2**	**0.555**
	Vessels	8.8	0.22
	Spares	9.4	0.235
	Technicians	4.0	0.100
Indirect Costs		**14.9**	**0.372**
Overhead costs		**10.0**	**0.25**
Total		**47.1**	**1.18**

Table 4-8 Averaged O&M costs of the reference wind farm

According to the O&M cost shown in Table 4-8, the averaged LCoE is recalculated to 63.3 €/MWh. In Table 4-9 a summary of the this LCoE elements is given.

LCoE Elements	Annual Estimation	% of LCoE
CAPEX x CRF	M€ 204.8	86.4%
OPEX	M€ 32.2	13.6%
AEP	3.746 TWh	---

Table 4-9 Averaged LCoE of the reference wind farm

Furthermore, it can be seen that 18.4% of total LCoE is due to M€ 47.1 yearly O&M costs as shown in Table 4-8 (part of it as OPEX and part of it as lost energy).

As shown in Table 4-8, the lost revenue during the downtime of WOs contributes to 40% of total O&M costs (excluding overhead costs). Therefore, for this baseline O&M strategy several sensitivity analyses (such as 2 SOVs instead of one or 24/7 working shifts) should be performed to optimize the baseline O&M strategy and reduce the downtime and associated lost revenue. The optimization of the shared O&M resources is not further discussed in this thesis.

In Paper I (Asgarpour & Sørensen, 2016) and Paper II (Asgarpour & Sørensen, 2015) more case studies on lifetime O&M cost calculation based on baseline O&M strategy are given. Furthermore, in (Asgarpour & Pieterman, 2014) updating of baseline O&M strategy based on available O&M data during the operational years of an offshore wind farm is further discussed and several examples are provided.

CHAPTER 5. SHORT-TERM O&M PLANNING

Besides long-term optimization of O&M planning, the O&M costs of offshore wind farms can be significantly reduced if existing corrective actions are performed as efficient as possible and if future corrective failures are avoided by performing sufficient preventive actions. In Figure 5-1, a framework of short-term O&M planning of offshore wind farms is given.

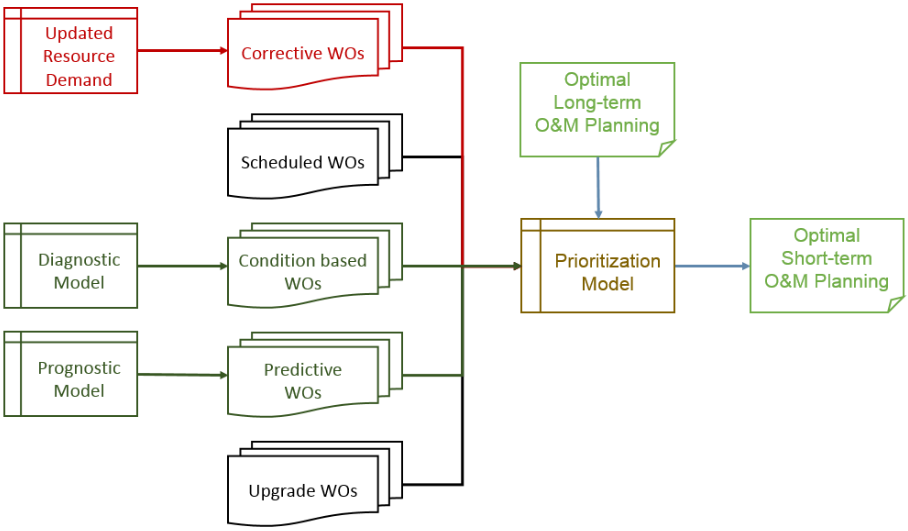


Figure 5-1 Framework for optimal short-term O&M planning of offshore wind farms

As seen in Figure 5-1, within this framework, the updated resource demand of corrective WOs is identified and optimal condition based and predictive WOs based on diagnostic and prognostic models are created. Then, using the optimal long-term O&M planning discussed in Chapter 4 and risk based models discussed in Chapter 3, the scheduling, costs and optimal prioritization of outstanding WOs in the CMMS are identified. The resulted optimal short-term O&M planning can directly be used in the next working shifts of maintenance hub to finalize outstanding corrective WOs as efficient as possible and to avoid future corrective WOs by implementing defined condition based and predictive WOs.

In the followings, first updating the resource demand and diagnostic and prognostic models are briefly discussed and then, two case studies for short-term O&M planning of the reference offshore wind farm are given.

5.1. CORRECTIVE MAINTENANCE

The existing corrective WOs can be optimized only if all available information from existing finalized WOs available in the maintenance history is used to update the resource demand.

5.1.1. UPDATING RESOURCE DEMAND

As discussed, during development phase of an offshore wind the resource demand of corrective WOs is not known and should be assumed. However, during the generation phase of an offshore wind farm the existing maintenance data can be used to update the baseline resource demand made during the development phase of an offshore wind farm. In Figure 5-2, a framework for updating the resource demand based on finalized corrective WOs in the CMMS is illustrated.

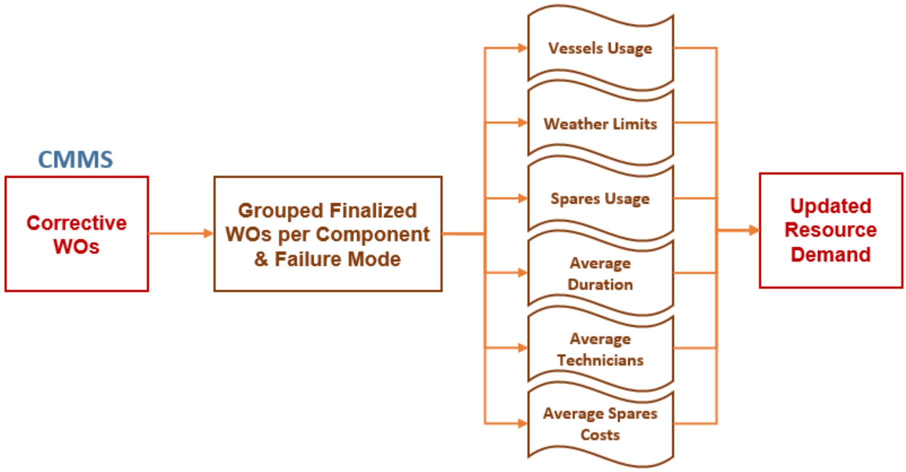


Figure 5-2 Framework for updating the resource demand based on maintenance history

As visualized in Figure 5-2, first the finalized corrective WOs should be grouped per component type and failure mode and then, the average duration and resource demand of each component failure mode group should be used to update the existing resource demand used in the scheduling model. In section 5.4.1 of this chapter a case study for scheduling and prioritization of outstanding corrective WOs based on the updated resource demands is given.

5.2. CONDITION BASED MAINTENANCE

As discussed already, the majority of O&M costs of offshore wind farms is due to unplanned failure of wind farm components. The O&M costs can be reduced significantly if the faults of wind farm components can be detected as soon as they occur and before they lead to a failure. The fault prediction of offshore wind components can be achieved within a diagnostic model.

5.2.1. DIAGNOSTIC MODEL

In Paper III (Asgarpour & Sørensen, 2017) a holistic Bayesian based diagnostic model based on several diagnostic agents or fault detection methods is introduced. In Figure 5-3, the framework of this diagnostic model is visualized. Within this diagnostic model a confidence matrix or Probability of Detection (PoD) model is defined, in which relevance or capability of each diagnostic agent for fault detection of each component or component failure mode is determined.

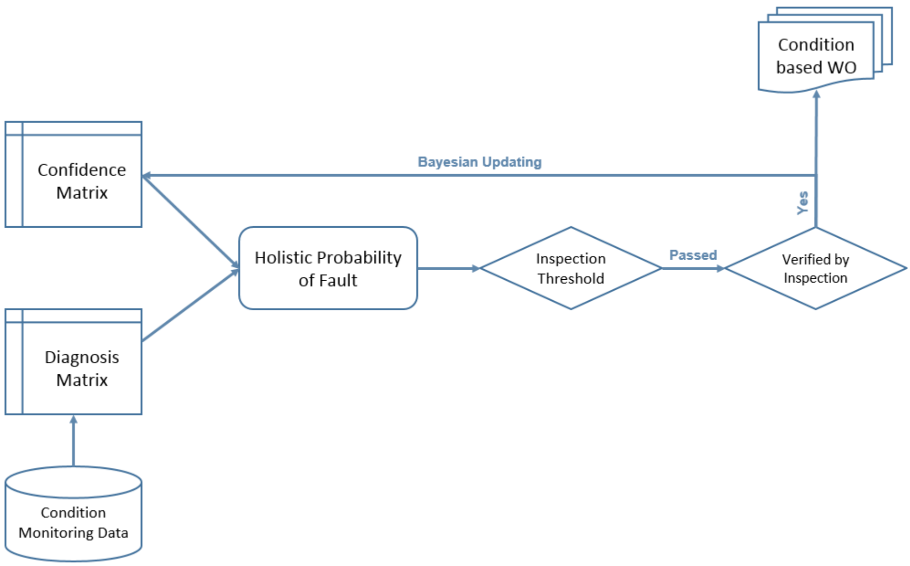


Figure 5-3 Framework of a holistic diagnostic model with Bayesian updating for offshore wind farms (Asgarpour & Sørensen, 2017)

Furthermore, in Figure 5-3 it can be seen that diagnosis of each diagnostic agent is given into a diagnosis matrix. Then, based on the defined confidence and diagnosis matrices, the holistic probability of fault for each component or component failure mode is calculated. Once the probability of fault for a given component or component failure mode is above a given threshold, an inspection should be done to verify the diagnosis. If the fault detection is verified by an inspection, then a condition based

WO should be created to avoid upcoming failures of that component. Additionally, based on Bayes' rule, the verified fault detection results can be used to update the initial confidence matrix.

In Paper III (Asgarpour & Sørensen, 2017) of this thesis, the diagnostic model discussed here is further explained in detail. In section 5.4.2 of this chapter, a case study for scheduling and prioritization of condition based WOs is presented.

5.3. PREDICTIVE MAINTENANCE

Corrective effort of offshore wind farms can be reduced to its minimum only if instead of failure probability, the reliability of wind farm components is defined by their degradation models and once their degradation goes above a given threshold (or their RUL goes below a given threshold), a predictive WO is executed to maintain the components. The degradation monitoring and fault prediction of wind farm components can be achieved with a prognostic model.

5.3.1. PROGNOSTIC MODEL

In Paper IV (Asgarpour & Sørensen, 2017) a hybrid prognostic model based on degradation and RUL models of offshore wind components is introduced. In Figure 5-4, the framework of this prognostic model is visualized. According to this framework and based on the degradation models defined in Chapter 2, initial degradation and RUL models of offshore wind components can be defined. Then, once degradation level of a component goes beyond a threshold, or once the RUL of a component goes below a given threshold, an inspection should be done to verify the predicted degradation level.

If based on the observed degradation level during inspection (determined by using a degradation matrix as explained in 2.2.4.1), the predicted degradation level of a component is verified, then a predictive WO should be defined to decrease the degradation level of that component or to prevent its future faults and failures.

Additionally, if based on an inspection it is proved that the predicted degradation level of a component is not correct, then based on Bayes' rule and Normal-Normal model (Jacobs, 2008), the observed degradation level can be used to update the prior degradation model.

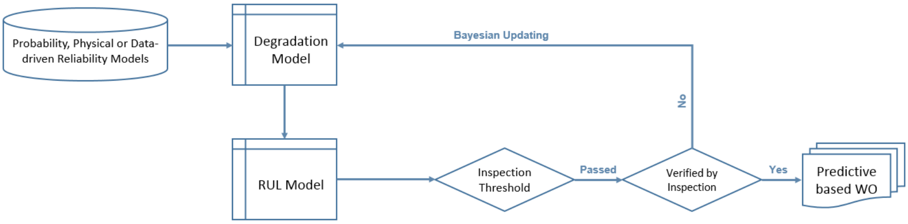


Figure 5-4 Framework of a prognostic model with Bayesian updating for offshore wind farms (Asgarpour & Sørensen, 2017)

In In Paper IV (Asgarpour & Sørensen, 2017) this prognostic model is discussed in detail. Furthermore, in section 5.4.2 of this chapter, a case study for scheduling and prioritization of predictive WOs is presented.

5.4. CASE STUDY

Similar to the case study presented in Chapter 4 for long-term O&M planning, in this section two case studies for short-term O&M planning of offshore wind farms based on the defined 800 MW reference offshore wind farm are presented.

5.4.1. CORRECTIVE PLANNING

In this case study, scheduling and prioritization of outstanding corrective WOs based on updated resource demand is presented. First, updated resource demand for the reference offshore wind farm is determined and then, based on the framework shown in Figure 5-1 hypothetical outstanding corrective WOs of the reference offshore wind farm are scheduled and prioritized in a way to lead into minimum operational costs.

5.4.1.1 Updated Resource Demand

In the followings, it is assumed the reference offshore wind farm defined in Chapter 4 is in operation for a bit more than five years and maintenance history for the following wind turbine components shown in Table 5-1 is available.

Main System	Components	RDS-PP Code
Wind Turbine		**MD**
	Rotor System	**MDA**
	Drivetrain System	**MDK**
	Yaw System	**MDL**
	Hydraulic System	**MDX**
	Control System	**MDY**
	Generation System	**MKA**
	Converter System	**MSE**
	Transformer System	**MST**
	Cooling System	**MUR**
	Nacelle System	**MUD**
	Tower System	**UMD**

Table 5-1 List of reference wind farm components with available O&M history

Based on the available historical maintenance data and updating resource demand model shown in Figure 5-2, the resource demand for corrective maintenance of each wind turbine component shown in Table 5-1 can be estimated.

In Table 5-2, the calculated resource demand matrix for corrective WOs of each wind turbine component based on averaged maintenance history data from 1st of January 2020 until 31st of March 2025 is shown. As seen in Table 5-2, the resource demand estimated from O&M history could be different from assumptions made for the baseline O&M planning.

Component	Duration (h)	Technicians	Spares (K€)
MDA	14	3	30
MDK	30	3	100
MDL	18	3	40
MDX	6	2	5
MDY	8	2	5
MKA	24	3	60
MSE	10	2	8
MST	18	3	30
MUR	12	2	4
MUD	14	3	8
UMD	20	3	10

Table 5-2 Updated resource demand for corrective WOs of wind turbine components based on the maintenance history

In Table 5-2, only resource demand of main component systems for only one hypothetical failure mode is shown. Similarly, resource demand of all component levels for all their failure modes can be estimated.

Moreover, it is assumed that during execution of WOs during the first five operational years of reference offshore wind farm the SOV could access the wind turbines only when the wind speed has been less than 18 m/s and the significant wave height has been less than 1.9 meters. Additionally, it is assumed that the required spare for corrective WOs (based on spares usage history) are available in the spare part inventory.

Now that required O&M resources for corrective WOs based on historical maintenance data are known, the outstanding corrective WOs can be scheduled and their O&M costs can be estimated. In this case study, it is assumed that by 31st of March 2025, there are six wind turbines down due to unplanned corrective failures. In Figure 5-5, the status of the reference offshore wind farm at this time is shown (green wind turbines are in operation and red wind turbines are down due to unplanned failures).

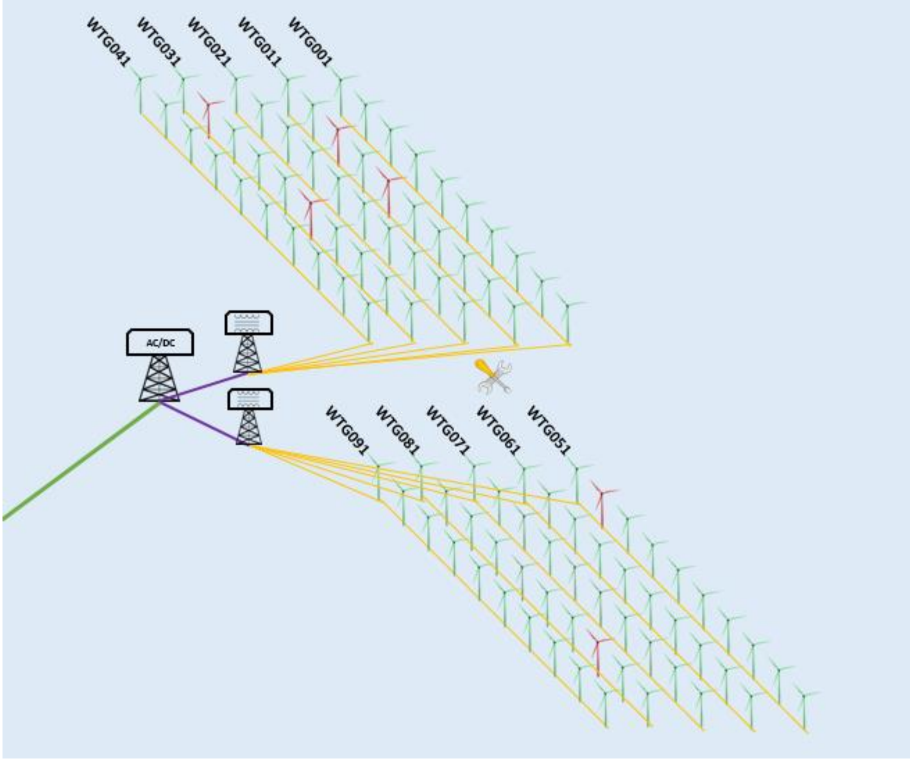


Figure 5-5 Status of wind turbines of the reference offshore wind farm by 31st of March 2025

If none of the wind turbine failures shown in Figure 5-5 can be resolved remotely, six outstanding corrective WOs should exist in the CMMS of the maintenance hub. In Figure 5-6, these six hypothetical outstanding WOs are shown.

ID	AlarmDate	NotificationDate	Status	System	Component	Category
1	2025-03-13 19:00:00	2025-03-13 21:00:00	Outstanding	WTG052	MDA	Corrective
2	2025-03-18 10:30:00	2025-03-18 19:30:00	Outstanding	WTG013	MDK	Corrective
3	2025-03-22 03:00:00	2025-03-22 06:00:00	Outstanding	WTG036	MUR	Corrective
4	2025-03-23 02:00:00	2025-03-23 05:00:00	Outstanding	WTG032	MDX	Corrective
5	2025-03-25 11:30:00	2025-03-25 13:30:00	Outstanding	WTG088	MST	Corrective
6	2025-03-28 14:00:00	2025-03-28 15:00:00	Outstanding	WTG015	MSE	Corrective

Figure 5-6 Outstanding corrective WOs in the CMMS of the reference offshore wind farm by 31st of March 2025

As seen in Figure 5-6, a few hours after the wind turbine alarm, a WO notification is created in the CMMS. The response time of alarm handling varies from only 1 hour to 9 hours. Each WO is identified by a unique ID and is associated with a unique wind turbine and component.

5.4.1.2 WO Scheduling

In order to schedule the WOs given in Figure 5-6, first their required O&M resources should be known. In Figure 5-7 the updated resource demand of these six WOs based on the updated resource demand given in Table 5-2 is shown.

ID	System	Component	Duration	Technician	Spares	StartDate	EndDate	LostTime	LostRevenue
1	WTG052	MDA	14	3	3e+04	NA	NA	NA	NA
2	WTG013	MDK	30	3	1e+05	NA	NA	NA	NA
3	WTG036	MUR	12	2	4e+03	NA	NA	NA	NA
4	WTG032	MDX	6	2	5e+03	NA	NA	NA	NA
5	WTG088	MST	18	3	3e+04	NA	NA	NA	NA
6	WTG015	MSE	10	2	8e+03	NA	NA	NA	NA

Figure 5-7 Updated resource demand of outstanding corrective WOs

As discussed in 3.1, besides resource demand of WOs, short-term weather and market forecasts are required for scheduling of outstanding WOs. The weather forecast is used to calculate the SOV accessibility and potential energy production of wind turbines at each time step. The market forecast is used to calculate lost revenue associated with potential energy production.

In this case study, the historical weather data for the same time period is used as short-term weather forecast and a Weibull distribution with scale of 57.14 and shape of 1.5 as illustrated in Figure 5-8 is used as daily market forecast.

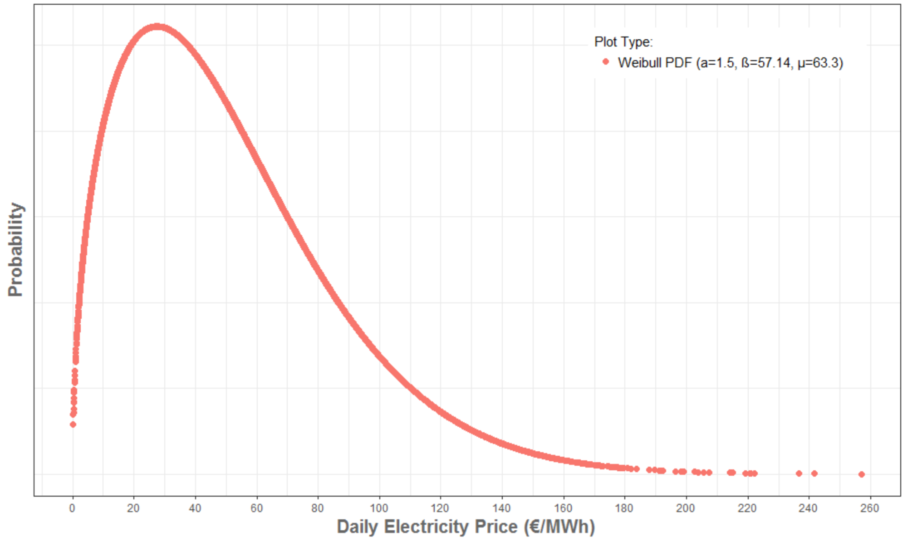


Figure 5-8 Market electricity price during 25 years of reference wind farm lifetime modelled as a Weibull PDF

In Figure 5-8 it is assumed that the daily market electricity price is never negative, which is not always true. The shape factor of this Weibull distribution is assumed to be 1.5 and its scale factor is found in a way that the average market electricity price be equal to the LCoE of reference offshore wind farm calculated in 4.3.2.5. Therefore, based on Equation (1.7) the scale factor of this Weibull distribution is calculated as:

$$\beta = {}^{\mu}\!\big/_{\Gamma\left(1+\frac{1}{\alpha}\right)} = {}^{63.3}\!\big/_{\Gamma\left(1+\frac{1}{1.5}\right)} = 57.14\ €/MWh \tag{5.1}$$

Now that outstanding corrective WOs, their resource demand and weather and market forecasts are known, the start date, the end date, lost time and lost revenue associated with each WO can be calculated. This can be done using the scheduling model discussed in Chapter 3.

The key of optimal WO scheduling is the right prioritization of outstanding WOs. As the baseline, it is assumed that the WOs are executed in their notification date order. In Figure 5-9, the scheduling results of corrective outstanding WOs of this case study executed based on their notification date order is shown.

ID	System	Component	Duration	Technician	Spares	StartDate	EndDate	LostTime	LostRevenue
1	WTG052	MDA	14	3	3e+04	2025-04-01 07:30:00	2025-04-01 13:30:00	447.5	78523.4
2	WTG013	MDK	30	3	1e+05	2025-04-01 08:00:00	2025-04-02 16:00:00	355.5	59393.1
3	WTG036	MUR	12	2	4e+03	2025-04-01 09:30:00	2025-04-02 15:30:00	272.5	39207.4
4	WTG032	MDX	6	2	5e+03	2025-04-02 08:30:00	2025-04-02 14:30:00	248.5	36574.4
5	WTG088	MST	18	3	3e+04	2025-04-02 09:00:00	2025-04-03 08:30:00	210.0	32067.6
6	WTG015	MSE	10	2	8e+03	2025-04-02 09:30:00	2025-04-03 12:30:00	140.5	20198.9

Figure 5-9 Scheduling of outstanding corrective WOs by their notification date order

As shown in Figure 5-9, the first WO has started on 2025-04-01 07:30 and the last WO is finalized at 2025-04-03 12:30. The total lost time and revenue associated with this scheduling can be calculated as:

$$T_{Loss} = \sum_{i=1}^{i=6} T_{Loss,i} = 1674.5\ h$$
$$Revenue_{Loss} = \sum_{i=1}^{i=6} Revenue_{Loss,i} = K€\ 266 \tag{5.2}$$

Moreover, in Figure 5-10 the availability or usage history of the access vessel and technicians during the execution of these WOs are visualized.

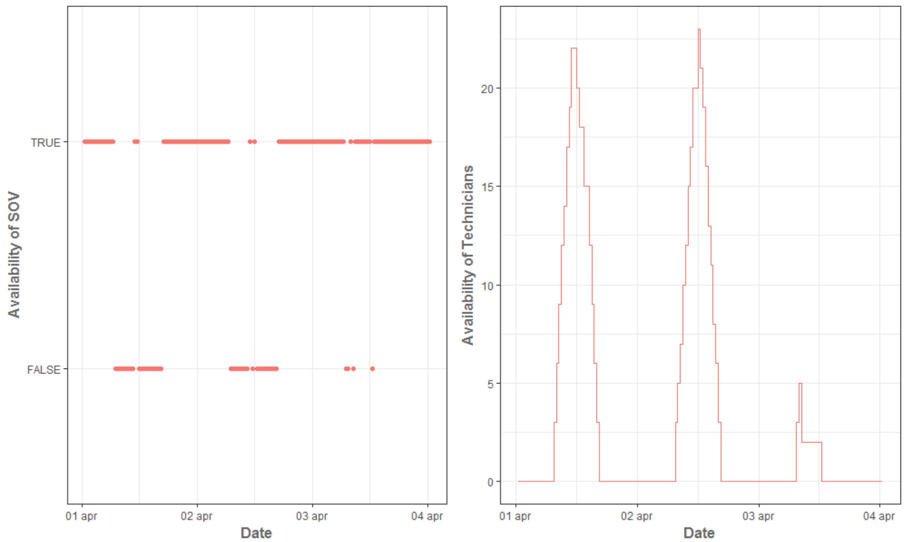


Figure 5-10 Usage history of the access vessel and technicians for execution of outstanding corrective WOs

In Figure 5-10, it can be seen that on the 2nd of April more than 20 technicians are required to finalize the outstanding WOs. The maintenance hub can request extra technicians for that day or rerun the scheduler with a limit on total available technicians.

5.4.1.3 WO Prioritization

In the previous section it was seen that execution of the outstanding WOs shown in Figure 5-7 based on their notification date order results into K€ 266 of lost revenue. Based on the prioritization model discussed in Chapter 3, the optimal prioritization of WOs can be found and total revenue loss due to WOs can be reduced. The optimal prioritization within this framework is based on the minimum lost revenue for execution of given WOs. In Figure 5-11, an overview of associate lost revenue of WOs given in Figure 5-7 based on all possible WO prioritization scenarios is shown.

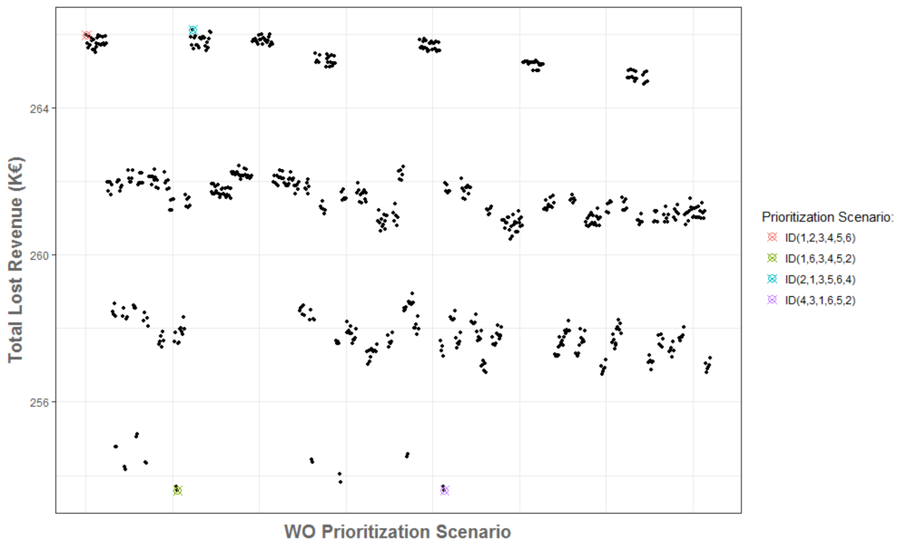


Figure 5-11 Lost revenue of different prioritization scenarios for WOs shown in Figure 5-7

In Figure 5-11 it can be seen that WOs order of ID(1, 6, 3, 4, 5, 2) and ID(4, 3, 1, 6, 5, 2) result into K€ 256.3, which is the minimum total lost revenue. Furthermore, it can be seen that associated lost revenue according to the baseline execution order of WOs, ID(1, 2, 3, 4, 5, 6), is very close to the maximum K€ 266.11 of lost revenue. In this example, by choosing the optimal prioritization, K€ 12.5 of total lost revenue can be saved. Similar lost revenue reductions can be achieved in every working shift if offshore wind corrective WOs are executed in their optimal order.

In addition to scheduling and prioritization of corrective WOs, a similar approach can be used for scheduling and prioritization of all outstanding WOs such as scheduled, condition based or predictive ones. In following case study, planning and prioritization of condition based and predictive WOs is presented.

5.4.2. PREVENTIVE PLANNING

During the lifetime of an offshore wind farm several preventive WOs can be created to minimize the associated costs of unplanned corrective failures. In section 5.2 of this chapter it was shown that based on a holistic diagnostic model, condition based WOs can be created efficiently once a component fault is detected. Similarly, in section 5.3 of this chapter it was shown that based on a hybrid prognostic model, predictive WOs can be created efficiently to avoid future faults or reduced the degradation of critical components. Once the condition based and predictive WOs are created, they should be optimally scheduled and prioritized to minimize their associated maintenance costs.

In this section, a case study based on the reference offshore wind farm for scheduling and prioritization of condition based and predictive WOs is presented. As instance in Table 5-3, two assumed condition based WOs and one assumed predictive WOs for wind turbine drivetrain and generator of three wind turbines of the reference offshore wind farm are shown.

Wind Turbine	**Component**	**Type**	**Estimated Time to Failure (days)**
WG054	MDK	Condition based	5
WG072	MDK	Condition based	45
WG039	MKA	Predictive	120

Table 5-3 Assumed detected faults for the reference offshore wind farm

As seen in Table 5-3, next to the detected or predicted faults of components an estimation of the remaining time to their failure is given. The remaining time to failure for condition based WOs can be estimated by combining experts' judgement on inspection outcome with diagnostic model results. The estimated remaining time to failure of predictive WOs can be taken directly from their RUL models.

The scheduling of these condition based and predictive WOs is demonstrated through a case study based on the reference offshore wind farm. As shown in Figure 5-12, it is assumed that three wind turbines highlighted in red are down due to unplanned failures and three other turbines highlighted in amber are in operation with detected or predicted faults (based on WOs in Table 5-3).

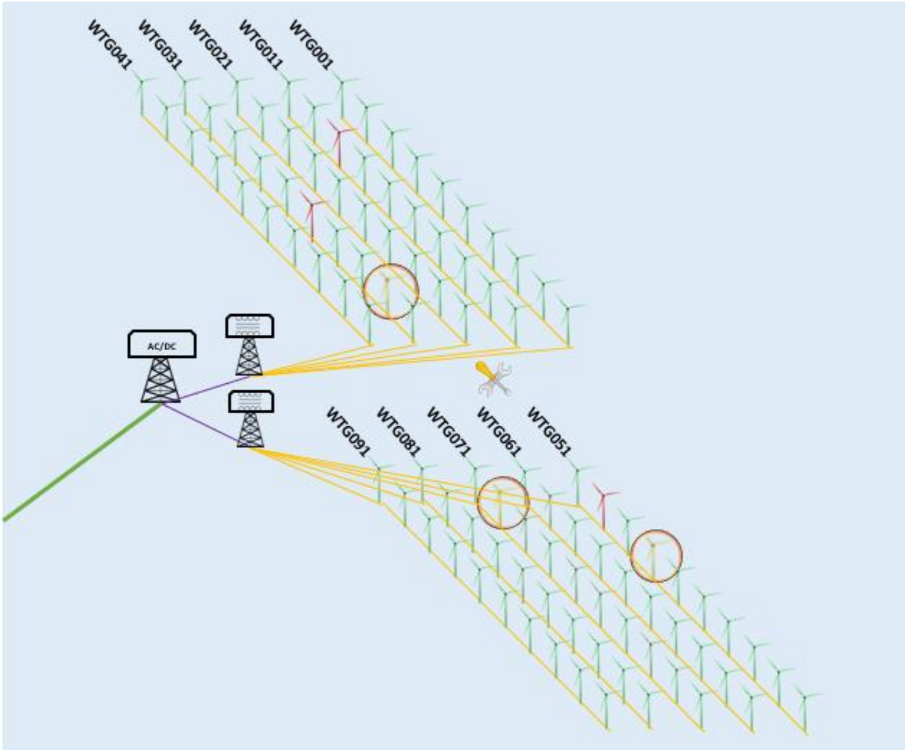


Figure 5-12 Status of wind turbines of the reference offshore wind farm by 1st of April 2025

It is assumed that all three condition based and predictive WOs have been added to the CMMS of the offshore wind farm by 1st of April 2025. In Figure 5-13 an overview of all outstanding WOs of the reference offshore wind farm by 1st of April 2025 is shown.

ID	AlarmDate	NotificationDate	Status	System	Component	Category	Duration	Technician	Spares	TargetEndDate	TargetLostRevenue
1	2025-03-13 19:00:00	2025-03-13 21:00:00	Outstanding	WTG052	MDA	Corrective	14	3	3e+04	NA	NA
2	2025-03-18 10:30:00	2025-03-18 19:30:00	Outstanding	WTG013	MDK	Corrective	30	3	1e+05	NA	NA
3	2025-03-22 03:00:00	2025-03-22 06:00:00	Outstanding	WTG036	MUR	Corrective	12	2	4e+03	NA	NA
4	NA	2025-04-01 00:00:00	Outstanding	WTG054	MDK	Condition based	18	2	2e+04	2025-04-06	5000
5	NA	2025-04-01 00:00:00	Outstanding	WTG072	MDK	Condition based	18	2	2e+04	2025-05-16	5000
6	NA	2025-04-01 00:00:00	Outstanding	WTG039	MKA	Predictive	18	2	2e+04	2025-07-30	5000

Figure 5-13 Outstanding corrective, condition based and predictive WOs of the reference offshore wind farm by 1st of April 2025

Similar to the case study presented in 5.4.1, the resources of corrective WOs are determined by using the updated resource demand. For both condition based and predictive WOs it is assumed that two technicians for 18 hours and K€ 20 worth of spares are required to finalize a WO. As seen in Figure 5-13, for condition based and predictive WOs target end date and target lost revenue values as decision rules of the scheduling and prioritization models are also defined. The target end date is defined based on the estimated time to failure values of Table 5-3. Target lost revenue is the maximum allowed lost revenue to make sure that execution costs of condition based and predictive WOs don't exceed their benefits.

Since the duration of all condition based and predictive WOs is assumed to be 18 hours, the target lost revenue is only dependent on stochastic daily electricity price shown in Figure 5-8. Therefore, the condition based and predictive WOs only should be executed when market electricity price is negative or very low to minimize their associated lost revenue. In this case study, the maximum lost revenue caused by condition based and predictive WOs is assumed to be K€ 5. The end date target can also be defined for corrective WOs with high priorities to make sure they are finalized before a certain date.

5.4.2.1 WO Scheduling

Similar to previous case study, as the baseline it is assumed that the WOs are executed in their notification date order. In Figure 5-14, the scheduling results of outstanding WOs executed based on their notification date order is shown.

ID	System	Component	Category	Duration	StartDate	EndDate	TargetEndDate	LostTime	LostRevenue	TargetLostRevenue
1	WTG052	MDA	Corrective	840	2025-04-01 07:30:00	2025-04-01 13:30:00	NA	447.5	78523.4	NA
2	WTG013	MDK	Corrective	1800	2025-04-01 08:00:00	2025-04-02 16:00:00	NA	355.5	59393.1	NA
3	WTG036	MUR	Corrective	720	2025-04-01 09:30:00	2025-04-02 15:30:00	NA	272.5	39207.4	NA
4	WTG054	MDK	Condition based	1080	2025-04-02 08:30:00	2025-04-02 12:00:00	2025-04-06	18.0	474.6	5000
5	WTG072	MDK	Condition based	1080	2025-04-02 09:00:00	2025-04-03 16:30:00	2025-05-16	18.0	335.2	5000
6	WTG039	MKA	Predictive	1080	2025-04-03 08:00:00	2025-04-03 13:30:00	2025-07-30	18.0	25.1	5000

Figure 5-14 Scheduling of outstanding corrective, condition based and predictive WOs by their notification date order

As shown in Figure 5-14, it can be seen that both target end date and target lost revenue of condition based and predictive WOs are met. The total lost time and revenue associated with this order of WO execution can be calculated as:

$$
\begin{aligned}
&T_{Loss} = \sum_{i=1}^{i=6} T_{Loss,i} = 1129.5\ h \\
&Revenue_{Loss} = \sum_{i=1}^{i=6} Revenue_{Loss,i} = K€\ 177.96
\end{aligned}
\qquad (5.3)
$$

Moreover, in Figure 5-15 the availability or usage history of the access vessel and technicians during execution of these WOs are visualized.

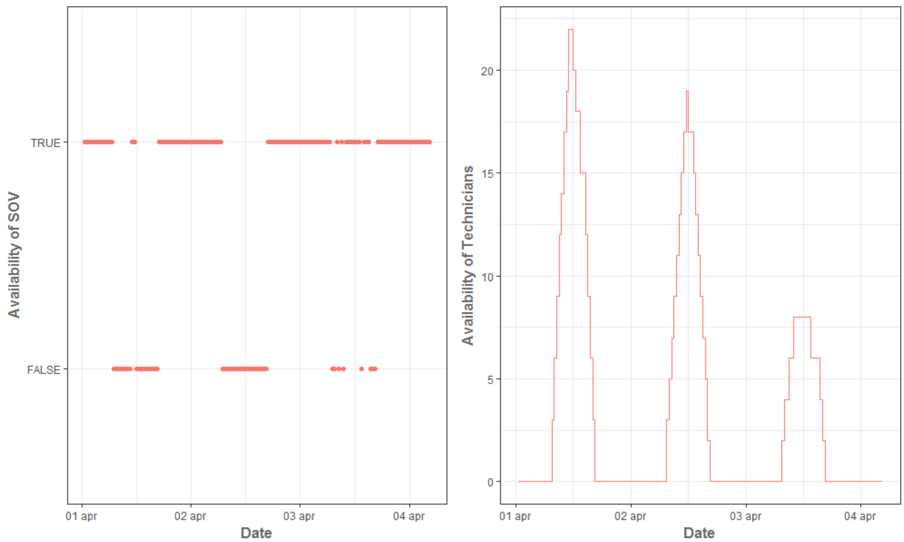


Figure 5-15 Usage history of the access vessel and technicians for execution of outstanding corrective, condition based and predictive WOs

In Figure 5-15, it can be seen that on 1st of April more than 20 technicians are required to finalize the outstanding WOs. The maintenance hub can request extra technicians for that day or rerun the scheduler with a limit on total available technicians.

5.4.2.2 WO Prioritization

Similar to prioritization of corrective WOs in the previous case study, the corrective, condition based and predictive WOs shown in this case study can be prioritized to make sure that their end date and lost revenue targets are met and at the same time, the total lost revenue associated with execution of these WOs is kept to its minimum.

In the previous section it was seen that execution of the outstanding WOs shown in Figure 5-13 based on their notification date order will result into K€ 177.96 of revenue loss.

Based on the prioritization model discussed in section 3.2, the optimal prioritization of WOs can be found and total revenue loss due to WOs can be reduced while both end date and lost revenue targets are met. In Figure 5-16, an overview of associated lost revenue of these six WOs based on all possible WO prioritization scenarios is shown.

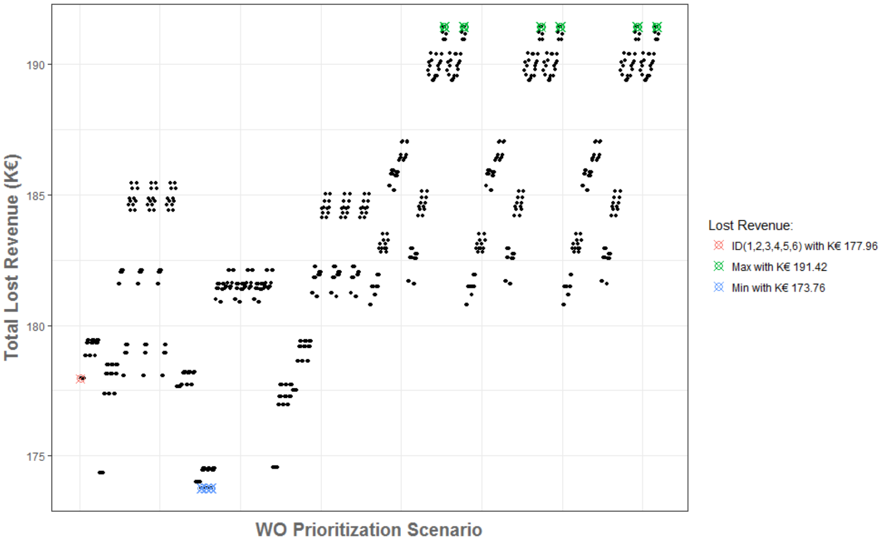


Figure 5-16 Lost revenue of different prioritization scenarios for WOs shown in Figure 5-13

In Figure 5-16 it can be seen that six prioritization scenarios of WOs such as ID(2, 3, 4, 1, 5, 6) result into the minimum total lost revenue K€ 173.76. It can be seen that original order of WOs ID(1, 2, 3, 4, 5, 6) is close to the minimum calculated lost revenue. Similarly, twelve prioritization of scenarios such as ID(4, 5, 6, 2, 1, 3) result into the maximum lost revenue K€ 191.42 since corrective WOs are delayed by condition based and predictive WOs.

In this example, prioritization of WOs can save K€ 17.66 of total lost revenue. Similar lost revenue reductions can be achieved in every working shift if the short-term O&M planning model shown in Figure 5-1 is used for optimal scheduling and optimization of all outstanding offshore wind WOs.

CHAPTER 6. DISCUSSION

In this thesis, rational and applied solutions for reducing direct and indirect O&M costs of an offshore wind farm based on risk and reliability models are defined and within several illustrative case studies are demonstrated. In this chapter, first conclusions on the thesis' approach to achieve its objective are given and then, several recommendations for future studies on this subject are proposed.

6.1. CONCLUSIONS

In this thesis, generic risk and reliability models are defined which can be used for both short- and long-term O&M planning of offshore wind farms. In Chapter 2, stochastic failure, degradation and remaining useful lifetime reliability models for offshore wind components are defined. The uncertainty of defined reliability models is taken into account by distribution of each variable. Furthermore, the Bayesian updating of prior failure and degradation reliability models based on all available information is demonstrated.

In Chapter 3, based on all available information and decision criteria, applied risk based cost, scheduling and prioritization models are defined. In the defined risk based O&M cost model, the failure model defined in Chapter 2 is used as reliability of wind farm components. In the scheduling model, a method for scheduling and cost estimation of each maintenance work order is proposed. Furthermore, in the prioritization model, a solution for cost reduction of implementation of outstanding maintenance work orders is introduced. The developed risk based models in Chapter 3 are interconnected, in which output of one model can be easily used as input into another model.

In Chapter 4 and Chapter 5, the application of developed risk and reliability models for O&M cost reduction of offshore wind farms within long-term and short-term O&M planning frameworks is presented. In Chapter 4, a long-term O&M planning framework is defined, in which lifetime O&M costs based on a given O&M strategy can be calculated. In operational years of an offshore wind farm, the long-term O&M planning framework can be used to optimize the shared O&M resources and hence, reduce lifetime direct and indirect O&M costs. Furthermore, the long-term O&M planning framework can be used to make informed decisions during end of warranty and end of design lifetime phases, which can result into significant O&M cost reductions. In the followings of Chapter 4, the discussed long-term O&M planning framework is used to demonstrate lifetime O&M costs of a reference 800 MW offshore wind farm. Furthermore, in Paper I (Asgarpour & Sørensen, 2016) and Paper II (Asgarpour & Sørensen, 2015) of this thesis and (Asgarpour & Pieterman, 2014), more examples on O&M cost reduction by long-term O&M planning of offshore wind farms are given.

In Chapter 5, a short-term O&M planning framework for optimal scheduling and prioritization of maintenance work order is introduced. Within this framework, the updated resource demand of corrective maintenance work orders can be identified. In a case study for scheduling and prioritization of outstanding maintenance work orders based on their updated resource demand, it was demonstrated that indirect O&M costs of only six corrective work orders of the reference offshore wind farm can be reduced by K€ 12.5. Similar cost reductions within each working shift of offshore wind farms can be achieved.

Furthermore, in Chapter 5, based on Paper III (Asgarpour & Sørensen, 2017) a diagnostic model and based on Paper IV (Asgarpour & Sørensen, 2017) a prognostic model for fault detection, degradation monitoring and fault prediction of offshore wind components are introduced. The condition based and predictive maintenance work orders created by discussed diagnostic and prognostic models, can avoid future corrective failures and therefore, reduce O&M costs. Moreover, within a case study for the reference offshore wind farm it was shown that using the proposed short-term O&M planning framework, the associated costs of condition based and predictive maintenance work orders can be reduced to their minimum. Within this case study it was shown that indirect O&M costs of only six corrective, condition based and predicative maintenance work orders can be redubbed by K€ 17.66 if the scheduling and prioritization model for their short-term planning is used. Similar cost reductions can be achieved in every working shift of an offshore wind farm if all outstanding maintenance work orders are scheduled and prioritized based on the discussed short-term O&M planning framework.

In this thesis, it was shown that direct and indirect O&M costs of offshore wind farms can be reduced to their minimum only if by using a risk and reliability based O&M planning model, optimal long-term and short-term decisions are made. The discussed risk and reliability models in this thesis are generic enough to be used for both short-term and long-term O&M planning models, can take into account all available information and are developed in a way to be easily implemented into any offshore wind asset management system.

6.2. FUTURE WORK

In future studies on this subject, the risk and reliability models developed in this thesis can be replaced with more accurate models. Instead of the exponential degradation reliability model defined in Chapter 2, a physical or data-driven degradation model can be used. Relevant physical models for degradation modelling of wind farm components are Paris' law for crack growth development (applied typically for degradation modelling of wind turbine blades), S-N curves and the Palmgren-Miner's rule for fatigue assessment (applied typically for degradation modelling of foundations or drivetrain mechanical components) and fracture mechanics models. Furthermore, for structural components, instead of classical reliability models discussed here, more accurate probabilistic reliability models based on their limit state equations can be formulated.

The risk based prioritization model in Chapter 3 can be optimized to reduce the processing time once many (e.g. more than six) outstanding work orders should be prioritized in one working shift of an offshore wind farm.

The diagnostic model defined in Chapter 5 can be further developed by introducing more accurate diagnostic agents for each failure mode of each wind farm component. Similarly, the prognostic model defined in Chapter 5 can be based on a more accurate physical or data-driven degradation model.

Last but not least, the developed short-term and long-term O&M planning models in this thesis can be incorporated into a pre-posterior risk based decision model, in which O&M planning is updated once new information is available and optimal O&M decisions based on unknown outcome of inspection and monitoring are made to maximize the total benefit. As instance, in Figure 6-1 a framework for risk based O&M planning of offshore wind turbines based on a pre-posterior decision model is shown (Sørensen, 2009).

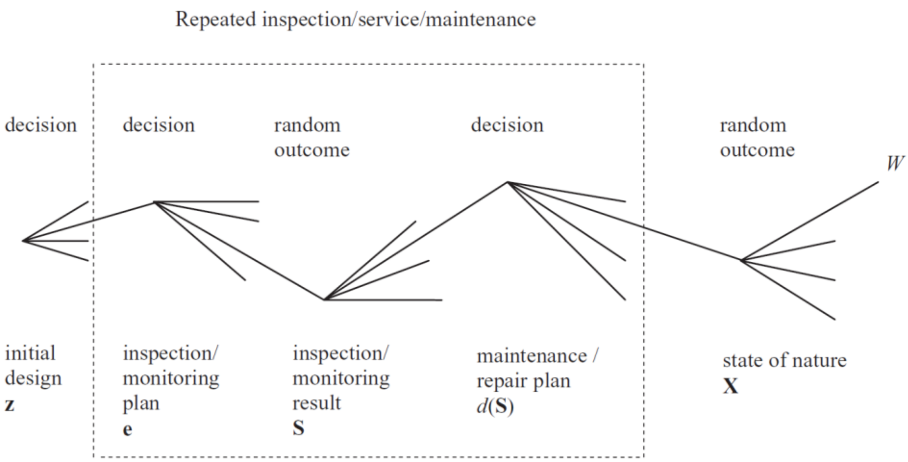


Figure 6-1 Pre-posterior decision tree for risk based O&M planning (Sørensen, 2009)

In Figure 6-1 it can be seen that first, during the development phase of a new offshore wind farm (or during the generation phase of existing offshore wind farms), an initial optimal decision (z) on inspection, service and monitoring plan should be made. Then, during the operational years of the wind farm, at each time step, an updated decision (e) on times and types of inspection, service and monitoring actions for the rest of the lifetime should be made, while the unknown outcome of the next inspection and monitoring (S) should be used in a decision model, d(S), to make optimal operation and maintenance decisions. Examples of the decision model d(S) could be “to do a maintenance if damage level higher than a certain threshold is observed" or "to stop the wind turbine if large vibrations are measured". It should be noted that the decisions on future inspection, service and monitoring plans (e) should be updated once new information is available. The total benefit (W) of the model is the total benefit gained minus total costs in the remaining part of the lifetime after the time of the decision.

In (J. S. Nielsen & Sørensen, 2014) an overview of several methods for risk based O&M planning of wind turbines is given. Besides the decision tree and crude Monte Carlo simulation techniques, in (J. S. Nielsen & Sørensen, 2014) the application of Bayesian Network (BN) and Markov Chain Monte Carlo (MCMC) simulation for risk based O&M planning with stationary strategies and application of LImited Memory Influence Diagram (LIMID) and Observable Markov Decision Process (OMDP) for risk based O&M planning with time-variant strategies is discussed in detail.

As the final note, in future studies on this topic it should be considered that an O&M planning model brings no added value to an offshore wind farm if it cannot be easily implemented into the existing infrastructure of offshore wind farms, no matter how accurate that O&M model is.

LITERATURE LIST

An, D., Choi, J., Kim, N. H., & Pattabhiraman, S. (2011). Fatigue life prediction based on Bayesian approach to incorporate field data into probability model. *Structural Engineering and Mechanics*, *37*(4), 427–442.

Asgarpour, M. (2016). Assembly, Transportation, Installation and Commissioning of Offshore Wind Farms. In *Offshore Wind Farms* (pp. 527–541). Elsevier. https://doi.org/10.1016/B978-0-08-100779-2.00017-9

Asgarpour, M., & Pieterman, R. van de. (2014). *O&M Cost Reduction of Offshore Wind Farms - A Novel Case Study*. Energy Centre of the Netherlands (ECN).

Asgarpour, M., & Sørensen, J. D. (2015). State of the Art in Operation and Maintenance Planning of Offshore Wind Farms. In *European Safety & Reliability Conference (ESREL)* (pp. 1119–1125). London. https://doi.org/10.1201/b17399-157

Asgarpour, M., & Sørensen, J. D. (2016). O&M Modeling of Offshore Wind Farms – State of the Art and Future Developments. In *Reliability and Maintainability Symposium (RAMS)*. Tucson: IEEE. https://doi.org/10.1109/RAMS.2016.7448057

Asgarpour, M., & Sørensen, J. D. (2017). Bayesian based Diagnostic Model for Condition based Maintenance of Offshore Wind Farms. *Energies*, (under review).

Asgarpour, M., & Sørensen, J. D. (2017). Bayesian based Prognostic Model for Predictive Maintenance of Offshore Wind Farms. *International Journal of Prognostics and Health Management (IJPHM)*, (under review).

Bagheri, S. F., Alizadeh, M., Nadarajah, S., & Deiri, E. (2016). Efficient Estimation of the PDF and the CDF of the Weibull Extension Model. *Communications in Statistics - Simulation and Computions*, *45*(6), 2191–2207. https://doi.org/10.1080/03610918.2014.894059

Bak, T., Graham, A., Sapronova, A., Florian, M., Sørensen, J. D., Knudsen, T., … Chen, Z. (2017). Baseline Layout and Design of a 0.8 GW Reference Wind Farm in the North Sea. *Wind Energy*, *20*(May), 1665–1683. https://doi.org/10.1002/we.2116

Ber, A., & Sørensen, J. D. (2016). Reliability Analysis of Fatigue Fracture of Wind

Turbine Drivetrain Components. *Energy Procedia*, *94*(January), 146–154. https://doi.org/10.1016/j.egypro.2016.09.209

Bronshtein, I. N., Semendyayev, K. A., Musiol, G., & Mühlig, H. (2015). *Handbook of Mathematics* (Sixth Edit). Dresden: Spriner.

Canizo, M., Onieva, E., Conde, A., Charramendieta, S., & Trujillo, S. (2017). Real-time Predictive Maintenance for Wind Turbines Using Big Data Frameworks. In *International Conference on Prognostics and Health Management (ICPHM)* (pp. 1–8). IEEE.

Carroll, J., McDonald, A., & McMillan, D. (2016). Failure Rate , Repair Time and Unscheduled O&M Cost Analysis of Offshore Wind Turbines. *Wind Energy*, *19*(6), 1107–1119. https://doi.org/10.1002/we.1887

Coronado, D., & Fischer, K. (2015). *Condition Monitoring of Wind Turbines: State of the Art, User Experience and Recommendations*.

Dinwoodie, I., Endrerud, O. V, Hofmann, M., Martin, R., & Sperstad, I. B. (2015). Reference Cases for Verification of Operation and Maintenance Simulation Models for Offshore Wind Farms. *Wind Engineering*, *39*(1), 1–14.

El-Thalji, I., & Jantunen, E. (2012). On the Development of Condition Based Maintenance Strategy for Offshore Wind Farm : Requirement Elicitation Process. *Energy Procedia*, *24*(January), 328–339. https://doi.org/10.1016/j.egypro.2012.06.116

Escobet, T., Sanchez, H., Sankararaman, S., & Escobet, T. (2016). Analysis of two modeling approaches for fatigue estimation and remaining useful life predictions of wind turbine blades. In *Third European Conference of the Prognostics and Health Management Society*.

Garcia, M. C., Sanz-Bobi, M. A., & del Pico, J. (2006). SIMAP: Intelligent System for Predictive Maintenance Application to the health condition monitoring of a windturbine gearbox. *Computers in Industry*, *57*, 552–568. https://doi.org/10.1016/j.compind.2006.02.011

Gray, C. S., & Watson, S. J. (2010). Physics of failure approach to wind turbine condition based maintenance. *Wind Energy*, *13*, 395–405. https://doi.org/10.1002/we

Guo, H., Watson, S., Tavner, P., & Xiang, J. (2009). Reliability analysis for wind turbines with incomplete failure data collected from after the date of initial installation. *Reliability Engineering and System Safety*, *94*, 1057–1063.

https://doi.org/10.1016/j.ress.2008.12.004

Hofmann, M. (2011). A Review of Decision Support Models for Offshore Wind Farms with an Emphasis on Operation and Maintenance Strategies. *Wind Engineering*, *35*(1), 1–16.

Jacobs, R. (2008). *Bayesian Statistics, Normal-Normal Model*.

Le, B., & Andrews, J. (2016). Modelling wind turbine degradation and maintenance. *Wind Energy*, *19*, 571–591. https://doi.org/10.1002/we

Nielsen, J. J., & Sørensen, J. D. (2011). On risk-based operation and maintenance of offshore wind turbine components. *Reliability Engineering and System Safety*, *96*(1), 218–229. https://doi.org/10.1016/j.ress.2010.07.007

Nielsen, J. S., & Sørensen, J. D. (2014). Methods for Risk-Based Planning of O&M of Wind Turbines. *Energies*, *7*, 6645–6664. https://doi.org/10.3390/en7106645

Nielsen, J. S., & Sørensen, J. D. (2017). Bayesian Estimation of Remaining Useful Life for Wind Turbine Blades. *Energ*, *10*(664). https://doi.org/10.3390/en10050664

Nijssen, L. (2006). *Fatigue Life Prediction and Strength Degradation of Wind Turbine Rotor Blade Composites*. Delft University.

Novaes, G. De, Leite, P., Maurício, A., André, P., & Rosas, C. (2018). Prognostic techniques applied to maintenance of wind turbines: a concise and specific review. *Renewable and Sustainable Energy Reviews*, *81*, 1917–1925. https://doi.org/10.1016/j.rser.2017.06.002

Obdam, T., & Braam, H. (2014). *User Manual of ECN O&M Tool V5*. Energy Centre of the Netherlands (ECN).

Shafaghi, A. (2008). Equipment Failure Rate Updating — Bayesian Estimation. *Journal of Hazardous Materials*, *159*, 87–91. https://doi.org/10.1016/j.jhazmat.2008.01.042

Shafiee, M., & Sørensen, J. D. (2017). Maintenance Optimization and Inspection Planning of Wind Energy Assets: Models, Methods and Strategies. *Reliability Engineering and System Safety*, 1–19. https://doi.org/10.1016/j.ress.2017.10.025

Sørensen, J. D. (2009). *Framework for Risk-based Planning of Operation and Maintenance for Offshore Wind Turbines*. *Wind Energy*.

https://doi.org/10.1002/we.344

Sørensen, J. D. (2017). Reliability Analysis and Risk-Based Methods for Planning of Operation and Maintenance of Offshore Wind Turbines. In *International Conference on Ocean, Offshore and Arctic Engineering* (Vol. 9, pp. 1–2). ASME. https://doi.org/10.1115/OMAE2017-62713

Stensgaard Toft, H., Branner, K., Nijssen, R., Lekou, D. J., & Pueyo, C. A. (2013). *Probabilistic methods for wind turbine blades*. European Energy Research Alliance (EERA).

Straub, D. (2009). Stochastic Modeling of Deterioration Processes through Dynamic Bayesian Networks. *Journal of Engineering Mechanics, 135*(10), 1089–1099. https://doi.org/10.1061/?ASCE?EM.1943-7889.0000024 CE

Tchakoua, P., Wamkeue, R., Ouhrouche, M., Slaoui-hasnaoui, F., Tameghe, T. A., & Ekemb, G. (2014). Wind Turbine Condition Monitoring: State-of-the-Art Review, New Trends, and Future Challenges. *Energies*, *7*, 2595–2630. https://doi.org/10.3390/en7042595

Technical Committee CEN 319. (2010). *EN 13306 Maintenance Terminology*. Brussels.

Technical Committee IEC 1 & 56. (1990). *IEC 60050-191 International Electrotechnical Vocabulary - Chapter 191 Dependability and Quality of Service*. Geneva. Retrieved from https://webstore.iec.ch/publication/184

Technical Committee IEC 88. (2009). *IEC 61400-3 Design Requirements for Offshore Wind Turbines*. Geneva. Retrieved from https://webstore.iec.ch/publication/5446

Technical Committee IEC 88. (2011). *IEC 61400-26-1 Time based Availability for Wind Turbines*. Retrieved from https://webstore.iec.ch/publication/5444

Technical Committee IEC 88. (2014). *IEC 61400-26-2 Production based Availability for Wind Turbines*. Retrieved from https://webstore.iec.ch/publication/5445

Technical Committee IEC 88. (2016). *IEC 61400-26-3 Availability for Wind Power Stations*. Brussels. Retrieved from https://webstore.iec.ch/publication/25625

Thöns, S. (2012). *Offshore Wind Turbine Support Structures*. Swiss Federal Institute of Technology Zurich (ETH).

Topham, E., & McMillan, D. (2017). Sustainable decommissioning of an offshore wind farm. *Renewable Energy*, *102*, 470–480. https://doi.org/10.1016/j.renene.2016.10.066

VGB PowerTech Service GmbH. (2013). *RDS-PP Application Guideline Part 32 Wind Power Plants*. Essen.

Welte, T., & Wang, K. (2013). Models for Lifetime Estimation - An Overview with Focus on Applications to Wind Turbines. In *International Workshop of Advanced Manufacturing and Automation (IWAMA)* (pp. 337–350). Trondheim: Akademika Publishing.

WindEurope. (2017). *Wind in Power: 2016 European Statistics*. Brussels. Retrieved from https://windeurope.org/about-wind/statistics/european/wind-in-power-2016/

Yildirim, M., Gebraeel, N. Z., & Sun, X. A. (2017). Integrated Predictive Analytics and Optimization for Opportunistic Maintenance and Operations in Wind Farms. *IEEE Transactions on Power Systems*, *32*(6), 4319–4328.

APPENDICES

Appendix A. Paper I

Asgarpour, M., & Sørensen, J. D. (2016). O&M Modeling of Offshore Wind Farms – State of the Art and Future Developments. In Reliability and Maintainability Symposium (RAMS). Tucson: IEEE. https://doi.org/10.1109/RAMS.2016.7448057.

Abstract

In this paper the state of the art in O&M models for O&M cost estimation of offshore wind farms is discussed and then, a case study for O&M cost estimation of an 800 MW reference offshore wind farm is given. Moreover, a framework for an ideal O&M strategy optimizer to achieve the maximum possible O&M costs reduction during operational years of an offshore wind farm is described and recommendations are given.

Appendix B. Paper II

Asgarpour, M., & Sørensen, J. D. (2015). State of the Art in Operation and Maintenance Planning of Offshore Wind Farms. In European Safety & Reliability Conference (ESREL) (pp. 1119–1125). London. https://doi.org/10.1201/b17399-157.

Abstract

Operation and Maintenance (O&M) costs of offshore wind farms are large contributors to the cost of energy. During last decades, methods have been developed for assessing the corrective maintenance costs, and many studies have been published for planning of preventive maintenance, but yet maintenance is not planned using advanced methods by taking all available information into account in a consistent manner. In this paper first a short literature review in O&M models for cost calculation of corrective maintenance and planning of preventive maintenance is given. Furthermore, an O&M study for a reference offshore wind farm is presented to illustrate the average costs and downtime for a typical offshore wind farm and to justify the necessity and potential of further development of current O&M models. At the end, a discussion on optimal O&M planning of offshore wind farms is given.

Appendix C. Paper III

Asgarpour, M., & Sørensen, J. D. (2017a). Bayesian based Diagnostic Model for Condition based Maintenance of Offshore Wind Farms. Energies, (under review).

Abstract

The operation and maintenance costs of offshore wind farms can be significantly reduced if existing corrective actions are performed as efficient as possible and if future corrective actions are avoided by performing sufficient preventive actions. In this paper a holistic multi-agent diagnostic model for fault detection and condition based maintenance of offshore wind components is presented. The diagnostic model presented is based on a probabilistic confidence matrix, which based on Bayes' rule can be updated once observations on the state of components are available. The presented diagnostic model defined in this paper is further explained within a case study for three wind turbine drivetrain components and based on information on vibrations, temperature and oil particles as diagnostic agents.

Appendix D. Paper IV

Asgarpour, M., & Sørensen, J. D. (2017b). Bayesian based Prognostic Model for Predictive Maintenance of Offshore Wind Farms. International Journal of Prognostics and Health Management (IJPHM), (under review).

Abstract

The operation and maintenance costs of offshore wind farms can be significantly reduced if existing corrective actions are performed as efficient as possible and if future corrective actions are avoided by performing sufficient preventive actions. In this paper a prognostic model for degradation monitoring, fault detection and predictive maintenance of offshore wind components is defined. The diagnostic model defined in this paper is based on degradation, remaining useful lifetime and hybrid inspection threshold models. The defined degradation model is based on an exponential distribution with stochastic scale factor modelled by normal distribution. Once based on an inspection outcome sufficient information on the actual degradation state of a component is available, the exponential parameters of the degradation model can be updated based on the Bayes' rule and Normal-Normal model. The components of the diagnostic model defined in this paper are further explained within several illustrative examples. At the end, a discussion and several recommendations for future studies on this topics are given.

ISSN (online): 2446-1636
ISBN (online): 978-87-7210-105-7

AALBORG UNIVERSITY PRESS