Sensitivity Analysis of Offshore Wind Farm Availability and Operations & Maintenance Costs Subject to Uncertain Input Factors

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IDCORE

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Abstract

The deployment of offshore wind farms (OWFs) has increased in response to the threat of diminishing fossil fuel resources, climate change and the need for security of supply. The cost of offshore wind generation has not reached parity with established forms of electricity production. Operators need to simultaneously decrease the total project costs and increase energy yield to achieve a levelised cost of energy of £100/MWh. However, aspects of the Operations and Maintenance (O&M) remain uncertain, either through stochastic processes or through inexperience in the field. One way to handle uncertainty is to define how much the variance in these aspects affect the cost and availability. The thesis in hand introduces an O&M model and seeks to quantify the effects of uncertain inputs using complex sensitivity analysis methods.

The sensitivity analysis is applied to an O&M computer simulation model for offshore wind that was developed prior to this project. Case study OWFs are identified to assess if the important factors are different when projects are comprised of a large number of wind turbine generators (WTGs) and are further offshore from the O&M hub port. The set of cases for the global sensitivity analysis comprises of three projects, to provide information applicable to the industry and demonstrate pertinence of sensitivity analysis on a case by case basis. A screening analysis, using the Morris method, is conducted to identify the most important factors on project cost and availability. This resulted in a list of twenty factors, relating to failure rates; duration of operations and information relating to vessels costs. An in-depth uncertainty analysis is conducted with the important factors to establish their distributions where possible. A global, variance-based sensitivity analysis, using the Sobol' method, is performed to quantify the effect on the variance of the two outputs.

No single factor dominated the effect on O&M cost and availability for all cases. For each case, one to five factors contributed most to output variances. As an example, for a case of 30 WTGs located 20km offshore from the O&M hub port, the output variances are mainly a result of the change of number of crew transfer vessels and heavy lift vessel mobilisation time for nacelle component replacement. For an OWF with more WTGs, further from shore; the availability variance is dominated by more routine repair operations. Moreover, costs are largely dominated by WTG reliability.

This work has confirmed that O&M costs are affected by the cost of deploying heavy-lift vessels even though only a small proportion of repairs require them. Significant factors are inconsistent across all the scenarios, supporting the conclusion that sensitivity analysis of each case is a necessary part of O&M costs and availability simulation. Using the most up-to-date information on current O&M practices, the analysis provides an indication of where to focus efforts for O&M cost reduction and improved availability.

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Declaration

I declare that this thesis was composed by myself and that the material presented, except where clearly indicated, is my own work. I declare that the work has not been submitted for consideration as part of any other degree or professional qualification.

Signed:

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Nomenclature, Abbreviations and Acronyms

Acronym	Name
BoP	Balance of Plant
CFD	Contract for Difference
CMS	Condition Monitoring System
CTV	Crew Transfer Vessel
CDT	Centre for Doctoral Training
DOWEC	Dutch Offshore Wind Energy Convertor
ECN	Energy Research Centre of the Netherlands
eFAST	Extended Fourier Amplitude Sensitivity Test
EU	European Union
FFD	Fractional Factorial Design
FMECA	Failure Modes, Effects and Criticality Analysis
GSA	Global Sensitivity Analysis
HLV	Heavy Lift Vessel
IEC	International Electrotechnical Commission
IFFD	Iterated Fractional Factorial Design
km	Kilometre
LCOE	Levelised Cost of Energy
LSA	Local Sensitivity Analysis
LWT	Landwirtschaftskammer
m	Metre
MTBF	Mean Time Between Failures
MTTF	Mean Time To Failure
MTTR	Mean Time To Repair
MWh	Mega Watt hour
NPV	Net Present Value
NREL	National Renewable Energy Laboratory
O&M	Operations and Maintenance
OAT	One at a Time
OEM	Original Equipment Manufacturer
OPEX	Total operational costs
OWF	Offshore Wind Farm
PDF	Probability distribution function
RADR	Risk Adjusted Discount Rate
RDS-PP	Reference Designation System for Power Plants
SA	Sensitivity Analysis
SCADA	Supervisory Control and Data Acquisition
SPARTA	System Performance and Reliability Trend Analysis
SRC	Standard Regression Coefficient
TP	Transition Piece
UK	United Kingdom

VTT	Valtion Teknillinen Tutkimuskeskus
WMEP	Wissenschaftliche Mess und Evaluierungsprogramm "Scientific Measurement and Evaluation Program"
WTG	Wind Turbine Generator

A/ B	Design matrixes
$A_{production}$	Production based availability for a WTG
A_{time}	Time based availability for a WTG
C_o/ C_e	Expected value of effects for odd and even groups for Cotter method
C_{st}	Cost of staff
D	Total varience
EE	Elementary effect
i	Time interval Input factor identifier
I_{conv}	Convergence indicator
j	Item number Output identifier
k	Number of input factors
l	Ident of perturbed point
M	Cotter sensitivity measure
m	Input that is not equal to i
N	Number of Monte-Carlo for variance based SA
N_t	Number of turbines
n	Number of components Model evaluations
p	Discretization of input factor distribution
$P_{potential}$	Potential produced electrical energy
P_{total}	Produced electrical energy within a period
r	Replications
S_i	Sensitivity measure of Sobol' main effects
S_T	Sensitivity measure of Sobol' total effects
t	Operational time
T	Functioning time
T_{down}	Time of which WTG is non-operational
T_{total}	Total time period of the turbine
v_h	Mean wind velocity
v_{ref}	Mean wind velocity at a reference height
x	input factor
X	Set of input factors
y	Output
Y	Set of model outputs

β	Shape parameter of Weibull function
Δ	Distance of perturbation of factor
η	Scale parameter for Weibull function
λ	Failures per turbine per year Mean value of vector generated by random Poisson distribution
μ*	Morris Sensitivity Index for non-linear and/or interactive effects
σ	Morris Sensitivity Index for linear effects
Ω	Region of investigation
M	Size of random Poisson distributed vector generated

1 Introduction

The purpose of this chapter is to provide a general background for the reader of the thesis. The first section gives a short history and current status of the offshore wind Operations and Maintenance (O&M) industry. The second section is an outline of the objectives, and formalising the scope of the project. The thesis' contribution to knowledge is stated in the third section and the final section outlines the contents of the rest of the thesis.

1.1 Thesis Background

The drive for low carbon sources of electrical energy generation has been building over the past decades in response to the threat of diminishing fossil fuel resources, climate change and the desire for diversification of the energy mix (Abdmouleh, Alammari, & Gastli, 2015). Countries within the European Union are bound to legal agreements for the increased use of renewable energy generation with a target for 20% of energy demand supplied by renewable energy by 2020 (Council Directive 2009/28/EC, 2009). Renewable energy forms a significant contribution to the energy mix, accounting for 7 % of energy consumption in the United Kingdom and 19% of electricity generation in 2014 (National Statistics, 2015). Wind energy has one of the highest profiles of all the renewable energy technologies.

Development of onshore wind turbine generators (WTGs) technology began in the 1970s and proceeded towards commercialisation in the 1980s. The first commercial wind project installed in coastal or near shore environments began in Denmark in 1991 at the Vindeby wind farm. Development continued through the decade with projects in Sweden and the Netherlands (Bilgili, Yasar, & Simsek, 2011). Offshore wind applications in the UK began in the early 2000s with the Blyth demonstrator wind farm installed in 2000 and North Hoyle wind farm in 2003 (Higgins & Foley, 2014). Since 2000 the European offshore wind industry has grown exponentially from virtually zero to 10,393.6 MW in 2015, and is the largest market for offshore wind in the world (European Wind Energy Association, 2015a). Driven by a new approach to environmentally aware electricity production and supported by both regulation and support mechanisms, the rate of installation of WTGs has accelerated. The UK's national ambition for offshore wind installed capacity is 13 GW by 2020 as recommended by the Committee on Climate Change (Department of Energy & Climate Change, 2011). This ambition, however, is limited by high costs. A key target for the industry is the reduction of the Levelised Cost of Energy (LCOE), for offshore wind technology, to £100 per megawatt hour (MWh) from an estimated cost of £149/MWh in 2010 (Heptonstall, Gross, Greenacre, & Cockerill, 2012; RenewableUK, 2012) in order to be competitive with conventional sources of electrical generation. A study done of LCOE values from completed offshore wind projects calculated a reduction of between £136/ MWh to £131/ MWh between 2010-2011 and 2012-2014 (ORE Catapult, 2015a). For comparison, the estimated LCOE, commencing in 2012, for combined cycle gas turbine, integrated gasification combined cycle coal plant and first of a kind nuclear power station is £80/ MWh, £122/ MWh and £81/ MWh respectively (Department of Energy & Climate Change, 2012).

The development of OWFs began in coastal locations with WTGs designed for onshore applications and has been moving further offshore, into deeper water with larger capacities ever since. The current average depth is 16m and the distance from shore is 29 km (European Wind Energy Association 2014) and this trend is set to continue into the future.

Figure 1 1 shows the relation between mean depth and distance to shore for European offshore wind projects (European Wind Energy Association, 2013). The projects highlighted in orange are projects online as of 2013 and the majority of which are located between 0 and 30 km from shore in depths of 0 and 25 m. The yellow markers show the projects under construction in 2013, between depths of 20 and 40m and located between 10 and 80 km from shore. Consented projects in green are located across a range of depths and distances from shore, up to 50 m deep and 100 km offshore. What is also noticeable is the increase in capacity between online and consented projects, shown by the diameters in the figure. The relationship between mean water depth and distance to shore for different European countries can be seen in Appendix A.

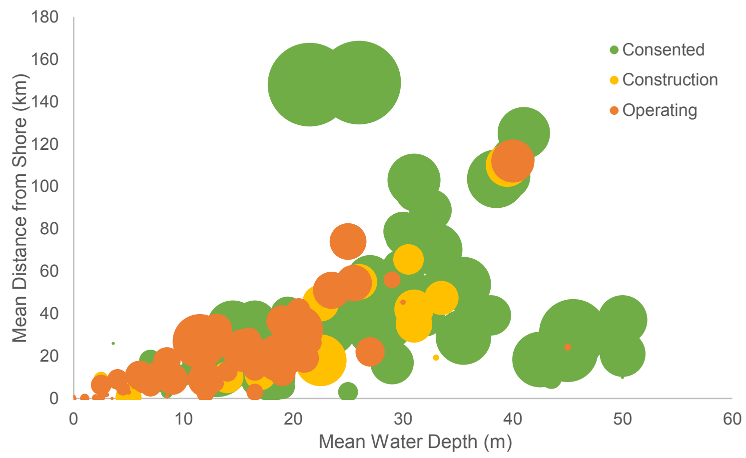


Figure 1-1: Relation between mean water depth and distance to shore for European offshore wind projects.

The operations and maintenance (O&M) phase of the project is estimated to account for 14% to 30% of total OWF lifecycle costs (Maples, Saur, & Hand, 2013; Musial & Ram, 2010). The value of 30% is for LCOE, which is susceptible to change from cost of financing. Offshore Wind Farm operators need to balance the cost of asset maintenance with the cost of unavailability to maximise profit made from the project. Aspects that operations teams can encounter during the O&M phase are the reliability of the WTGs and supporting structure, accessibility via vessels and working within weather windows, transfer of technicians and components to WTGs, meteorological conditions and monitoring the conditions of the WTGs. Working in an offshore environment presents challenges that make operation of OWFs different to those onshore, such as transporting technicians and equipment to the turbines in vessels. Whilst experience in working in these environments can be transferred from the established offshore oil, gas and maritime sectors, there is still an inherent amount of aleatory and epistemic uncertainty (Hora, 1996), leading to attached risk on the profitability of projects.

The major sub-systems of a single WTG unit are shown in Figure 1-2 along with the major offshore foundation types. The major components within the nacelle of a WTG with a gearbox are shown in Figure 1-3 including a gearbox. Some WTGs on the market do not include gearboxes are direct drive designs. Of the 57 commercially available offshore WTGs that provide information of the drive train, 11 have a direct drive system with no gear box (4C Offshore Limited, 2014b). Figure 1-4 shows the size of market available offshore WTGs with rotor size and capacity using data from 4C Offshore Limited, 2015. The different configurations of gearbox and direct drive are shown. A detailed description of WTG configurations by technology can be found in component design chapter of the Wind Energy Handbook (Burton, Jenkins, Sharpe, & Bossanyi, 2011). With respect to O&M, the difference between fixed foundations and floating allows for different approaches, for example, towing floating turbines and supporting structures back to base rather than repair in-situ. However as there are no commercial scale floating wind projects, there are no data on how these approaches will effect O&M costs at commercial scale.

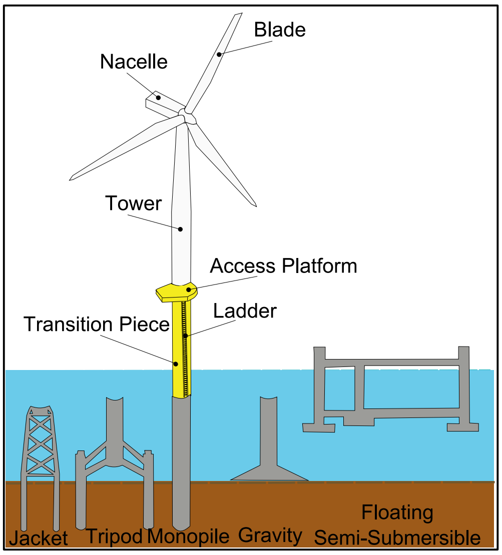


Figure 1-2: Components of an offshore WTG and foundation types. Not drawn to scale.

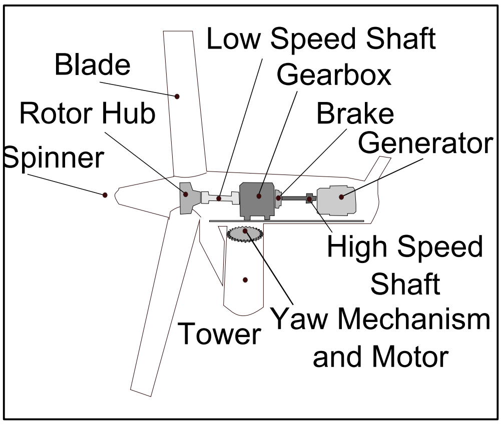


Figure 1-3: Major components in generic WTG nacelle

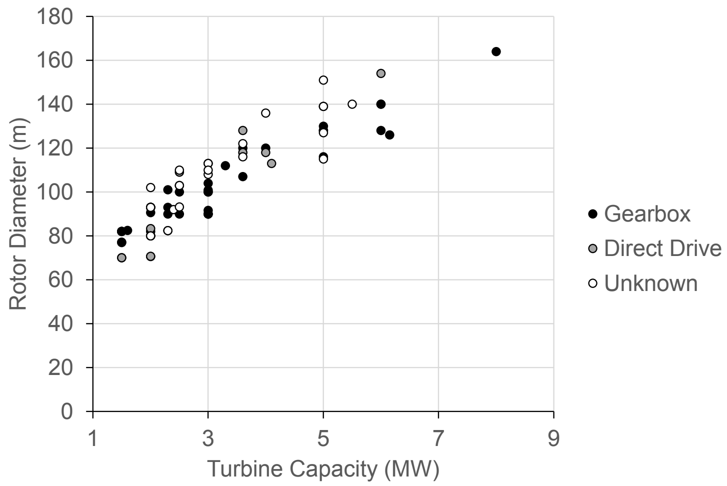


Figure 1-4: Available offshore WTG capacity and rotor size.

The energy in the wind is captured by the blades, converting kinetic energy to mechanical torque. This is transferred to the generator via the drive shaft. Between the rotor and the generator is the gearbox, which determines the generator input speed. Direct drive WTGs are becoming more common now due to previous gearbox related reliability issues (Van Bussel, Boussion, & Hofemann, 2013). It has been suggested that the reliability issues were caused by the gearbox manufactures not having full knowledge of the potential loadings on the system (Van Bussel et al., 2013). Simulations for design loading are only at a constant turbulence intensity value (~12%) where as in real operations the turbulence intensity around the rated wind speed can be over a wider range. The cause of the various loadings on the rotor and drive train components is the combination of wind speed variability from wind shear across the blades and turbulence, yawing of the blades, and the interaction with the mechanical driven power control systems of the WTG. The power output of the WTGs can be controlled in a number of ways. The entire rotor can track the wind direction for optimal power capture through yawing. When the wind speed is high, the power output delivered to the drivetrain is kept constant to prevent overloading, through the blades, as seen in Figure 1-5 (Burton et al., 2011). This can be done passively through stall control or actively through the pitching of the blades. This is controlled via the control systems. The power quality is controlled through the electrical power systems.

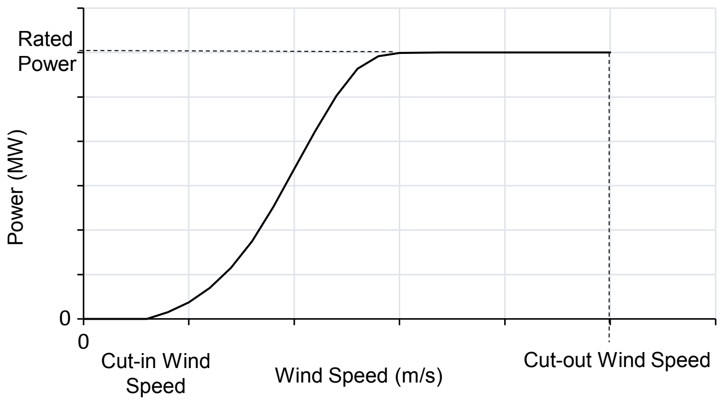


Figure 1-5: Illustration of a WTG power curve.

The nacelle of the WTG is supported by the tower which also houses supplementary power and control systems and holds the rotor blades at an optimal power capture position. The electrical power is transmitted down the tower through cables and out of the WTG through a cable supporting system, typically a J tube, or is free hanging down the supporting structure of the tower and emerges from the foundation through a seal. The tower, nacelle and rotor is supported by a submerged structure and foundations; either fixed to the seabed via a gravity base, pilled or pinned, or floating on the surface (Higgins & Foley, 2014) as shown in Figure 1-2. The number of WTGs in an OWF can be from a single WTG at demonstration or test site, to many hundreds. At the time of writing (2015), the largest operating OWF is London Array with 175, 3.6 MW WTGs, manufactured by Siemens, but plans for future projects exceed this number. The combined number of WTGs at the Dogger Bank licensing area could be up to 400. For large wind farms, the electricity from all the units is brought together via inter-array cables to an offshore substation which holds transformers and converters, if required, to transmit the electricity back to shore on export cables (Madariaga, De Alegría, Martín, Eguía, & Ceballos, 2012). Inter-array cables can be between 20 kV and 36 kV, usually 33 kV, and export cables are between 30 kV and 220 kV (Pardalos, Rebennack, Pereira, Pappu, & Iliadis, 2013). The substation and cables are critical aspects of the wind farm, where loss of function could result in the loss of power from large sections or the total wind farm. Typically, the risk of loss of power from the entire site is reduced by incorporating redundancies into the cable and substation systems. The level of redundancy that is designed is a balance between the capital costs and the risk of failure.

For the required investment to take place in offshore wind projects, financiers need to understand the value of the return of investment. For future projects, the value of return is not certain, therefore estimations are made of the cost and how much profit is made. The amount of electrical generation from wind energy projects are particularly susceptible to uncertainty, when compared to other energy generation projects, as the "fuel" source is variable. Additionally, the operations phase is especially open to uncertain factors as the time frame is longer than during the development and construction phases. To manage this uncertainty, a range of cost estimations is normally calculated, within which is the expected value. In Crundwell, 2008, from a finance perspective, risk is considered to be the probability of a true value being below the expected value. A more general approach to risk can also be the product of probability of an event happen and a measure of the consequence. To quantify the risk of a future project, multiple operational scenarios can be estimated using a computer model. The value of the project is estimated using the Net Present Value (NPV) which is the sum of present project cash flows over time. Future cash flow is discounted to the present using the discount rate. The discount rate is the rate of return of an alternative form of investment with a similar financial risk. Risk exterior to that included in the discount rate, is accounted for via the risk-adjusted discount rate (RADR), which adds a premium to the original discount rate (Crundwell, 2008). If a NPV result is positive, the project will add value and return a profit. If it is negative, then it will not be over the lifetime of the project. The high discount rates will remove perceived value in the project and make it less visible as a viable project to invest in, regardless of the true value. The premium on top of the discount rate can be calculated by using the variance of cash flows (Crundwell, 2008). By reducing the uncertainty around the costs and availability using sensitivity analysis, the risk premium is reduced and the project is more favourable.

It is useful to classify uncertainty in two ways. The first is aleatory uncertainty, where the occurrence of an expected value is probabilistic. The second is epistemic uncertainty, which comes from not having enough information or knowledge, but is knowable (DNV, 2007; Hora, 1996). Aleatory uncertainty can also be called physical uncertainty as it is inherent to the system. Epistemic uncertainty can be a result of statistical uncertainty from not having enough data points, model uncertainty due to imperfect models or measurement uncertainty which comes from imperfectly measuring of a system (DNV, 2007). Examples of these two types of uncertainty are given in the context of offshore wind projects:

- Knowledge of the wind conditions of a site: Uncertainty around the likely wind speeds can be epistemic if there is only a small dataset of historical wind speeds available for long term predictions. Meteorological conditions also have their own aleatory uncertainty due to the probabilistic nature of the system, particularly for short and medium term prediction of the wind speeds, direction and wave heights.
- The effect of maritime environment on failure type and frequency of WTG components: This is a source of epistemic uncertainty due to the novelty of the industry and lack of information on a large scale. Failure frequency is considered a probabilistic system so could also be a source of aleatory uncertainty.
- Effect of external loading, such as waves, on the WTG structure: again, here is uncertainty that can be reduced with computer simulations and structural testing so is a source of epistemic uncertainty. The original wave condition is aleatory.

These examples are just a demonstration of the complexity of the system in question with regards to sources of uncertainty. A computer model can be used to understand the effect of uncertainty on the project profitability. This can direct efforts on reduction of uncertainty, if such reduction is possible. Where there is aleatory uncertainty in an aspect, direct reduction may not be possible but knowing the limits of the effect of such uncertainty can, in effect, reduce the uncertainty around the uncertainty. In cases of epistemic uncertainty, again, the reduction of true uncertainty or risk might be unobtainable, however, by understanding its effect can reduce the perceived risk.

1.2 Thesis Introduction

1.2.1 Research problem

As shall be seen in the following chapters, offshore wind project viability is susceptible to uncertainty and tackling this within the O&M phase can make a significant contribution. There are two different types of uncertainty: aleatory and epistemic. Computer simulation models can be used to investigate uncertainty through Sensitivity Analysis (SA). Identification of target areas of uncertainty can eb aid uncertainty reduction, help with project financing and help to choose most profitable options. The main sensitivity analysis process utilised in this thesis is shown in Figure 1-6.

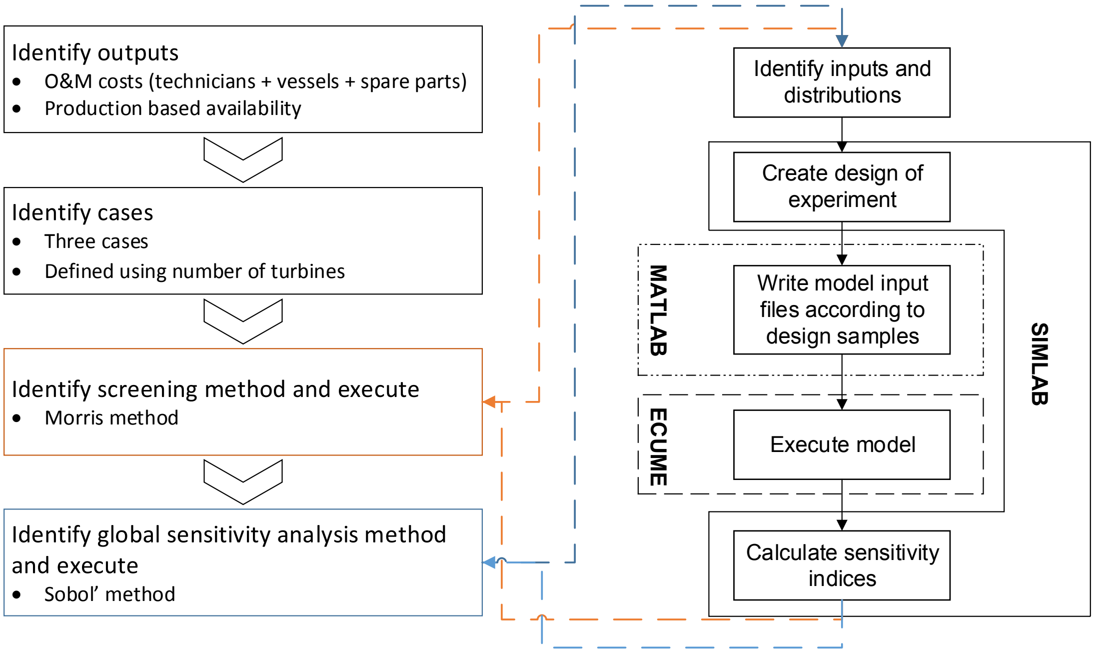


Figure 1-6: Outline of sensitivity analysis process

1.2.2 Project Aim, Objectives and Scope

The aim of this project is to investigate the effect of uncertainty of aspects of O&M of offshore wind on the costs and availability.

The project objectives are as follows:

1. Identify the current state of the art regarding the operations of OWFs and challenges that the sector faces.

2. Identify the aspects of O&M that contribute the most variance to the operational costs and the availability, considering the uncertainty from the inputs in a computer simulation model.

3. Using this information, decrease the uncertainty surrounding those aspects by incorporating field data from current operating OWFs.

1.2.3 Thesis Contribution to Knowledge

The contribution of this thesis is demonstration of truly global and complex sensitivity analysis methods applied in an offshore wind operations and maintenance context for the first time. This serves the aim of identifying the most important aspects contributing to the variance in O&M costs and availability. It builds on the work of previous investigators (Hagen, 2013; Hofmann & Sperstad, 2013a), see Section 4.1, who have applied local and simplistic methods of sensitivity analysis on their own offshore wind O&M models.

Once key aspects have been identified using a local method of sensitivity analysis, then reliability theory and field data is used to improve the knowledge of uncertainty surrounding these aspects. The methodology can be used by other model developers and users and applied using their own models and cases. Their results can be compared with those in this thesis. In Chapter 4 and 5, readers are provided a contemporary account of how an OWF is managed and how real data from the operating wind farm data is combined with data from the industry.

Additionally, a framework for classifying the uncertainty of O&M inputs is provided to communicate the difference in the quality based on the source of data.

1.2.4 Project and Thesis Outline

Chapter two is a comprehensive review of the literature around the main topics concerned in this thesis. For offshore wind, key terms and definitions used through the thesis are introduced. Key results from significant bodies of work in offshore wind reliability are explored and overviews of other available computer models for O&M assessment are listed.

Chapter 3 introduces the offshore wind O&M model and confirms it as a reliable and robust via a process beginning with validation against an operational offshore wind project, demonstration of use with OWF project under development and comparisons with other OW O&M models.

Chapter 4 and 5 delivers the methodology and the results from the sensitivity analyses, starting with factor screening using a local method and then progressing on to a global analysis. For each analysis, the work and results of uncertainty analysis around each input, is provided.

Chapter 6 discusses the results of the analyses, relating them back to the uncertainty analysis of the inputs.

Chapter 7 concludes the thesis by providing the main conclusions and putting them back into the context of offshore wind O&M. Limitations of the study and further work are also discussed.

1.2.5 List of Publications

Martin R, Lazakis I, Barbouchi S, Johanning L. Sensitivity analysis of offshore wind farm operation and maintenance cost and availability. Renewable Energy 2016;85: 1226–36. doi:10.1016/j.renene.2015.07.078.

Dinwoodie I, Van Endrerud O-E, Hofmann M, Martin R, Sperstad IB. Reference Cases for Verification of Operation and Maintenance Simulation Models for Offshore Wind Farms. Wind Engineering 2015; 39:1–14. doi:10.1260/0309-524X.39.1.1 and DeepWind 2015. Trondhiem.

Martin R, Lazakis I, Barbouchi S. Analysis of Input Factors To Operations And Maintenance of Two Offshore Wind Farm Case Studies ; A Screening Process. Renewable Power Generation Conference (RPG 2014), Naples, 2014.

Yu X, Martin R, Barbouchi S, Ingfield D, Lazakis I, Seraoui R. Determining the Applicability of Onshore Wind FMECAs to Offshore Wind Applications. EWEA Offshore, Frankfurt, 2013.

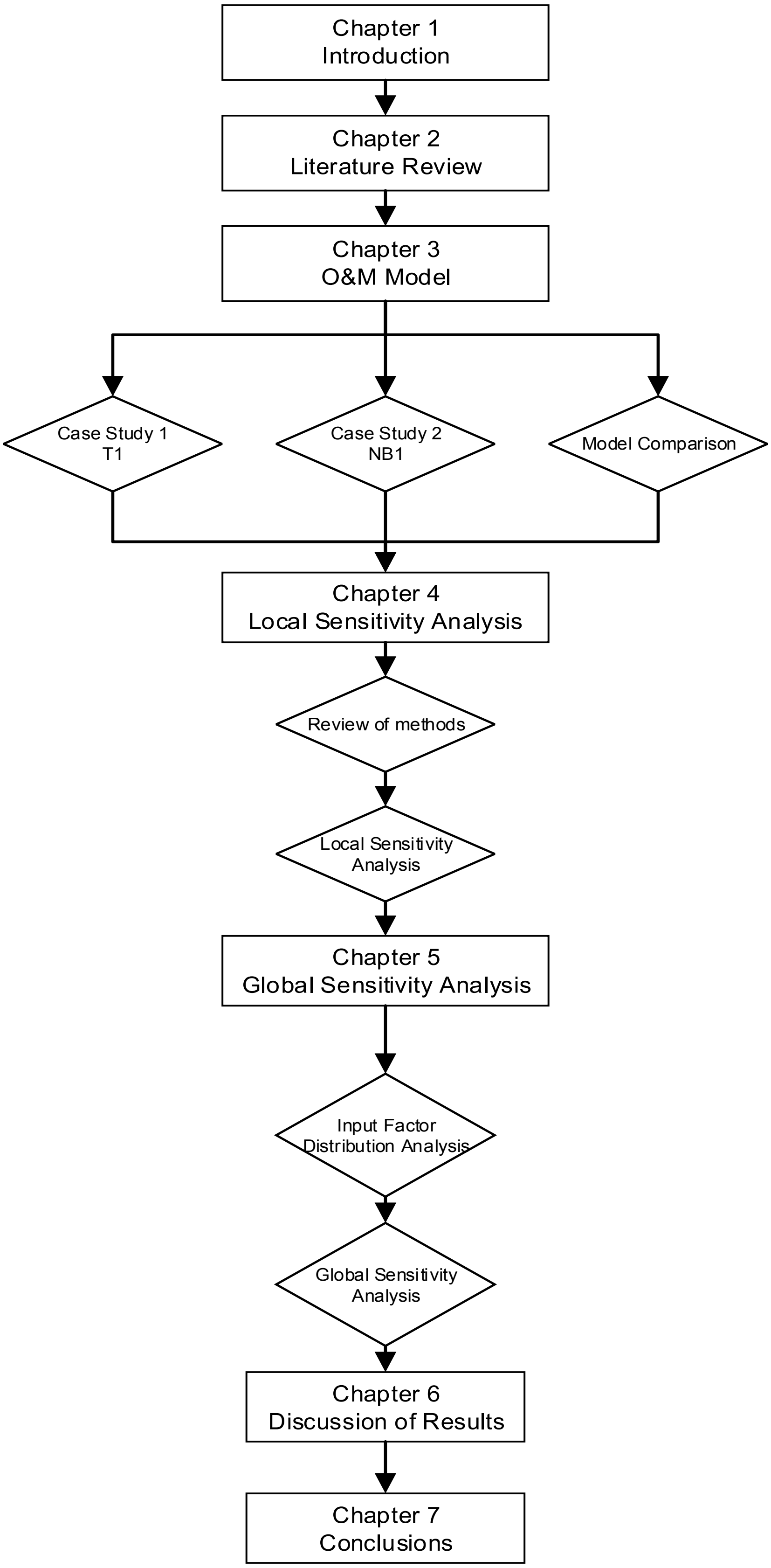


Figure 1-7: Thesis structure flowchart

2 Literature Review

2.1 Introduction

This literature review summarises the most up to date research and practises in reliability, availability and maintenance for OWFs. As this thesis focuses on offshore wind sector, Section 2.2 describes the differences between the O&M of onshore and offshore projects. Section 2.3 provides details of costs estimation and the theoretical background of reliability and availability. It will provide definitions of terms used in the thesis, introduce the main tools used and outline the latest work in the field. Section 2.4 is a review of important academic contributions to the field of offshore wind O&M relevant to this thesis. Section 2.5 is a review of reliability data sources currently in the public domain. Section 2.6 is a state of the art of computer modelling for cost and availability estimation.

2.2 Difference between Offshore and Onshore Wind

In the past, the design of offshore WTGs was similar to their onshore counterparts. In the early stages of WTG technology development, fixed speed WTGs with squirrel cage induction generators were used. The need for increased reliability of plant has brought with it newer generating technologies; variable speeds with synchronous or induction generator and gearbox or direct drive (Islam, Guo, & Zhu, 2014). Configurations of offshore WTGs are similar to onshore, with emphasis on having as reliable systems as possible. However offshore WTGs have been subjected to different working conditions, presenting technical challenges for WTG manufacturers, installers, owners and operators. This is particularly relevant with the move to larger capacity of the farms and further from O&M ports and into deeper water. This results in alterations of the WTG and supporting structures. The most immediate difference between onshore and offshore WTGs is the foundation type. Onshore, there are two types of ground-embedded foundation; slab or pile, the use of which is dictated by the geological conditions (Hau, 2006). The variety of offshore foundations is wider, as seen in Section 1.1. Other technical differences include the nacelle housing, which is designed to keep moisture out; the tower has been redesigned to account for wave loading. Operational and environmental differences includes a move to larger capacities with fewer transportational and visual constraints (Anaya-lara, Campos-Gaona, Moreno-Goytia, & Adam, 2014). Offshore WTGs are subject to different environmental conditions which may have implication for occurring failure modes (Tavner et al., 2012). The combination of wave and tidal loading, in addition to wind loading and a more corrosive maritime atmosphere, has led to a suspicion that failure modes maybe different offshore. However, failure modes of the Horns Rev and Egmond aan Zee OWFs are explored further by Tavner, identifying that failure modes are similar to onshore wind farms (Tavner et al., 2012). A recent summary of failure modes for offshore WTGs is presented by Luengo & Kolios 2015 within the context of life extension and stresses the importance of failure mode analysis and the use of Condition Monitoring System (CMS) though the project life time for life extension.

Access to WTGs is not as simple as on land. Geographically remote farms means long travelling times of several hours depending on vessel speed and distance to the O&M port. Offshore wind farms require hiring or purchasing of vessels or helicopters, as opposed to a "van scaled" operation for accessing onshore farms. Maintenance personnel require specialist training for working offshore in addition to being able to work at heights, confined spaces and turbine maintenance technical skills. Challenging meteorological conditions means that there are limits to the time available to perform maintenance, called weather windows.

These factors mean that the time-based availability; which will be defined in Section 2.3.2, of an OWF is, on average lower than onshore. An analysis of the average annual system time-based availability, where all shut-downs are considered except for wind speed based and cable unwinds, of over 300 onshore wind farms revealed a world-wide mean of 96.1%. Although it is found that 50% of wind farms recorded an availability of 97.1% or higher (Graves, Harman, Wilkinson, & Walker, 2008). During the first years of the UK's Round 1 offshore wind sites, some projects reported individual average availability of 82% (Busfield, 2010). Recent estimates on the average availability in OWFs Europe-wide is 90-95% (Tavner et al., 2012) indicating improvement. Whether this is due to improving reliability or better maintenance practice is unclear as, shall be seen below, more complicated WTGs can be susceptible to higher failure rates. Introduction of new WTG models and units complicate the analysis as state-of-the-art models can provide better reliability but also new units can be susceptible to early-life failures.

Whilst experience in working in maritime environments can be transferred from the offshore oil, gas and seafaring sectors, there is still an inherent amount of uncertainty with regards to the operation of an OWF, leading to attached risk on the profitability of projects.

The presence of risk, in any project, will have an associated financial disadvantage, whether it is an increase cost of finance, insurance premium or additional cost related to increased factors of safety. In a methodological framework for uncertainty analysis, (de Rocquigny, Devictor, & Tarantola, 2008), the goals of uncertainty analysis are outlined as:

U	Understand	Understand the influence uncertainty has
A	Accredit	Quality assurance for the model itself
S	Select	Compare performance and optimise
C	Comply	Demonstration of compliance with an external criterion

(de Rocquigny et al., 2008)

Computer modelling tools for offshore O&M have been developed to achieve these goals which incorporate WTG operational information, meteorological data and accessibility decisions to estimate the total cost of an OWF during its operational life time (Hofmann, 2011).

2.3 Operation and Maintenance of Offshore Wind Projects

2.3.1 Cost of Offshore Wind O&M

Estimates of industry O&M costs can be made with onshore data but the costs for their offshore counterparts are likely to be higher due to the different access methods between onshore and offshore. Additionally, the cost of lost production is potentially higher as a major failure occurring during a long spell of bad weather could leave a WTG non-operational for months. The overall profitability of the project, during its operational life is affected by the direct annual costs of maintenance and the indirect costs through loss of production (from both internal and external sources). Therefore, for cost effective operation, the rate of WTG failure needs to be reduced through reliable components and effective maintenance and control. When they do fail, the cost of repair needs to be minimal and fixed as quickly as possible. The study of effective maintenance revolves around optimisation of these elements.

It is difficult to understand the full life-cycle project costs early on in a project as, in most cases, Original Equipment Manufacturers (OEMs) take responsibility for the maintenance of the WTGs for a fixed price during the initial years of the warranty period, typically 5 years. Figure 2-1 shows the installed capacity of offshore wind in Europe between 1991 and 2014 based on year of commissioning from the 4C Offshore online database (4C Offshore Limited, 2015). Assuming that the initial warranty is five years long, then, as of 2014, 60% of European OWFs are still being maintained by the OEM (4C Offshore Limited, 2015). It is a challenge to compare the O&M costs in different geographical locations because of variation of licensing and fees imposed on OWFs in different countries.

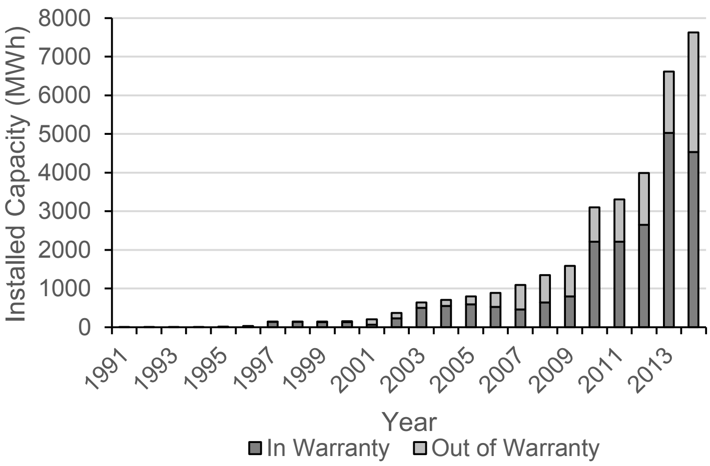


Figure 2-1: Installed capacity of OWFs in Europe **(4C Offshore Limited, 2015)**

With this in mind, attempts have been made to provide average values of O&M costs. A review by the National Renewable Energy Laboratory (NREL) in the United States has surveyed literature for estimated operating costs for offshore wind in 2010. The range of estimates is between £7/MWh and over £46/MWh with a mean value of £25/MWh for studies conducted between 2009 and 2011. An exchange rate of 0.64 £ per $ is used. These values are for pre-tax annual operating costs (Tegen et al., 2012). The cause of the broad range of estimates can be attributed to the variation in the methodologies used to collect the information such as using historical experience, publicly available data and surveys of developers. Also these high level costs are not attributed to component, leasing and other O&M costs, which may be the cause of the variation if the studies do not involve all of these costs.

The Crown Estate in their Guide to an Offshore Wind Farm, have given an O&M cost of £25 - £40 million for a 500 MW wind farm (BVG Associates, 2010). No information about the assumptions behind the estimate is given but The Crown Estate has been working with developers during the leasing rounds for UK waters and it is possible that this value is direct from wind farm operators. In order to compare with the cost values from the NREL study with those from The Crown Estate, the total project costs is translated into costs per MWh through assuming a capacity factor of 0.3 and 0.4. The annual operating costs are between £14/MWh to £37/MWh considering a capacity factor of 0.4, and £19/MWh to £50/MWh with a capacity factor of 0.3. The capacity factor is the ratio of amount of energy generated (or estimated to be generated) in a given time period to the total potential generation; typically the WTG capacity multiplied by the number of hours in the same time period. Assuming a capacity factor of 0.3 appears to be close to the NREL estimates but without further information on what is included in The Crown Estate value it is uncertain if these results are comparable.

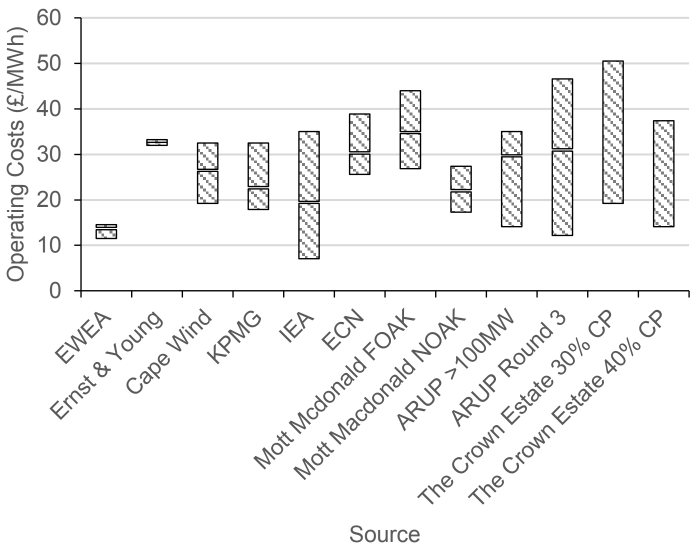


Figure 2-2: Estimated offshore wind O&M costs **(BVG Associates, 2010; Tegen et al., 2012)**

It is important to keep in mind that total O&M costs can consist of not only the cost for technicians, parts and vessels, but also the costs for onshore facilities, insurance, and other operational costs. Other costs, which are not included in this thesis, are the

fees paid to Offshore Transmission Owners, legal costs and costs of supply.
Unless otherwise stated, for this thesis the costs included are:

- Logistics
    - Crew Transfer Vessels
        - Annual charter rate (fixed cost)
        - Cost of fuel based on a) consumption rate (ton/hour), b) fuel costs (£/ton) c) average speed and d) distance (variable cost)
    - Heavy Lifting Vessels
        - Daily rate (variable cost)
        - Cost of fuel based on a) consumption rate (ton/hour), b) fuel costs (£/ton) c) average speed and d) distance (variable cost)
        - Mobilisation costs (variable cost)
    - Helicopters
        - Annual rental cost (fixed cost)
- Turbines
    - Component and repair costs (variable cost)
- Technicians
    - Training cost (fixed cost)
    - Annual salary (fixed cost)

2.3.2 Availability and Reliability of Offshore Wind

The availability of a project is an important indicator of the performance of an OWF. The instantaneous electrical generation of the WTGs will be governed primarily by the wind speed as shown in the power curve, shown in Figure 1-5.

Offshore wind farm developers have the ability to optimise the electrical generation through the site location, choices in the WTG model and layout optimisation (Pillai, Chick, Johanning, Khorasanchi, & de Laleu, 2015). For conventional OWFs during operation, these parameters are fixed. The primary option within an operators control to achieve the most amount of electrical generation is the amount of time the WTGs are in a state where they can produce energy. Ideally, the operator deploys a maintenance regime which keeps the probability of failure low and is able to react and repair failures as quickly as possible. Through this the downtime is minimised and production is maximised.

The British Standard for the term availability defined as:

The ability of an item to be in a state to perform a required function under given conditions at a given instance of time or over a given interval, assuming that the required external resources are provided. BS 3811:1993

With regards to offshore wind, the required function is generating electricity. Availability is generally reported monthly or yearly. The external resource is the wind. Therefore, if the instantaneous wind speed is less than the cut-in wind speed, as seen in Figure 1-5, the WTG will not generate electricity but will be available. The British Standard gives a generic definition. A specific time-based availability definition for wind power systems has been devised by the International Electrotechnical Commission (IEC) for the availability IEC 61400-26.

The fraction of a given operating period in which a WTG Generating System is performing its intended services within the design specification.

As the instantaneous electrical generation varies according to the power curve, the total electrical generation over a period of time is not linear to the time period. Therefore, availability can be considered in both time and production terms.

Time availability is:

$$A_{time} = \frac{T_{total} - T_{down}}{T_{total}} \quad [1]$$

Where A_{time} is the time-based availability given as a decimal or percentage, T_{total} is the total time period and $T_{down}$is the period considered as "down time". Similarly production based availability is:

$$\mathrm{A_{production}} = \frac{\mathrm{P_{total}}}{\mathrm{P_{total}} + \mathrm{P_{potential}}} \quad [2]$$

Where $A_{production}$ is the product based availability, P_{total} is the amount of generated and $P_{potential}$ is the potential amount of energy lost due to downtime.

Annual production-based availability is of more interest to operators as it accounts for the seasonality of the wind speed and reparability throughout the year. When calculating time-based availability, any downtime will have equal importance throughout the year. In reality, downtime in the summer, when the average wind speed is lower, will be less important than in the winter, where the average wind speed, and lost potential revenue, is higher. However, as the instantaneous generation of WTGs fluctuates with wind speed, the process of determining P_{total} is more complex than T_{total}.

The added complexity comes from calculating $P_{potential}$. If the plant is non-operational then the wind speed data from the anemometer may be disrupted. If this occurs then, an operator could take data from a neighbouring WTG if available or an average of the entire farm. The accuracy of this method will depend on the proximity of the two wind farms. If the wind farms are close they can share a similar wind regime but if the non-operational WTG is in the wake of its closest neighbour then $P_{potential}$ could be overestimated. Also, the wind turbine model needs to be similar for this method to be used. If wind speed data is available, then an operator could use power curves to estimate $P_{potential}$. There is a choice to use a power curve supplied by the manufacturer or a historical one, calculated from the past performance of WTG at the site.

Actors in the wind farm may calculate availability using different approaches to gain insights in the operation of the project. For example, an OEM who is maintaining WTGs under warranty is likely to be required to sustain a level of availability in order to protect the financial interests of their customer. The calculation of availability will focus on the WTG units and not of aspects out of their control, such as requested shutdown of the wind farm from an external party, such as a grid operator. However, the operator may want to consider availability as a key performance indicator of the project so may include external shut down requests. The availability of just the WTG units is often called the technical availability and for the entire wind farm, the term standard availability is used. There is no universal standard on reporting availability and operators use different approaches from each other. The IEC provide tables such as Table 2-1 to classify approaches.

Table 2-1: Overview of the information categorisation of counters of WTG performing uptime according to the International Electrotechnical Commission, 2010

<table>
<tr><td colspan="5">Information Categories</td></tr>
<tr><td>Mandatory Level 1</td><td>Mandatory Level 2</td><td>Mandatory Level 3</td><td>Mandatory Level 4</td><td>Optional</td></tr>
<tr><td rowspan="13">Information Available (IA)</td><td rowspan="8">Operative (IAO)</td><td rowspan="3">Generating (IAOG)</td><td>Full Performance (IAOGFP)</td><td></td></tr>
<tr><td rowspan="2">Partial Performance (IAOGPP)</td><td>Derated</td></tr>
<tr><td>Degraded</td></tr>
<tr><td rowspan="5">Non-Generating (IAONG)</td><td>Technical Standby (IAONGTS)</td><td></td></tr>
<tr><td rowspan="2">Out of Environmental Specification (IAONGEN)</td><td>Calm Winds</td></tr>
<tr><td>Other Environmental</td></tr>
<tr><td>Requested Shutdown (IAONGRS)</td><td></td></tr>
<tr><td>Out of Electrical Specification (IAONGEL)</td><td></td></tr>
<tr><td rowspan="4">Non-Operative (IANO)</td><td colspan="2">Scheduled Maintenance (IANOSM)</td><td rowspan="3">Response
Diagnostic
Logistic
Failure repair</td></tr>
<tr><td colspan="2">Planned Corrective Actions (IANOPCA)</td></tr>
<tr><td colspan="2">Forced Outage (IANOFO)</td></tr>
<tr><td colspan="2">Suspended (IANOS)</td><td>Scheduled Maintenance
Planned Corrective Actions
Forced Outage</td></tr>
<tr><td colspan="3">Force Majeure (IAFM)</td><td></td></tr>
<tr><td colspan="4">Information Unavailable (IU)</td><td></td></tr>
</table>

A different approach to availability is shown in Figure 2-3. The reliability of the WTG is described in the section below. The maintainability and the serviceability reflect the ease, from a time perspective, to conduct corrective maintenance or a planned preventative maintenance activity respectfully. Corrective maintenance is a reactionary activity to restore the state of a WTG to operational after a failure. A preventative maintenance activity occurs before a failure and is usually a time-based activity an example being a scheduled annual servicing. If disregarding the effect of offshore location on the reliability of the WTG for a moment, then it can be argued that the theoretical availability is similar for offshore and onshore WTGs. The next tier of aspects; the accessibility and maintenance strategy are what differentiate the availability of offshore and onshore projects. Accessibility is the ease of access to the site. The distance from the O&M port contributes to this, as well as the capabilities of vessels used to reach the WTGs. The maintenance strategy comprises the methods and approaches employed to keeping the WTGs operational, as in the choice of a corrective or preventative strategy and how a CMS is applied.

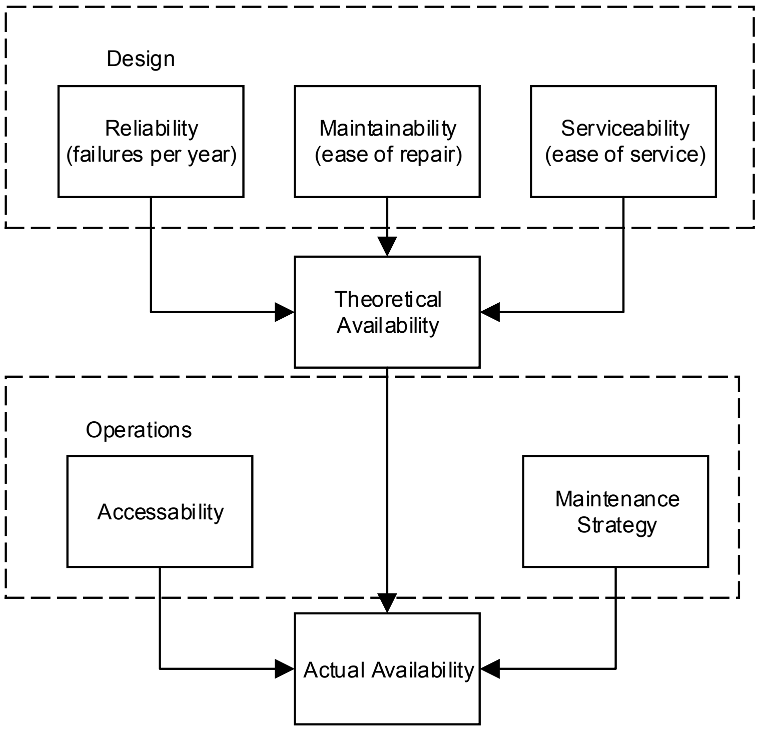


Figure 2-3: Availability and relationship with reliability, accessibility and maintenance strategies.(Van Bussel & Bierbooms, 2003)

The British standard for reliability is as follows:

The ability of an item to perform a required function under given conditions for a given time interval. BS 3811:1993

A concise introduction into reliability analysis definitions and terms is provided in Rausand & Hoyland 2004. It categorises three ways to measure reliability of non-repairable components; the time to failure; a reliability, survivor or hazard function and a failure rate. The time to failure (TTF) is the probability of the component failing with a given interval. A reliability function is the reciprocal of the time to failure and is the probability that an item will not fail within a given interval. The failure rate function is the probability of an item failing in a given interval given that the component has survived up to time so far (Rausand & Hoyland, 2004). This work uses failure rates and mean time between failures only. The failure rate is derived from:

$$\lambda\,(\mathrm{i}) = \frac{\mathrm{n(i)}}{\sum_{\mathrm{j=1}}^{\mathrm{n}} \mathrm{T_{ji}}} \qquad [3]$$

Where λ is the failure rate as a function of i which is the interval, n is the number of components that fail from a population, j is the item number and T is the functioning time. Therefore failure rate is a ratio of failures in a total time period. This time period can be in millions of hours of operation, such as in the oil and gas industry's OREDA reliability data handbook (OREDA Participants, 2002) or, more commonly for WTGs, in years. The number of the population used for n and the time T is subject to amount of data available. In Section 2.5.1, failure rates for offshore wind components are provided from 10 databases. The number of WTGs in database populations range between 70 and 1500. The time intervals are unknown.

Another way of expressing reliability is the Mean Time to Failure (MTTF) or Mean Time Between Failures (MTBF). These values can be derived from operational data of the components or WTGs. During the normal period operation of assets the failure rate is the inverse of the MTBF:

$$\lambda = \frac{1}{MTBF} \qquad [4]$$

And the repair rate is the inverse of the Mean Time To Repair (MTTR) (Rausand & Hoyland, 2004; Tavner, 2012):

$$\mu = \frac{1}{MTTR} \qquad [5]$$

The probability of failure over the lifetime of the component is categorised into three stages. At the beginning of the component lifetime, the failure rate is higher with the component susceptible to "infant mortality" and at the end due to "wear-out". The stable middle stage is called the "useful life". This evolution of failure rate through a component lifetime can be expressed using the Weibull distribution (Bedford & Cooke, 2009; Tavner & Xiang, 2007). Other distributions can be used but this is the most common in WTG reliability (Bedford & Cooke, 2009; Yalcin Dalgic, Lazakis, Turan, & Judah, 2015; Karyotakis, 2011; Martin-Tretton, Reha, Drunsic, & Keim, 2012; Ribrant, 2006; Spinato, 2008). The distribution is defined by two parameters; β which is the shape parameter and η is the scale parameter. The theoretical shape of the bathtub curve is shown in Figure 2-4 and is usually determined from empirical reliability information of components. In the early life of the components, β is less than one. In the useful life section, β is equal to one and when components wearing out, β is greater than one.

Some realities of offshore wind O&M not commonly assessed in other texts, are introduced by Stiesdal & Madsen, 2005. One example is that a significant amount of downtime, which is used to form the availability calculation, are the result of errors rather than failures resulting in maintenance activities. The bathtub curve is also introduced in the paper as part of an Availability, Reliability and Maintenance model developed by Siemens Wind Power. In addition to the three bathtub phases outlined above and shown in Figure 2-4, the authors introduce a fourth curve, called the premature serial failure curve, to represent serial defects that do not fall under the early-life phase but maybe due to rapid product development (Stiesdal & Madsen, 2005). As this fourth phase is not reflected in the computer model that will be used in the subsequent sensitivity analysis of this thesis, this additional premature serial failure phase is not considered further.

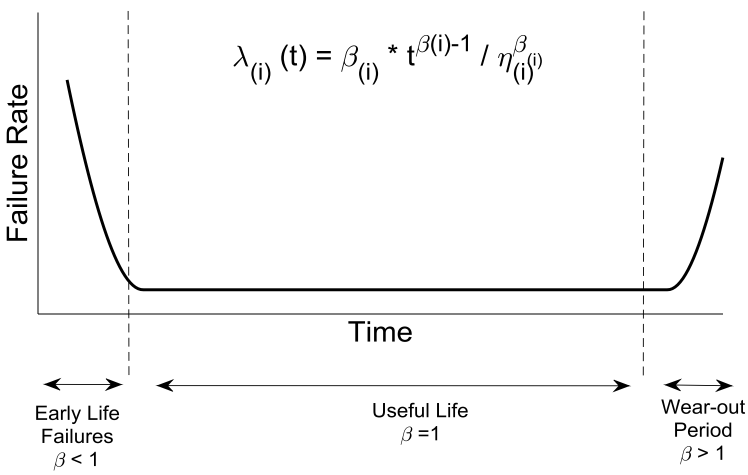


Figure 2-4: Diagram of a theoretical bath tub curve for a repairable system, (Bedford & Cooke, 2009; Rausand & Hoyland, 2004)

The British military standard for failure is:

The inability of a unit to meet a desired standard of performance. MoD Standard 00-45 Part 1 (British Standards Institution, 1993)

There can be many types of failure of operation of an offshore WTG. A failure can be counted if the WTG stops producing electricity for any technical reason. On these occasions the WTG will restart either restart itself automatically or remotely by the Operational Control Centre, and the amount of downtime is minimal. Generally, these are regarded as "stops" rather than "failure". At the other end of the severity spectrum, a failure of a major component, such as the gearbox or the generator, requiring repair or replacement may incur considerable cost and downtime. The repair or replacement that requires consumables of significant weight is likely to require chartering of a specialist vessel to reach the nacelle. Waiting for such vessels in addition to waiting for a period of good weather can result in long periods of downtime, sometimes many months.

Failure information, collected for reliability analysis, should consist of the following parts:

- **Failure mode**: the symptom of the failure, e.g. shorting of circuits, creep, cracking
- **Cause:** intrinsic: the weakness or flaw. Extrinsic- mishandling.
- **Effect**: grading of the outcome of failure; non relevant, partial, complete and critical (Birolini, 1997).

2.3.3 Methods of Reliability Analysis

A qualitative approach to failure analysis is a Failure Modes Effect Analysis / Failure Modes, Effects and Criticality Analysis (FMEA/FMECA). It is presented in a table format and identifies the effect of failures throughout the system and additionally has room for inclusion of mitigating methods and can accept quantitative data or more qualitative information such as fuzzy logic. A Fault Tree Analysis or Event Tree Analysis (FTA/ ETA) is concerned with the sequencing of the failures and any resulting cascading effect. The FMEA/FMECA, considers the single failure occurrences and their effect on either the function or component (Smith & Hinchcliffe, 2003). FMEA is usually performed during the design stage of equipment and begins with identifying the lowest level of component likely to receive maintenance. For example, during a normal maintenance plan, if a faulty or failed component is likely to be replaced, rather than looking down into a further subcomponent failure to fix, then this marks the limit of FMEA, and any further consideration would be a waste of effort. The FMEA is driven by the failure mode of the subcomponents and then mapping the effects throughout the system in tabular form. It is normally used as one of a number of steps towards producing an informed maintenance plan (Smith & Hinchcliffe, 2003). In their "World Class Maintenance" method, (Smith & Hinchcliffe, 2003), give FMEA as the 5th step in a 7 step systematic process along with system boundary identification; functional block diagram; failure identification; logical gate tree analysis and finally preventative task identification.

The general process for the FMEA is as follows:

i) Define the system, sub systems and number of levels to be analysed and perform functional analysis.
ii) Build a reliability block diagram (RBD) which show the relationships between the systems identified in (i). In many cases, for simplicity and to demonstrate the "worse-case scenario", the RBD for wind turbines has been serial all through the systems
iii) Identify the failure modes and that could occur and the effect on subsequent levels. Judgement of experienced experts is required for the identification process, along with, possibly, the operational logs of equipment similar to the one under scrutiny.
iv) Assign a severity level to each failure mode of the worst possible outcomes. The severity level class is given in Table 2-2
v) Identify all of the ways in order to detect the failure events, mitigating design measures and actions.
vi) Document process in a table and report.

Table 2-2: Severity categories

Category	Severity	Description
I / A	Catastrophic	A failure which may cause death or weapon system loss.
II/ B	Critical	A failure which may cause severe injury, major property damage, or major system damage which will result in mission loss.
III / C	Marginal	A failure which may cause minor injury, minor property damage or system, damage which will result in minor delay or loss of availability or mission degradation.
IV / D	Minor	A failure not serious enough to cause injury, property damage or system damage but which will result in unscheduled maintenance or repair.

One of the most complete examples of application of FMEA practices to onshore wind turbines is (Arabian-Hoseynabadi, Oraee, & Tavner, 2010). The purpose of the paper is to demonstrate the applicability of FMEA's during the design stage of a turbine and show how a design change of a component could a) affect the reliability of the WTG, and b) how the FMEA process could be used to detect these changes and to compare between designs.

The test case used is a 2 MW, variable speed, doubly-fed induction generator (DFIG) with a gearbox, and is the same generic configuration used for the Reliawind project. The design change in the study is from a DFIG generator to a brushless doubly-fed generator (BDFG). Considering the type of generator to be used in a turbine, from the point of view of an OEM is a significant decision with regards to reliability and cost of production. Implementing a change in generator type, such as demonstrated in this paper, would be useful for an operator to understand how their choice of OEM if they offered products exclusively with DFIG, BDFG or Direct Drive, for example) could affect the reliability and therefore the profitability of the project.

The FMEA process used follows the hardware approach of the MIL-STD-1629A (1980) standard, with some minor modifications:

- Identify the systems, components and subcomponents subject to study;
- Identify the failure modes;

- Identify the root causes and match with failures modes;
- Calculate the risk priority number (RPN) based on the frequency of occurrence and detection of the root cause with a value of severity of the failure mode.
- The RPNs are aggregated for sub-assemblies, all the way to the single turbine and high risk systems can be identified.

In this paper 107 parts, 16 failure modes and 25 roots causes have been "generated" and "identified" but there is practically no information on how this was achieve. The reader can infer that the failure modes have come from the Reliawind project based on one of the authors' involvement with the project, the use of the software Relex to perform the FMEA and that the same generic turbine has been used. The severity of the failure modes and the occurrence rating of the root cause are based on "engineering judgement" and standard scaling tables, which have been adapted to be "more appropriate" for wind turbines. It is normal for the ratings to be adapted for a particular industry, although the author does not clarify any specific reasoning for the choice of scaling. One can speculate it is because of the lack of detailed information in the public domain on failures of wind turbines and their causes. The FMEA was repeated for the generator and gearbox systems with a BDFG.

The RPNs for each system have been normalised to the highest assembly failure rate and RPN. The product of the severity and occurrences factors have been compared with the failure rates from key wind turbine databases. The results are comparable generally except for electrical controls and grid electrical system. A cause of this discrepancy given by the authors is the increased detectability of electrical failures. In all cases the FMEA appears to under predict the level of failure.

The resulting RPN for the generator and gearbox systems was lower for the WTG that had a BDFG (972 and 749, respectfully) rather than DFIG (1204 and 909). With no field data on BDFG, it is not possible to validate this result in the field.

This paper is a good demonstration of the application of FMEA to wind turbines, and the results support other findings with regards to the ranking of different systems. The background information on the source of failure and root cause data used in the study is lacking. If viewed in isolation from other papers and projects, it would be difficult to identify any process of section and scaling of the severity and occurrence/detection values. A lot of this work has been conducted through the Reliawind project although the link is not overtly expressed within the main body of the paper.

Another onshore WTG FMEA is presented in Kahrobaee & Asgarpoor, 2011 but with an attempt to quantify the output through assigning a cost for each failure mode. Although the authors call it a “Risk-Based FMEA”, it is very similar to an FMECA, with the critical factor as cost and ignoring any social or environmental factors. The purpose of the conference paper is to demonstrate their method. Again this method is based on the hardware approach of the MIL-STD-1629A but with the additional costs criticality added. Once the systems and sub-systems have been identified then the failure modes and root causes are presented but little information is given on where these come from.

The failure modes are limited to malfunction and damage of the major sub systems and the effects are not considered. The frequency of occurrence is sourced from the German and Swedish wind turbine failure databases. If there is any treatment of the data based on capacity, it is not mentioned in the paper. The detectability of the failures is estimated from the ratio of detected failures to the total amount (the number of actual failures plus those that were detected before a failure could occur), which is highly dependent on the amount of sensors installed on the each subsystem and how closely the turbine is monitoring. If considering a single turbine, then this should be easy to find, however is not so clear if using historical data from different turbine types and size. The cost function is found from the sum of the spares, servicing, simplified loss of production costs and labour. The case study is conducted on a 3MW onshore direct drive turbine using Microsoft Excel as a platform. The approach is highly simplified and conducted on a well-known tool so that it is an accessible for wind turbine operators. It is likely this method and tool described in this paper is more applicable for small scale wind turbine operators, such as independent owner/operators.

The inclusion of a cost criticality criteria means that it can be used as part of a RCM plan, as shown in the paper, however it is not the most sophisticated approach, as, in the drive for simplicity, it ignores the *effects* of failure on the subsequent systems and only considers the major failure modes. With regards to the Cost Priority Number (CPN) the most at risk components are the generator, the electrical system, converter and the blades.

The Reliawind project was a Framework Program 7 funded EU project that was run between component manufacturers, research institutions, wind turbine manufacturers and operators in order to increase reliability in wind turbines. The project ended in 2011. Work package number 2 was to develop a complete reliability model of a generic wind turbine using information from the project partners. The Whole System Reliability Model is constructed from a reliability block diagram (RBD) and FMECA. The reliability information was sourced from:

- Service experience of component manufacturer partners
- the Military Handbook for the Reliability Prediction of Electronic Equipment (MIL-HDBK-217F)
- Reliability Prediction Procedure for Electronic Equipment (SR-332 Issue 2)
- Reliability Data Handbook – A Universal Model for Reliability Prediction of Electronics Components, PCBs and Equipment (IEC 62380 Ed.1 RDF 2003)
- Handbook of Reliability Prediction Procedures for Mechanical Equipment (NSWC-07)
- Non Electronic Parts Reliability Data
- Supplier data

(PTC-Relex & Durham University, 2007)

The RBD and FMEA were conducted for two types of generic turbine i.e. non model or technology specific. Both are three-bladed, three-stage gearbox with DFIGs and hydraulic pitch control. The R80 represents turbines rated at 1.5MW – 2MW with a rotor diameter of between 80-90m and the R100 represents turbines that are bigger with rated capacities of between 3MW – 5MW and rotor diameters of between 120m – 130m. The criticality analysis is conducted with the R100 turbine.

The FMEA standard used is the MIL-STD-1629 with a component based approach. In addition to the FMEA, a criticality analysis is conducted, as well as information on the maintainability of components and a DMEA where the components susceptibility to damage is considered. The experts used to conduct the FMECA are described as "maintenance people". The severity, occurrence and detectability levels are the same as in MIL-STD-1629. The FMECA was conducted using the Relex software platform as they are a project consortium member. This project used failure rate information from reference texts for generic components combined with the servicing experience of some of the project partners and their maintenance teams rather than using the wind turbines reliability databases that the other reviewed papers have used. The combination of wind farm operators, WTG and component manufacturers provided a unique opportunity to perform this with normally closely protected data. With this in mind, however, the background information remains confidential.

The Reliawind project is, probably, the most in depth study into the failure modes and effects of onshore wind turbines conducted to date. The output into the public domain however remains limited to several reports and publications but no access to the underlying data. Whilst not exclusively for onshore wind turbines only, the Reliawind project did not approach the differences in reliability issues between onshore and offshore.

A recently published work on FMECA of offshore WTGs (Sinha & Steel, 2015) has focussed on improving the failure analysis procedures by initially identifying the most critical components qualitatively of which to subject a modified FMECA process to. The paper provides a structure in order to map the boundaries of the study (sub-assemblies to components), identify the failure effects, calculate the RPN and prioritise due to risk through providing field names for each of the steps. Additionally, the RPN calculation is modified by offering a series of Yes/No questions to derive the S, O and D values in order to reduce subjectivity in the process.

2.4 Offshore Wind O&M in Literature

One of the first scientific publications in the field of offshore wind O&M was an assessment of access options to identify scenarios that increase availability and decrease direct costs (Van Bussel & Schöntag, 1997). This conference article looked at O&M strategies for an OWF with 100 x 1 MW WTGs. It considered access via small boats and helicopters, as well as having a vessel for heavy lift capabilities for lifting components of a greater weight than the internal crane, assigned to the OWF permanently. The costs and availability are evaluated using a Monte Carlo programme with stochastic weather and failure event generation modules. The conclusions are that an OWF of 100 WTGs requires a permanent lifting facility as long as the failure rate for lifting operations is higher than half the present failure rate. For this study, it is assumed that only the blades would require a heavy lifting vessel for repair with a failure rate of 0.44 out of a total of 1.79 failures /WTG /year. After ten years of operational experience in the offshore wind industry, there has not been the uptake of permanent heavy lift facilities for large OWFs as the author suggests. This is most likely because the annual fixed costs of a heavy lift vessel (HLV) is estimated to be 3.1 million European Currency Units, which is £2.29m at 1997 exchange rates or approximately £6,200 /day. Considering that the daily charter rates for large vessels on long term basis (20 year market) can be five times this (Dinwoodie, Mcmillan, Revie, Lazakis, & Dalgic, 2013), this assumption is too low, thus, over estimating the cost effectiveness of permanent heavy lift facilities.

A later report by the same author provides a review of technology trends for OWFs O&M issues (Van Bussel & Henderson, 2003). There are two approaches to improvement of OWF O&M in 2003.The first is to make the success of technician transfers less sensitive to wind and wave conditions and the second is to make WTGs more reliable through simplification and using of CMS.

Also in 2003, the results of the Dutch Offshore Wind Energy Converter (DOWEC) project are published by a research consortium led by the Energy Research Centre of the Netherlands (ECN) (Rademakers & Braam, 2003). The report details improvements, such as changes in maintenance strategy, accessibility and failure rates, made to a base line wind farm in order to calculate the change in costs of O&M. The improvements are suggested by the DOWEC team, presumably experts in O&M. The method of assessing the effect on cost that the improvements make is a summation of the time taken and extra direct and indirect costs compared with the baseline. The assumptions made on the time for cranes to be mobilised have no reference, so it can be presumed the figures originate from industrial knowledge. A simple sensitivity analysis is conducted of the failure rates to investigate whether individual improvements to components will be effective in reducing the total failure rate whilst remaining cost effective. The sensitivity of unavailability to the significant wave height and wind velocity is linked to the correlation between the two meteorological parameters. A horizon is established which defines which of the parameters is more influential on the availability. The variables in the uncertainty analysis are; waiting time, frequency failure of the WTGs and repair data. The uncertainty of these variables is described using a PERT distribution function (Rademakers & Braam, 2003).

The conclusions drawn by these early studies into OWF O&M have not changed during the operational period of the industry. Accessibility and reliability of the WTGs are major aspects and the use of CMS in cooperation with optimised maintenance strategies to reduce the working time offshore is still important for decreasing costs and increasing the availability of plant. An empirical analysis of approximately 450 offshore WTGs by Carroll, May, et al. 2015 found that there is a 4% higher average time-based availability in the WTG population with CMS installed.

Research and development of methodologies and technologies to improve accessibility, reliability and condition monitoring is conducted in both academic and industrial spheres. Transfer of technicians to the Transition Piece (TP) can limit the allowable time for technicians to conduct maintenance as it is dangerous to move from the vessel to the access ladder in high wind and wave conditions. A competition run by The Carbon Trust research programme has highlighted new innovations in access for vessels and personnel. The traditional form of access from a vessel to the TP is for technicians to transfer from a fixed point to a relative moving point. However, many of the new designs allow technicians to move from a fixed point of the vessel onto another relative fixed point of a motion compensating arm, and to another relative fixed point of the TP. Two examples are the Amplemann A-Type system, a vessel with a structure heave compensation system, or Uptime's motion compensation system (Ampelmann, 2015; Uptime International AS, 2010).

Using systems to monitor the condition of critical components can help with the reliability of the WTGs and mitigate the effects of failure on costs and availability. Vibration, contamination of lubricants and corrosion can lead to wear in gearbox components such as bearings. Wearing can develop into serious problems like scoring, fatigue, fracture, cracks and pitting for components themselves or transferal to other components. This may lead to a need for major replacement activities. The cost to the operator will be for component replacement, vessel charter costs and the indirect loss of production costs. The cost of the replacement gearbox could be £300,000 and if replacing onshore the cost of a crane could be £50,000 (Hamilton & Quail, 2011). For offshore, the cost of a vessel with heavy lifting capabilities (HLV) could be £150,000 /day (Yalcin Dalgic, Lazakis, & Turan, 2013). A repair operation may only require the vessel for a shift or two but if chartered during a period of bad weather, the operator will be paying close to full price for the vessel in port waiting for a weather window. The vessel will have limits of wind speed, wave height and wave period in which it is safe to lift. During a winter season, the time when all these parameters are below the vessel limits may be less than the required operation time. Therefore the replacement may not be possible for months. Within this period, the operator will be losing out on the revenue that WTG may have generated. For example, a 3 MW WTG, with an estimated mean 40% capacity factor in 90 days could generate 2,952 MWh of energy. If selling the energy at an estimate of 100 £/MWh, the indirect cost to the operator of waiting for a repair for 90 days would be £259,200. A condition monitoring system, such as oil or vibration sensors, uses data from the WTG to track changes in its condition. Statistical analysis is used to predict the condition of the WTG and detect possible future failures. This information can be used to replace a component early but during a period of good weather or to prolong the life of a component through changing the operation of the WTG.

The recent research on O&M for OWFs has been holistic in trying to incorporate all aspects of O&M; with focus on combining reliability along with access and maintenance as an entire system. At the centre of Figure 2-5 are the objectives of most research; to contribute to the reduction of downtime of plant, reduction in the cost or a combination of the two leading to a lower cost of energy. The middle layer shows aspects of O&M. The outer layer shows some of the topics of research currently in progress. The different aspects of O&M often require different skill sets, such as marine engineering for vessels, reliability analysis and operations research. Research topics often straddle these areas, resulting in a multidisciplinary approach.

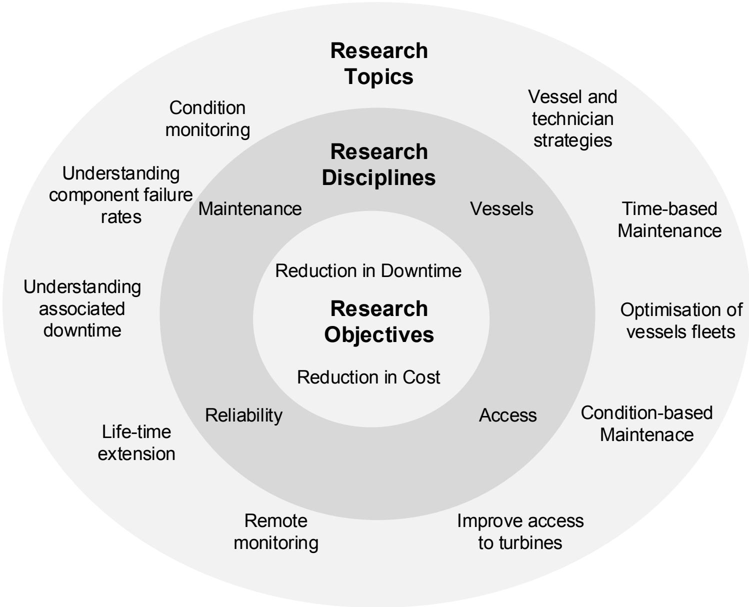


Figure 2-5: Holistic approach to offshore wind O&M

The current method of assessing all these aspects is to use a computer model to simulate the operational lifetime of an OWF. Details of the models are described in Section 2.6 but an example of the application is given here.

The combined efforts of multidisciplinary departments at the University of Strathclyde have produced a multifaceted suite of tools for OWF O&M analysis. The most recent is a simulation tool which includes environmental conditions, operational analysis of transport, failure analysis and repair (Y Dalgic, Lazakis, Dinwoodie, McMillan, & Revie, 2015). The model user can define a wind farm and choose to vary some parameters. The model uses Monte-Carlo simulations to provide a range of results. The user can then use this matrix of results to identify optimum solutions or help with decision-making activities. To demonstrate the model, a case study is used with 150 x 3.6 MW WTGs, 37 km from the O&M base. Seven input factors are varied including the start month of the preventative maintenance as well as the prioritisation of condition monitoring and preventative maintenance. Using the results from the model, 10 “best” and “worst” configurations are identified, with the objective function being the total costs per unit energy including the lost production. The cumulative research, including other outputs such as charter costs analysis (Yalcin Dalgic et al., 2013) and vessel optimisation (Yalcin Dalgic, Lazakis, Turan, et al., 2015; Yalcin Dalgic, Lazakis, & Turan, 2015) is a good example of the holistic, model based approach to OWF O&M research.

2.5 Wind Turbine Failure Databases

2.5.1 Onshore Wind Turbine Failure Rates

Catalogues of failure rate databases have been compiled and reviewed in a number of theses and papers (Carlsson, Eriksson, & Dahlberg, 2010; Hameed, Vatn, & Heggset, 2011; Ribrant, 2006). The most prominent databases, regularly used in offshore wind failure models are shown in Table 2-3 and Appendix B, and include the Wissenschaftliche Mess und Evaluierungsprogramm (WMEP) from Germany, the Valtion Teknillinen Tutkimuskeskus (VTT) from Finland and Windenergie report. Appendix B shows a collection of failure rate and WTG stops data from both onshore and offshore sources. The data are from papers and reports in the public domain, rather than direct from the databases. Even with framing the data within comparative years, each database uses its own topology with regards to collecting and presenting data. For example, in Appendix B failure rates are found for both "instrumentation" and "weathervane/ anemometer". Across different databases, failure rate for instrumentation could include or exclude the anemometer. The complete breakdown of what is in each category, for each database and how each component failure is categorised, is unknown.

The WTG populations contributing data to the databases are in different countries, with different number of WTGs, with different capacities over different time spans, with different ages. There is a compounding of information as the WindStats Newsletter contains the failure information of the VTT and the Danish Energy Agency databases.

Whilst the difference make it challenging to compare failure rates directly, it does allow for analysis of how these differences impact on reliability of WTGs.

A study has been done comparing reliability of WTGs in three different locations in Germany, one of which is on the North Sea Coast. The study looked at the failures statistics at the three sites using data from the WMEP database and local weather station data from the sites. Cross correlation is found between the failures and the wind speeds and humidity (Tavner et al., 2012). One of the locations of the studied wind farms is on an island so could be said to approximate an OWF. The wind farm at this location had a higher proportion of failures in the electrical system than the other two which are more inland. This study was the first to establish that there is a relationship between the weather, location and failure rates. It falls short of making definite statements with regards to the effect on failures of being offshore due to lack of data.

Studies have found that environmental and operational parameters of the WTGs affect the failure rates (Tavner et al., 2012). The predominant causes of failure may vary due to climate and geography and applying database failures from one climate to another may result in inaccuracy. Hameed et al 2011 gives an example where icing in Finland is one of the highest causes of failure whereas in Germany it may be vibration (Hameed et al., 2011). Figure 2-6 shows the average failure rate across components. In the results from the WMEP or Scientific Measurement and Evaluation Program, frequency of failure is higher than those from Sweden or Finland. This is perhaps a reflection of the data collection rather than reliability of WTG in those countries.

As the WMEP data provides a split into WTG capacity, this has allowed researchers to look at the effect of capacity on failure rates. The WMEP data shows that the WTGs over 1 MW have higher failure rates than between 500 kW and 1 MW and more in depth studies have arrived at the same conclusions with regards to capacity (Tavner & Xiang, 2007; Tavner et al., 2012).

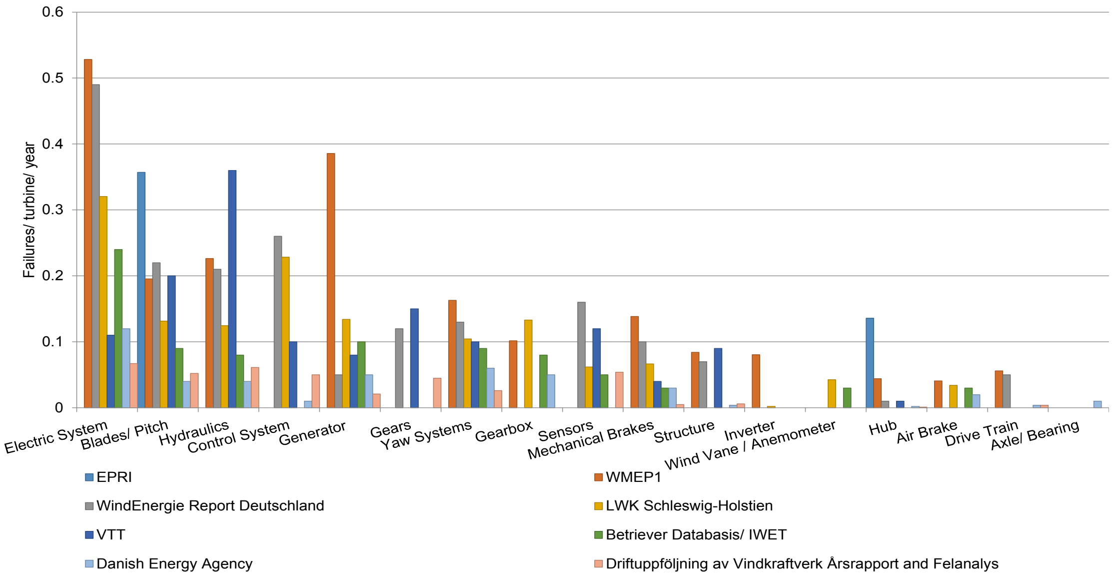


Figure 2-6: Published WTG component failure rates from different databases (Carlsson et al., 2010; Ribrant, 2006; Tavner et al., 2012; Van Bussel & Zaaijer, 2003)

Data from the WMEP databases has been used to investigate frequency of component failure and relate to the amount of downtime caused. Using the maintenance records of 1500 onshore WTGs, failure rates and downtimes for major components have been identified (Faulstich, Hahn, & Tavner, 2011). It is found that failures that resulted in downtime of less than one day represent 75% of failures, but only 5% of the cumulative downtime. Failures resulting in downtime greater than a day account for 25% of the number of failures but contribute to 95% of the downtime as can be seen in Figure 2-7. By multiplying the downtime per failure and the failure rate, the components that contribute the most downtime to the total can be identified. The most problematic component from the study is found to be the electrical system, the failure of which resulted to a mean annual downtime of almost 0.9 days for the WTGs in the data set (Faulstich et al., 2011). The electrical system is a series of components and circuits that control the electrical output of the generator and protect the turbine and the grid system (Burton et al., 2011).

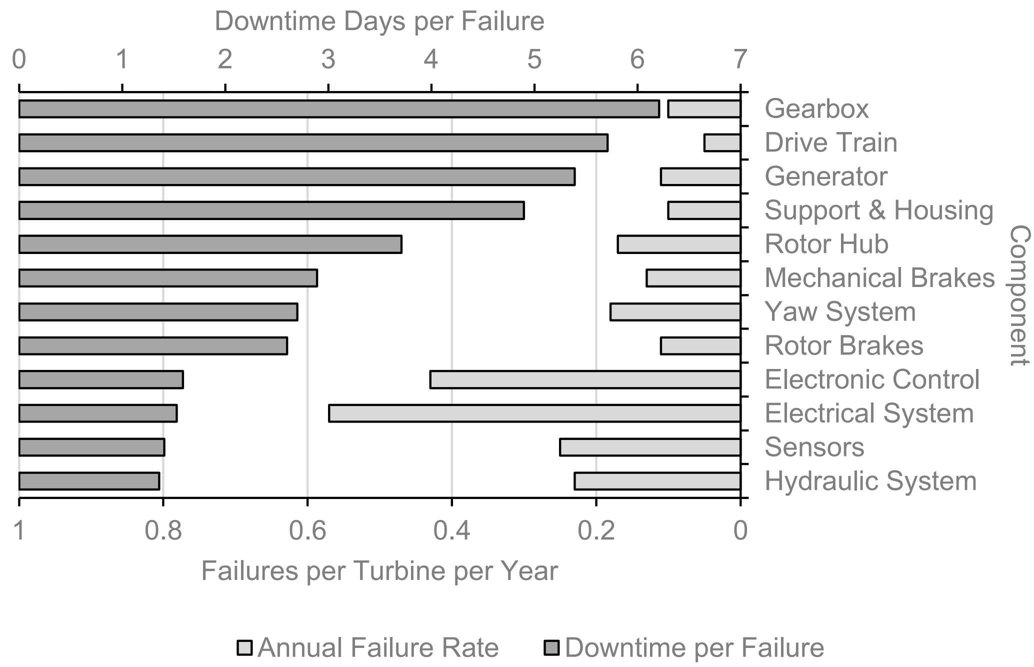


Figure 2-7: Failure rate and mean downtime per failure for components from 1500 onshore WTGs (Faulstich et al., 2011)

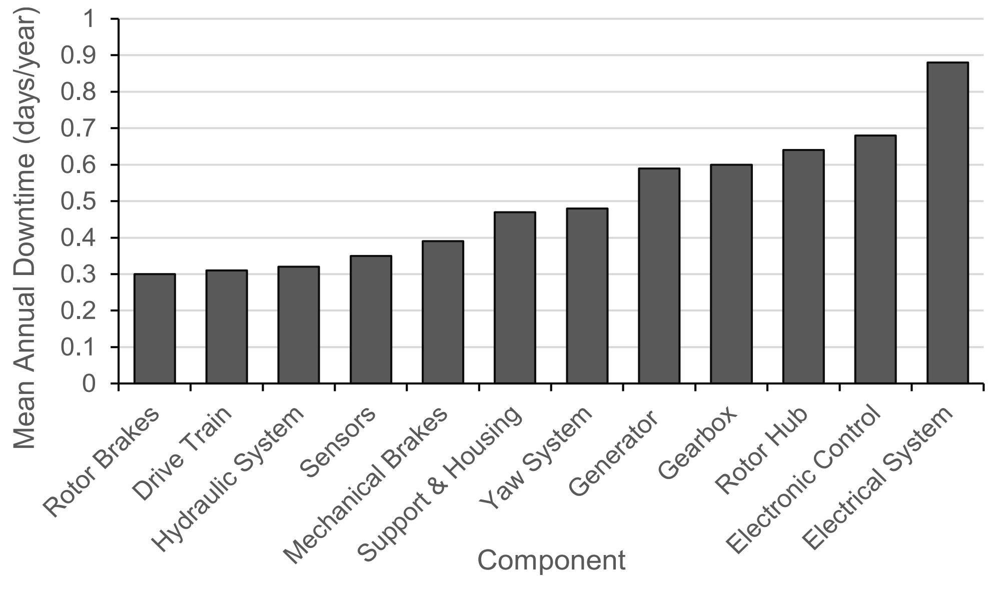


Figure 2-8: Mean annual downtime of onshore WTG components (Faulstich et al., 2011)

Table 2-3: List of WTG failure databases reviewed in literature

Name	Type	Country	WTG Num.	Years	Issued
Valtion Teknillinen Tutkimuskeskus (VTT)	Database: Failure rates, Downtimes and causes (Hameed et al., 2011)	Finland			Monthly /Annually
WMEP	Failure rates, time of repair, strategies, and causes (Hameed et al., 2011)	Germany	1500	1986-2006	
Driftuppföljning av vindkraftverk, årsrapport	Report: Statistical data of performance, failures, and downtimes (Ribrant, 2006)	Sweden			Annually
Fenanalys	Database: Information about failures.	Sweden		Since 1989	
Windenergie Report Deutschland	Report: Statistical data on performance, failures and downtimes	Germany			Annually
Vinstat	Database: Daily total production and operational mode	Sweden	800	Since 1988	Monthly /Annually
Landwirtschaftskammer (LWT)		Germany,	100	1994-2004	Once
Reliawind	Database and topology: Using SCADA system and operational records with a common topology	Europe wide	350	2008-2011	
Windstats Newsletter	Database & Report: Trends in production, failure and maintenance related data. Constitutes the data from VindStat, VTT, Betriever-Databasis/ IWET and the Danish Energy Agency	Sweden, Denmark, Germany, Finland		Since 1987	Quarterly

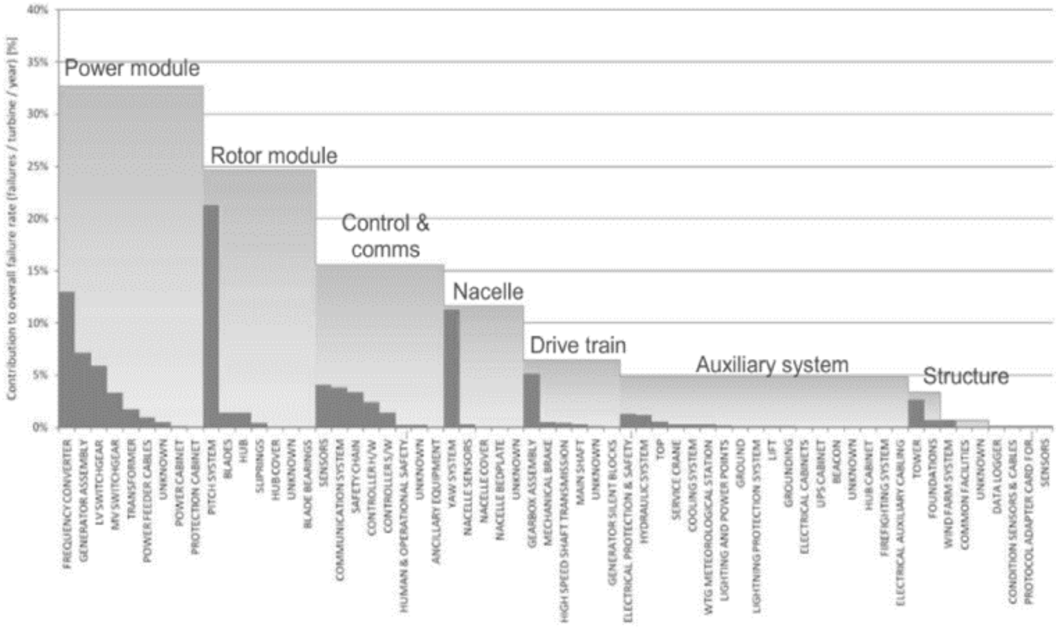


Figure 2-9: Normalised failure rate of sub-systems and assemblies for onshore WTGs of multiple manufacturers in the database (Wilkinson et al., 2010)

The collection of data occurs within similar time frames, in the late 1990s and early 2000s; apart from the Electric Power Research Institute (EPRI) Californian database which was collected in the 1980s/ 1990s. The late 1990s and early 2000s saw expansion of WTG installation onshore so there was the need at the time for more information to reduce operating costs - a similar requirement that the offshore industry has now. The WMEP and VTT databases are funded through EU Projects but as the financial support has now run out, data is contributed to on voluntary basis. Several authors have noted that the quality of data is reducing over time due to reduction of wind farms providing data after becoming a voluntary program (Carlsson et al., 2010). One of the principal failure databases, the Windstats Newsletter is still producing quarterly reports as a commercial enterprise. Figure 2-7 shows that the least reliable components are the electrical system, control system, drive train, hydraulics and instrumentation, but the amount of error in the combined datasets mean that this should be interpreted with caution. Figure 2-9 shows the failure rates from the Reliawind project expressed as a percentage of the total failures. The Reliawind project aims are to identify and understand the critical failure and mechanisms through developing a common taxonomy for data collection and building a database based upon SCADA data and service records. The data is collected through a standard format table which captures information based on the events, information on the turbines and their configuration. This would require pre-processing of the data from the SCADA system. The problem of not having common categories for comparison is a principal one. For example, in Figure 2-9, the highest proportion of failure rates is from the pitch system, but in Figure 2-6, the “pitch system” is included with the “blades/pitch.” The Reliawind project process was to go back, develop a single topology and collect data based on this, avoiding ambiguity where possible. The main outputs from the Reliawind project, aside from the data like Figure 2-9, is the call for standardisation of the data collection process. The uptake of the procedure for data contributing to a single database has been minimal and the efforts have not been utilised. Subsequent data collection programs (see Appendix E) have decided to use different formats.

2.5.2 Offshore WTG Failure Rate Analysis

A noticeable issue from Appendix B s that there are a number of databases for onshore wind but fewer equivalents for offshore. The first found in the review is for number of stops /WTG /year from the Egmond ann Zee wind farm (Tavner, 2012). Stops will rarely result in failure and may only require an automatic, remote or local restart.

A recently published study of reliability of offshore WTGs by Carroll, McDonald and McMillan (2015) is the closest equivalent to the onshore reliability analysis to date. The paper studies the maintenance information from approximately 350 WTGs from between five and ten wind farms for a five year period (Carroll, Mcdonald, & McMillan, 2015). Some particulars regarding the information, such as the exact capacities, number of wind farms and WTG age, is undisclosed for commercial reasons. Using work order and material usage databases from an unspecified WTG manufacturer, failure events are identified and categorised according to material cost and components. Repairs costing below €1,000 are designated “minor repair”, between €1,000 and €10,000 are a “major repair” and greater than €10,000 are “major replacements”. For each event, the number of technicians and repair time is calculated. It is found that the average annual failures per WTG is 8.3 of which 6.2 are minor repairs, 1.1 are major repairs, 0.3 are major replacement and 0.7 are unclassified.

Results are further broken down into contributions from subassemblies and year of operation. It shows the average failure rate in relation to the average wind speed of the WTG. It is found that the five components with the highest failure rates are the pitch/hydraulics, ‘other’ components (ladders, hatches doors etc.), generator, gearbox and blades. The failure rate of the generator and converter from a similar analysis using onshore data from 2222 WTGs are compared to the offshore results (Carroll, Mcdonald, et al., 2015). The same methodology is used, making one of the most direct comparisons available in the literature, although it is unknown if the source of the data is from the same manufacturer or the extent of the overlap between WTG capacities and configurations. It is found that, for all of the categories the failure rate for offshore WTGs is eight times higher, which the author suggests could be due to higher offshore wind speeds, lower maintenance standard from complicated access or that the offshore WTGs capacity are a larger and, as seen by the WMEP data, possibly more prone to failure. The analysis has been conducted on primary data directly from the manufacture although it appears as some interpretation into the work order database is required. The simple methodology has allowed a close comparison with onshore failure rates, which has previously been a challenge as, perhaps with the exception of the offshore and onshore WMEP databases, the data has been not collected in the same manner. This paper may prove to be important in the offshore wind O&M field, however, the results of which are published too late to be incorporated into the work of this thesis.

Even with the publication of Carroll, McDonald and McMillan 2015, the total population of offshore wind reliability statistics is limited to 350. For this reason there are calls for a dedicated OWF database with a standard collection form from as many wind farms as possible and incorporating WTGs from different OEMs. An offshore version of the WMEP database is in the process of development, however, no failure statistics have been published as yet. Another project has been established to collect performance and reliability data from UK OWFs. The System Performance and Reliability Trend Analysis (SPARTA) project has so far collected one years’ worth of data (ORE Catapult, 2015b) and is presented fully in Appendix E. A number of the publications have suggested standard forms and topology for collection of failure modes and a detailed example of which can be found in the appendix of Reliawind

Deliverable Report 6.7 (Tavner, 2011). An alternative to the Reliawind taxonomy is the Reference Designation System for Power Plants (RDS-PP) which has a working group to establish coding structures for WTGs (RDS_PP, 2015). The details the taxonomy are available for purchase. This taxonomy has been adopted by the SPARTA project. Information from the SPARTA project has been used in the analysis to determine the distributions of some of the inputs in Section 5.5. Therefore details of the SPARTA project and an assessment of its first year in operations has been provided in Appendix E.

Another similar project in development is the Windenergy-Information-Data-Pool (WInD-Pool), by the Fraunhofer Institute. This is similar to SPARTA, as it combines data from multiple wind farms for the purpose of supporting improved operation of those wind farms. This project builds on the efforts from the onshore WMEP programme. Those involved with both SPARTA and WInD-Pool are collaborating to make sure that as many benefits from these projects are achieved.

2.6 Offshore Wind O&M Computer Models

In this section different offshore wind O&M models are outlined and parallels are drawn. To draw these comparisons, a brief study of computer model characterisation is undertaken. The definition is used to compare the O&M models for offshore wind. It is also used to consider what SA methods are used on model types for non-offshore wind models in Chapter 3.4.4.

2.6.1 Model Characterisation

In order to define a generic model characterisation framework, examples of computer models from a variety of fields outside of operations research, are used; from biology to oceanography. Models can be classified in the following manner (Gertsev & Gertseva, 2004):

- Homomorphic vs Isomorphic
- Time dependent vs Stationary
- Gnoseological

Isomorphic models are perfect mathematical models where every element of the system of interest is modelled. Rarely is it possible to include every single element of the system of interest, because they are complex, or some aspects are unknown about when models are constructed so the majority of models could be considered *homomorphic*. The term *gnoseological* is used to describe models that are used to learn about the real system under study. Therefore all models that are reviewed are considered *gnoseological* as they are tools for finding out more.

Therefore we arrive at the first applicable dichotomy: time dependant vs stationary. Within the *time-dependent* models, Gertsev & Gertseva 2004 gives us a further subset of six terms:

- Future time vs Past time
- Continuous vs Discrete
- Deterministic vs Stochastic
- Analytical vs Numerical
- Dominant vs Subdominant

When considering a time-dependent model, *continuous* models allow a model user to analyse at any time between $t = 0$ and $t = n$ and $\delta t = inf$, whereas *discrete* models have discrete time steps of $\left[t_i, t_{i+j}, \dots, t_n\right]$ where i is the initial time and j is the time step. For a discrete model, the outputs are known at t_i and t_{i+1}but not in between. An important dichotomy is *deterministic vs stochastic,* where deterministic models, given the same input parameters arrive at a single output, no matter how many simulations are run. Stochastic models, however, have a source of randomness within the model so that, given the same input parameters, the output can be different. *Numerical* models involve simulation of the parameters to prescribed set of equations. *Analytical* models are simpler. *Dominant* and *subdominant* terms are related to the relationship between the model build and the real world (Gertsev & Gertseva, 2004).

For operations research models, the terms that are the major classifications pairs given in Eiselt & Sandblom 2010 are the deterministic/ stochastic (or probabilistic) and discrete/continuous although not all model reviewed in the examples are operations based.

2.6.2 Models

A number of computer models have been produced, or are currently under development for the purposes of estimating the costs of OWFs during operation. State of the art reviews on existing offshore wind cost models have been conducted previously. A comprehensive review was conducted as part of the NOWITECH project, in order to determine whether a new O&M model was required (Hofmann, 2011). The report provides a description of all the offshore wind decision support tools found during its extensive survey. Sixteen decision support tool for O&M are identified and are shown in Table 2-4, and are a mixture of both commercial and academic. It gives thorough details, where available, but does not compare the models with each other or critically evaluate their performance. It can serve as a useful source of information on what is being developed by other institutions. In this review, the list of O&M models has been updated with new developments of the tools features. The models described here are ones where details are available in the public and/ or academic domain. It is likely that others exist, particularly ones developed by wind operators, so therefore Table 2-4 cannot be considered and exhaustive list.

2.6.2.1 NOWIcob

The objective of Hofmann 2011 is to validate the idea of developing a new tool within the NOWITECH project as none of the pre-existing tools are fit for purpose. The resulting NOWITECH tool, called NOWIcob, has since been developed and is being used to help commercial operators. NOWIcob is a complete life cycle tool made up of several modules; a main module to structure the calculations; meteorological; failure; logistics; power production and economics (Hofmann & Sperstad, 2013b). A feature is that it allows for a choice of input for failure simulation; either failure rates or a Weibull distribution and also that the losses from the WTG due to the wake of other machines and conductive losses are considered. The model is controlled from Excel and the simulations are performed in MATLAB®. The model is stochastic with regards to the meteorological and failure models and it is believed to be a discrete time-based model.

2.6.2.2 ECN O&M Tool and OMCE

The ECN O&M Cost Estimator (OMCE) tool is for short term predictions (1 to 3 years) and the ECN O&M Tool is for long term. The OMCE has a number of maintaining and repairing modules (called building blocks); metrological conditions; logistics; loading on the WTGs; condition monitoring data and failure. In terms of validation of the OMCE model, outputs are compared against real costs of offshore wind, no mention is given to the methodologies or results. The ECN O&M Tool has been validated by Germanicher Lloyd (now part of DNV-GL) and used within the industry (Obdam, Rademakers, Braam, & Eecen, 2007) and the health monitoring model within the OMCE has been validated as it was developed as part of We@Sea project (Rademakers, Braam, Obdam, & Van de Pieterman, 2009). The OMCE is, overall, deterministic but can incorporate a stochastic module for failure rates which outputs a cumulative distribution function (CDF) of costs (Rademakers et al., 2009).

Table 2-4: O&M decision support tools. Table adapted from Hofmann 2011

Name of Model or Developer	Developed By	Still Under Development?	Reference
Jesse Andrawus.	Robert Gordon University	No	Andrawus 2008
U. Bharadwaj	Loughborough University, TWI Ltd	-	Bharadwaj et al. 2007
CONTOFAX	TU Delft	-	Van Bussel & Bierbooms 2003
ECN O&M Tool	ECN	Yes	Van de Pieterman et al. 2011
Iberdrolas tool	Iberdrola	-	Lopez 2010
University of Stavanger Offshore Wind Simulation Model	University of Stavanger	Yes	Van Endrerud et al. 2014
Mermaid	Mojo Maritime / University of Exeter	Yes	Morandeau et al. 2013
NOWIcob	NOWITECH / SINTEF Energy Research	Yes	Hofmann & Sperstad 2013b
O2M	DNV-GL Renewables	Yes	-
OMCE	ECN	Yes	Van de Pieterman et al. 2011
Strathclyde Wind CDT O&M Model	University of Strathclyde	Yes	Dinwoodie & McMillan 2014

The development of ECN's O&M tool has been well documented in papers, reports and conference proceedings (Obdam et al., 2007; Rademakers et al., 2009; Rademakers, Braam, Zaaijer, & Van Bussel, 2003; Van de Pieterman et al., 2011). An early version of the model is compared with TU Delft's CONTOFAX (Rademakers et al., 2003). The failure rates used in the analysis are normalised to 1. The two models present different cost results because of the way in which the models handle weather windows. The paper does not critically evaluate either model, focusing more on how they can be used to optimise O&M. An example is given of using a small crane vs. a larger permanent crane with a cost benefit analysis.

2.6.2.3 Iberdrola O&M Tool

Offshore wind operator, Iberdrola, are internally developing on an in-house O&M optimisation tool (Hofmann, Heggset, & Nonås, 2010). In addition to using statistical meteorological module and simulating failure rates to produce weather window statistics, Iberdrola's model also considers the electrical layout and infrastructure for optimisation. The model combines the optimal strategies of O&M with optimal electrical array layouts (radial and ring networks). This allows for the effect of the level of redundancy on the optimal O&M plans to be considered. The output appears to be that, once the model has been run, the NPV and internal rate of return are given for both radial and ring network topologies for a number of O&M strategies. Little has been published on this tool and the underlying calculations are unknown.

2.6.2.4 O2M

The O2M tool has been developed by DNV GL Renewables for commercial use in their consultancy business. As such as, little information has been published about it. However it has been used to investigate the effect of serial failure in an OWF and its consequence on the farm's availability over a long period of time (Redfern & Phillips, 2009). The results showed that the MTBF had a significant effect on the availability of the farm; that if the serial failures occur with MTBF of less than 1000 hours (in a 100 WTG farm) then the O&M system became overwhelmed. The date at which the failures begin is also varied through each month of the year. The fixed cost remained consistent whist there is a 2% difference in costs between the minimum and maximum due to loss of earnings. In the paper, an attempt is made to validate the O2M model simulation using an incident of serial failures at Horns Rev wind farm in 2004. The result between the simulation and an estimate of availability, made from production data, agree. The model assumes that the maintenance strategy is purely reactionary, dealing with each failure as it occurs where as in reality, once a serial defect has been detected; preventative maintenance or replacement will occur. This shortcoming is recognised by the author.

2.6.2.5 CONTOFAX

The CONTOFAX model, developed by TU Delft, focuses more on maintenance strategies and assets; incorporating meteorological data and simulates failures down to component level (Hofmann et al., 2010). The components can be the WTG itself but also the availability of vessels, crew, spare parts and equipment. The model has been used in van Bussel & Bierbooms 2003 to simulate the effects on O&M costs using different access methods. The model is discrete, calculating states at each one hour time steps. The model has a probabilistic failure event generator module (Koutoulakos, 2008).

2.6.2.6 Marine Economic Risk Management Aid (Mermaid)

The Mermaid model, developed by Mojo Maritime consultancy and the University of Exeter, has been designed to improve the assessment of installation and maintenance of marine energy devices but can also be applied to offshore WTGs. The focus is on the costs of a single maintenance operation, such the installation of devices, rather than on a project life time basis as many of the other models are (Morandeau et al., 2013). As well as calculating cost and weather windows, the model takes into account how the weather can affect the project efficiency and has the opportunity for postponement of the activity.

2.6.2.7 CDT Wind Strathclyde Model

The University of Strathclyde have developed a suite of models to support their research activities in the field of O&M of offshore wind. The Centre for Doctoral Training in Wind Energy Systems has developed an O&M simulation model in order to calculate costs and availability. At the core of the model is a failure event generator based on a Weibull distribution intensity function. The model also has a probabilistic climate model with which to simulate a time series of meteorological data (Dinwoodie et al., 2013). The climate model is a correlated wind and weather model. This can be used alongside a decision support model based on Bayesian beliefs networks and a probabilistic model which can also be used for the assessment of CMSs for WTGs (Dinwoodie et al., 2013; Dinwoodie, Van Endrerud, Hofmann, Martin, & Sperstad, 2015).

The tool developed by the Wind Energy CDT is sometimes coupled with a tool developed by the Naval Architecture and Marine Engineering department. This model incorporates a failure module, which generates failures at a given time step based on whether a random value generates between 0 and 1 is greater or less than a system hazard rate (Yalcin Dalgic, Lazakis, Turan, et al., 2015). The climate is generated from sampling of existing meteorological time series in order to represent realistic data but in a stochastic fashion. This provides the wind speed and wave climate to the repair module. If the weather limits are below a threshold assigned to the vessels for a minimum amount of time, then the repair operations can begin. After a repair, the hazard function is reset and the WTG is considered as 'good as new' (Yalcin Dalgic, Lazakis, Turan, et al., 2015). This model is used for investigating the optimal strategies for different vessel types (Yalcin Dalgic, Lazakis, Turan, et al., 2015; Yalcin Dalgic, Lazakis, & Turan, 2015).

2.6.2.8 University of Stavanger Offshore Wind Simulation Model

The model developed by the University of Stavanger is used to support offshore wind O&M research activities within the NORCOWE project. It is also been presented and utilised by commercial operators for key decision and strategic planning actions. It used a multi-method approach for analysis and has agent-based and discrete-event paradigms (Van Endrerud et al., 2014). It has a maintenance planning element as well as O&M logistical simulation. The approach to failure generation is similar the University of Strathclyde's Wind Energy CDT model and the NOWIcob model as a time dependent, non-homogenous Poisson process is used. The meteorological data can be either historical or synthetically created using a Markov-chain process.

2.6.2.9 MARINTEK Vessel Optimisation Model

There are few computer models for offshore wind O&M for optimisation. The vessel optimisation model developed by SINTEF and MARINTEK can be to solve fleet optimisation problems for offshore wind farms (Halvorsen-Weare, Gundegjerde, Halvorsen, Hvattum, & Nonås, 2013). The benefit of an optimisation model as opposed to a simulation model from the point of view of an operator is that analysis time can be saved thorough not having to simulation multiple possible vessel strategies. The objective function of the model is the minimum fixed and variable costs of vessels, vessel bases and the expected downtime of delayed maintenance. One interesting feature is that it incorporates penalties in the form of costs for not completing maintenance within a set time horizon (Halvorsen-Weare et al., 2013).

2.6.3 Model Comparison

Very few of the models discussed here have been truly validated against the performance and costs of a real OWF for the entire project cycle, perhaps with the exception of the ECN model.

There are a number of parallels between the models discussed here. At the core of the majority of models is a stochastic process where meteorological variables and failure events are randomly generated according to a model. These variables are produced and outputs calculated using Monte Carlo simulation. In addition to this core, the models have additional capabilities like incorporating the availability of access vessels and crew or considering redundancy through the inter array grid. These aspect help to simulate the costs of O&M more accurately and provide more choices to the user. None of the models found have all of these aspects integrated into them.

Interested parties in research of offshore wind O&M tend to develop their own models rather than using already produced one, leading to the large number of models in this review. This is due to the requirement for the models to reflect the slightly different needs, approaches and strategies of the developers or the commercial developers. In the past, it has mainly been research institutions who are the main model developers to aid in their investigative activities. However, in recent years, the commercial operators, like EDF and Iberdrola, have been more open about their own in house model development activities.

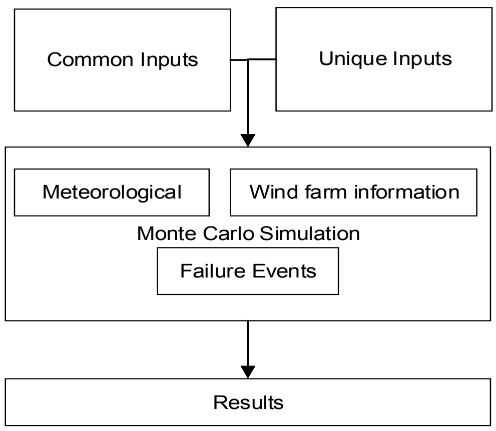


Figure 2-10: Flowchart of generic offshore wind O&M computer simulation model

3 ECUME Offshore Wind O&M Software Tool

3.1 Introduction

This chapter introduces the computer model, outlining the model and its inputs and outputs. ECUME has been developed by the Industrial Risk Management department of EDF R&D for over 10 years. It has been built to support the development of EDF Group's offshore wind portfolio in France and the U.K. The development and manufacturing of the model and its interface was conducted prior to this project by risk management experts from EDF R&D in collaboration with wind energy project developers.

Application of the model is demonstrated through three case studies. The first is of an operational wind farm, the second various scenarios of a proposed OWF and the third is a generic case in comparison with some of the models described in Section 2.6.2.

In order to ensure that the model used in the following case studies and SA is simulating the real world system correctly, the conceptual model and the computerised model need to be verified and validated. In this project, verification is the process of checking that the model is performing to the specifications of the model. Validation is the process of assessing the models' ability to replicate the real-life system under study. Sixteen methods for validation are outlined in Sargent 2013 and are summarised here. Below each generic description is a brief example of their relevance to the model along with a section reference where further information can be found in this thesis.

Animation: Graphical representation of model outputs through time.

The mean costs and availability from the Monte Carlo simulations, along with other outputs of the model can be displayed on an annual basis as a standard result of the simulation runs. See Section 3.2.

Comparison to other models: The outputs of the models are compared with results from different models, ideally models that are known to be validated.

An input /output model comparison of ECUME with other models has been conducted in Section 3.4.3.

Data Relationship Correctness: The known relationships between the data values provide correct values.

As an example; there is a linear relationship between the electricity sale price and the loss due to downtime output.

Event Validity: Comparison of events in models to those that occur in the real system.

As no OWF has reached the end of the operational life, modelled life-time to real life-time comparison cannot take place. A comparison on an annual basis can be conducted as long as enough data is collected during that year to ensure the model is accurately depicting the O&M activities as conducted in Section 3.4.1.

Face Validity: Experts in the real life system are consulted if the internal parameters are correct.

Consultation of the conceptual model is established during the design phase of the model and independent verification of the results for a particular project occurred with operators of the T1 OWF and the results are shown in 3.4.1. Operators are consulted for inputs used in the case studies in Section 3.4.1, 3.4.2 and in the LSA and GSA. Over the course of the three year project, the expertise of the operations team were consulted, as well as other professionals related to the industry.

Historical Data Validation: Use of historical data for inputs and comparison of outputs.

There is a lack of historical data with which to test against the model against but a comparison of first year operations has been made with the data available and the results shown in Section 3.4.1

Internal Validity: A representation of the spread of results from a stochastic process provides an indication of the validity of the model.

One of the outputs of the model is the distribution of the costs from the Monte Carlo simulations. This provides the model user an idea of the variability caused by the probabilistic nature of the failure event generator and the meteorological modules within the model. See Section 3.2.

Parameter variability-SA: Investigation of the relationship between the inputs and the outputs. Validation comes from checking that the results of the model SA mimics the real system.

A local and global sensitivity analysis are conducted in Chapter 3.4.4.

Due to the lack of historical data for the operability of OWF in both the public domain (due to commercial sensitivities of operators) and in the private domain (due to lack of experience), Event Validity, Historical Data Validity and Predictive Validity are difficult to successfully apply. Internal Validity representations, in the form of distribution of O&M costs, and Animation, are part of the outputs of the model.

3.2 ECUME

3.2.1 Model Overview

The ECUME software tool evaluates the O&M costs and the cost of wind farm unavailability using site meteorological data (either real or modelled), failure information of WTG components and user inputted strategies for maintaining the WTGs (Douard, Domecq, & Lair, 2012). A distribution of possible costs is calculated through Monte Carlo analysis to give the user more information in order to make O&M decisions. Figure 3-1 shows a simple schematic of the organisation of the ECUME tool.

The meteorological data is input as a time series which is used to determine the length of access windows for maintenance operations. The historic data is randomised on an annual basis. The failure rate model is used to simulate a failure occurrence using an inverse transformation sampling algorithm to formulate dates according to the bathtub curve. These two modules are fed with user inputs shown in the boxes in Figure 3-1. The mean cost, time and production based availability, as well as exceedance probabilities for a number of outputs are calculated using Monte Carlo simulation (Douard et al., 2012). ECUME is used to assess the estimated costs of a particular strategy based on the best available data (either from experience or from literature) and compare with other possible maintenance strategy solutions. The distribution of costs is important when comparing two strategies. Consider Figure 3-2 where the total O&M costs (ΣOPEX) distributions from two different fictitious projects are compared. If just considering the mean ΣOPEX, the project with a dashed line, would be favourable to the project full line; however when looking at the probability distribution of these functions, the full line project has a smaller standard deviation. This provides those entities that are interested in the financial aspects of projects, more information on the risks.

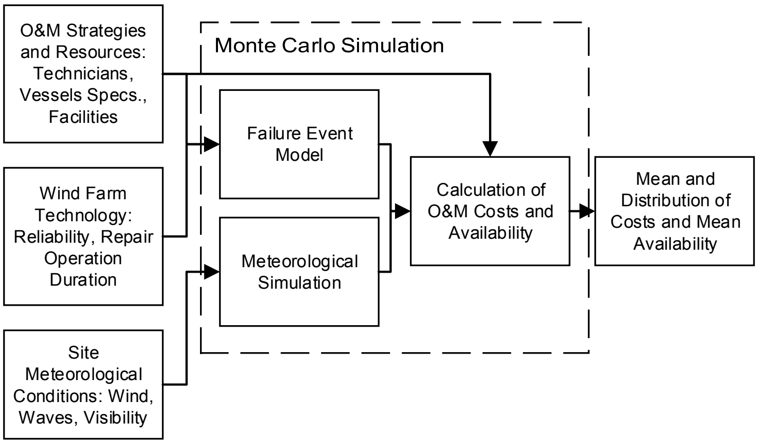


Figure 3-1: Schematic of ECUME model (Douard et al., 2012)

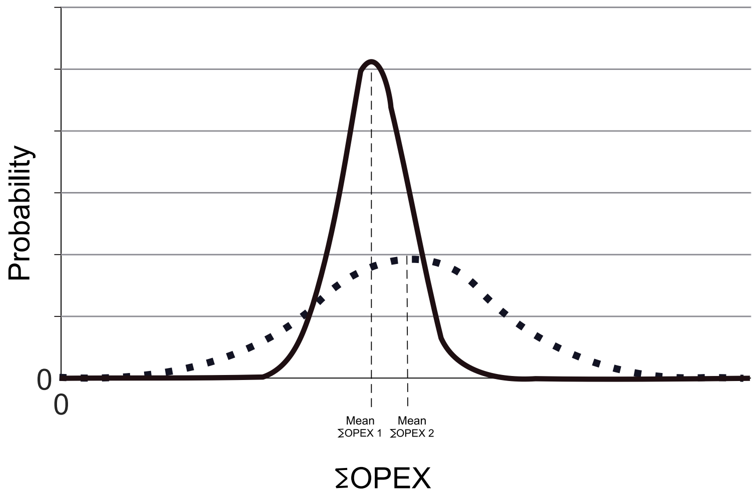


Figure 3-2: Illustration of total costs from two different O&M strategies (Douard et al., 2012)

3.2.2 Model Inputs

The term input factor is used to define all of the variables that go into the model. The term scenario is used to describe a subset of variables that describe one part of the O&M, such as an access strategy using crew transfer vessels (CTVs) or helicopters. The term case is used to distinguish between the different wind farms that are being studied. So that a single case may have been several scenarios modelled.

A sample of wind farm case input factors would be:

- Number of WTG units
- Capacity of WTGs
- Distance from O&M base
- Meteorological data representative of the site, see Section 3.3.1 for how the meteorological model works
- Reliability of WTGs in the form of failure rates
- The type of repair actions required
- Project lifetime
- WTG capacity factor

A sample of scenario inputs would be:

- Number of technician teams allocated to either corrective maintenance or preventative maintenance tasks
- Type of vessels
- Number of vessels

The inputs and scenarios are linked through choices of the model user. The number of model inputs will depend on the complexity of the case and scenario. A simple case would be to model a WTG as a single unit and a more complex case would be composed of subassemblies: a simple scenario would define a single vessel type. Even a simple scenario would require a minimum of 50 individual input factors. A complex study would break the WTG down into subassemblies or components. A complex case would have multiple repair types, failure rate, procurement lead time and cost for each component. A reasonable case to model could be five subassemblies (Blade/Pitch; Generator; Electrical System; Control System; Mechanical Brakes) and five repair types (manual reset; minor repair; medium repair, major repair and major replacement). This would result in over 75 input factors in the repair category alone. Very few of the input factors are mandatory which allows for the model to be flexible of what case is modelled and how complex it can be. The components are treated separately and component failure will result in total or percentage loss of power generation from the entire unit. Every input requires to be added manual as there are no inbuilt databases. All of the cost inputs are deterministic.

3.2.3 Model Outputs

There are two key outputs from the model; the total costs for O&M and the availability (both time-based and production-based). ECUME also provides a wide range of other outputs at the end of the simulation for the users to see how the scenario copes and identify where improvements can be made, including:

- Monthly availability on a time and production basis
- Mean significant wave height and wind speed for each month
- The number of vessel access days allowed by the met ocean conditions.
- The number of sailing days for the transfer vessels
- The number of mobilisations days for specialist vessels.
- The offshore work load for the technical teams
- The number of and reason for standby days split between limitations in the technicians, met conditions and vessels.
- The number of completed preventative maintenance trips performed.

The mean value of both the time and production availability is given but also exceedance probabilities at user defined levels, for each month and year of operation. The mean value is given as P50, where the probability that the cost or availability will be less than or equal to that value is 50%. The user defined level xx means:

$$P(y_j \leq Pxx) = xx\% \qquad [6]$$

Where y is the output identified by index j.

The costs of the O&M scenario are broken down into WTGs (costs of repairs and spare parts), the logistical costs (vessels costs), costs of technicians and the operational costs (which are user defined such as fixed overheads and shore based operations). The costs are given on an annual basis throughout the project lifetime. All of these costs are summed to the annual gross total along with the production-based availability and the cost of unavailability. The costs are shown graphically as a distribution from the Monte Carlo simulations.

3.3 Model Execution

In a normal scenario analysis, a modeller would vary scenario input factors, complete a set of model evaluations and compare results until arriving at an optimal solution or a range of possible solutions. The model has been designed to simulate the entire project lifetime and consider the results in yearly time steps. Studies using the model are usually conducted during pre-development phase. They can also be conducted during operation to investigate future options for O&M scenarios.

3.3.1 Meteorological Module

The first algorithm run in the model is the meteorological model which takes the time series of meteorological data and calculates the weather windows for maintenance operations. In version 8.2 of ECUME, a year's worth of wind and wave data is selected from the time series randomly and concatenated on a year by year basis to last the entire project life. This method means that, as long as the time series is long enough, the weather windows will be representative of the site. As seen in Section 2.6.2, other offshore wind O&M models have more stochastic meteorological modules which employ techniques such as Markov Chains. The current methodology of using historic data directly means that the simulations are limited to that experienced in the time series, whereas stochastic methods can simulate weather scenarios outside of those experienced in the time series input.

3.3.2 Failure Module

The user inputs the likelihood of component failure through the failure rate (failures /WTG /year). An additional option is provided for the user to determine the bathtub curve from a questionnaire, thereby utilising expert knowledge if empirical data is missing.

The failure event model is driven through an inverse transform sampling algorithm to generate random numbers based on the probability functions of the three stages of the bathtub curves.

An event date is generated according to each distribution in turn. If the date is before the end of the period in question then the component is in a failed state. If the final "wear out" period is reached, then a failure incident is initiated. The corrective maintenance is conducted once there is an adequate weather window, i.e. the met-ocean conditions are within the operational limits of the vessels required. Here, two types of uncertainty are introduced into the model, that of the random sampling of dates based on the failure Weibull curves (aleatory), and that of the curves themselves as these cannot be firmly established from previous operational experience (epistemic).

3.3.3 Cost Calculation

The information from the met ocean data and the failure event simulation model is used with the user inputs to simulate the costs and availability of the farm. The model simulates the repair of a WTG according to the specifications of the commissioning wind farm operator in association with the ECUME developers and the algorithms are internal to ECUME. The transit aspects of the model are calculated using the distance to the O&M port and the speed of the vessels.

3.3.4 The Monte Carlo Simulation Algorithm

The user sets a maximum number of Monte Carlo iterations, the default of which is 1000. There is also an integral convergence criterion to the model so the iterations will cease when the evaluated value of the OPEX is less than 0.1% of the estimated mean of the averages of samples, as the distribution of sample means will be normal according to the central limit theorem. The chosen value of 0.1% is arbitrary and it is often difficult to reach the convergence criteria in a reasonable amount of iterations. If the user defined number of iterations, default is 1000, is reached before the convergence criteria is satisfied then an indicator, I_{conv}, is provided of the form:

$$I_{conv} = \frac{1.96 \times \frac{\sigma(\widehat{OPEX})}{\sqrt{n}}}{\hat{E}[OPEX]} \times 100 \qquad [7]$$

Where n is the number of iteration histories and $OPEX$ is the total O&M cost. By multiplying by 1.96 standard deviations, the 95% confidence interval with the estimated mean is obtained. The time taken for each simulation is largely dependent on the complexity of the scenario and number of turbines units, which increases exponentially. For a moderately complex case with a single unit, convergence occurs within approximately 25 seconds. The same case with 20 units takes approximately 435 seconds to complete.

The meteorological, failure and cost estimation modules are run and results are generated in a single iteration. A Monte Carlo analysis is performed to establish a range of results. For the majority of results the distribution is represented as a mean value and two further user defined x confidence levels to show the value where a x%

of the results are more favourable. The full distribution gross total costs are shown graphically.

Using the model characterisation framework that is established in Section 2.6.1, it shall be applied to ECUME. Because of the modules within ECUME, described above, have a source random number generation in the metrological model, failure event model and the Monte Carlo simulator to generate the mean from numerous simulations, the model is stochastic. The date generated from the inversed transform sampling algorithm are date basis, and that the user can only interpret the costs on a monthly and annual basis, therefore it is discrete.

3.4 Model Verification

The purpose of this section is to verify the model's ability to perform as expected. The OWFs that have been used in the subsequent analysis are based on two real projects, however, to maintenance commercial sensitivities, they have labelled T1 and NB1. T1 is an operation wind farm in the UK and NB1 is a proposed wind farm which has subsequently been declined consent.

Operators of offshore wind project T1 are consulted for inputs used in the case studies in Section 3.4.1, 3.4.2 and in the LSA and GSA. Over the course of three years, the expertise of the operations team were captured to feed into the input factors in addition to other relevant personnel. The nature of this capturing was through series of unstructured interviews in face to face meetings. These meetings were often focused on other research activities and not solely about the sensitivity analysis. This meant that a wider scope of information was obtained than just the inputs of the model. They also helped to place the model within the context of real life operations and identify where the model diverges from what occurs in real life. As well as operators, the following personnel were consulted in a similar manner throughout the course of the project. Information from whom directly fed in to the input factors used in the case studies and sensitivity analysis:

- Crew boat operators, skippers and crew
- Performance optimisation analysts
- Asset managers
- Onshore operations managers and analysts

- Finance teams
- Representatives from third party stakeholders such as the Crown Estate and Offshore Renewable Energy Catapult
- Other academic researchers in the field of offshore wind

3.4.1 T1

The purpose of the thesis is to explore the uncertainty introduced through the input factors affecting cost and availability using the pre-existing computer model. The influence of other sources of uncertainty need to be limited for the purposes of the subsequent analysis. Two sources of uncertainty come from the computer model itself; the in-built stochastic nature of the model and also whether the model is built to accurately reflect the real life O&M system.

The purpose of this section is to legitimise the model, proving that it is fit to be used in the subsequent analysis. The results of the SA should be clearly linked to the inputs and not outcomes from unforeseen behaviours within the model. To do this, the behaviour of the model is tested against that of a real OWF.

The ideal test of the model against a real system would be a direct comparison against all inputs and outputs; requiring that the model is isomorphic. Whilst the model attempts to incorporate all of the aspects regarding O&M, it is still a simplified version. There are aspects missing which affect the real system outputs, even in an infinitesimal way, such as the failure of vessels, preventing the vessel launch for repair operations. The model cannot also incorporate the changes that may occur in the strategies over time that come from learning or adaptation to external parameters. Details from the real-life system need to be collected to match the outputs of the model through the study period.

At this current point, neither is the model isomorphic nor complete information from a real-life system available to match with the model.

The only information available with which to make a comparison between the model and a real–life system is from the first year of the T1 OWF. The wind farm consists of 27, 2.3 MW WTGs. The centre of the wind farm is 9 km away from the O&M port as shown in Figure 3-3.

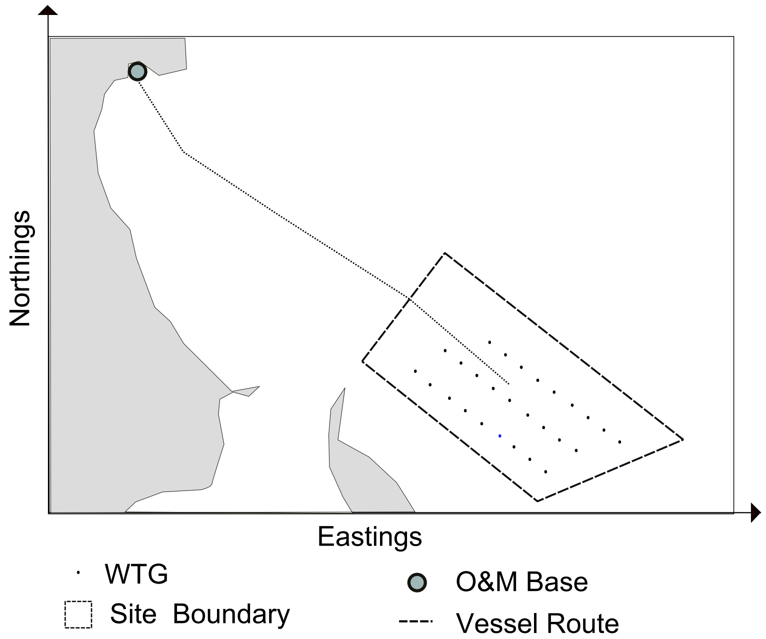


Figure 3-3: Illustration of T1 case

According to the theoretical bathtub curve shown in Figure 2-4 , the beginning of the WTGs life are potentially more susceptible to failures, suggesting that using the beginning of the T1 OWF may not be representative of the majority of the life-time of the project. Without further data, this is deemed enough to test the model alongside other verification methods explained in further studies.

The objective is to define the case and scenario in consultation with the wind farm operators; to run the model as close as possible and to compare to the total costs and time-based availability. At the time to the analysis, the real total is an estimation as not all costs had been accounted for. Data about the other model outputs such as the proportion of postponed repair action causes was not recorded at the time.

At the time of the input gathering, a lot of the specific data to T1 was unknown so information from alternative sources are found. As the data is specific to an operational wind farm, the information is considered to be commercial and is confidential. However, several aspects modelled are not specific to the project or have been previously published so can be provided here.

The first step is to try to replicate the operations at the case and compare with the results of the simulations of the wind farm. T1 was commissioned in 2013, therefore has been two years of operational experience. Not all of the data gathering mechanisms had been established from the point of commissioning which leads to some challenges in replication of the first year of operations. For example, no on-site wave buoy data was collected until 18 months into operations, and records of the maintenance activities are not available until 12 months into operations. Where gaps in the information exist, alternative sources and judgement have been used, which have subsequently been verified by the operators team at the wind farm.

Ideally, the model would be run with the same historical data recorded at the site. Unfortunately, a complete record of the meteorological conditions is not available due to technical problems with the communications to the site and lack of wave monitoring devices.

For the meteorological model, at least a years' worth of wind speed and wave height data is needed. The wind speed data is taken from the SCADA system for one of the WTGs located in the southern end of the wind farm. The most complete set of data was between the dates of 06/03/2014 and 06/03/2015. The original five second data is averaged over each hour. As a wave buoy was not installed at the site until early 2015, a complete year of measured data is not available. To make a complete meteorological data set the onsite wave data is augmented with data from a wave buoy located 38 km away from Centre of Environment Fisheries and Aquaculture Science WaveNet program (Centre for Environment Fisheries and Aquaculture Science, 2015). The buoy is located in a water depth of 65m and is a Directional Waverider MkIII. The data available from this buoy is available between 12/05/2014 and 03/08/2015. As the WaveNet buoy is located further out from the shore it is exposed to rougher conditions than the site buoy. To remove this bias the mean difference between the significant wave height of the site buoy and the WaveNet buoy, when data availability overlapped, is subtracted from the remaining WaveNet data to estimate the wave conditions at the site. This still resulted in two and a half months' worth of missing wave data. For the missing dates, hind cast significant wave height data from the site is used from the same period in a single year which corresponded closest to the data measured on site during 2015 when data is available. For this time period (March to mid-May in Figure 3-4) the wind speeds and wave height are not linked.

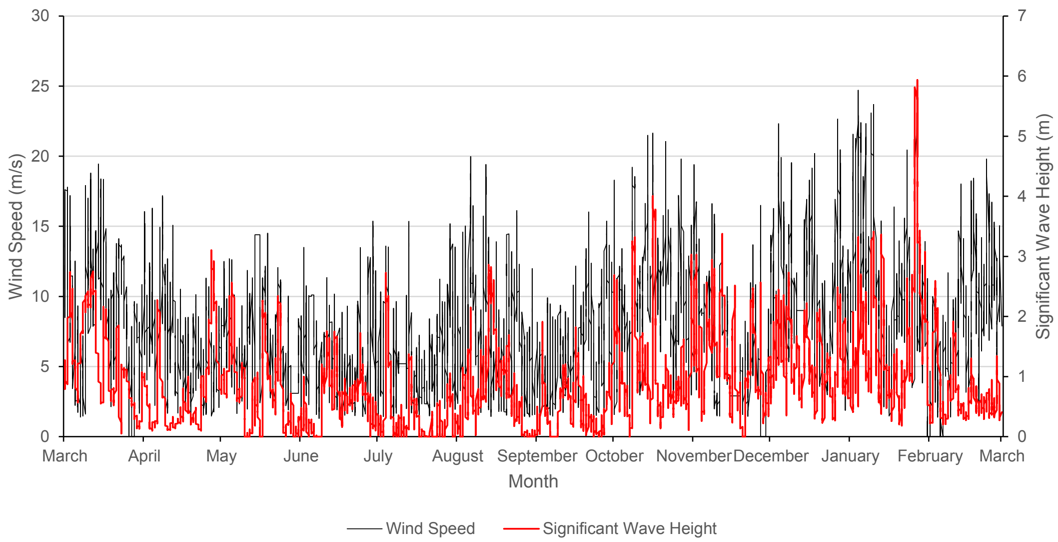


Figure 3-4: Meteorological time series data for T1 2014 – 2015

The wind farm is still under warranty with the OEM, therefore the costs of repairing the WTGs, including spare parts, technicians and vessels is covered through fixed annual service fee. Modelled costs that are the responsibility of the operator include the construction of the onshore facilities, including staff salaries, the wave buoy and installation additional monitoring sensors and their upkeep. These costs have been disclosed for use within the analyses presented in this study but are held in commercial confidence so therefore cannot be published.

The maintenance scenario has been replicated as close as possible to the real operations. The number of technicians and the size of the teams in the model remains fixed but in real operations the values vary according to demand. The average value of team size and the number of teams over the year is taken. The vessel capacity, speed and operational limits are taken from the specification of the same vessels used at the site. During the first year of operations, no specialist vessel, other than the CTVs are required for maintenance. The failures are categorised into minor and major via length of operation time according to Table 3-1.

Table 3-1: Failure type definition for cases

Failure Type	Operation time
Minor	< 11 hours
Major	> 11 hours

During the first year, a serial defect is encountered, that required work to be conducted on all the WTGs. This defect cannot be designated a failure as it did not stop the WTG from operating, however the actions to resolve the issues incurred significant down-time and greatly affected the availability. An attempt has been made to reflect this work with a "failure" requiring 700 hours /WTG for investigation and 100 hours for preventative actions. The failure rates (not including the preventative work outlined) are taken from the maintenance logs of the WTGs, recorded on a daily basis, the condition of the WTGs and what actions have been taken by the technicians. An average annual failure rate of 2.4 failures /WTG is found. This is a lot less than the first year WTG failure rate found by Carroll et al. 2015, which includes a wider range of turbine models. The reason for this may be because of the difference in WTG manufacturer and make, the difference in data collection and that the downtime caused by preventative maintenance reduce operating time, having a direct effect on the measured number of failures. For the annual servicing, the average time is taken along with the average number of team members. The number of teams assigned is based on the average number of WTGs visited for annual serving tasks simultaneously.

The results of the model simulations are measured against the real operations where data is available.

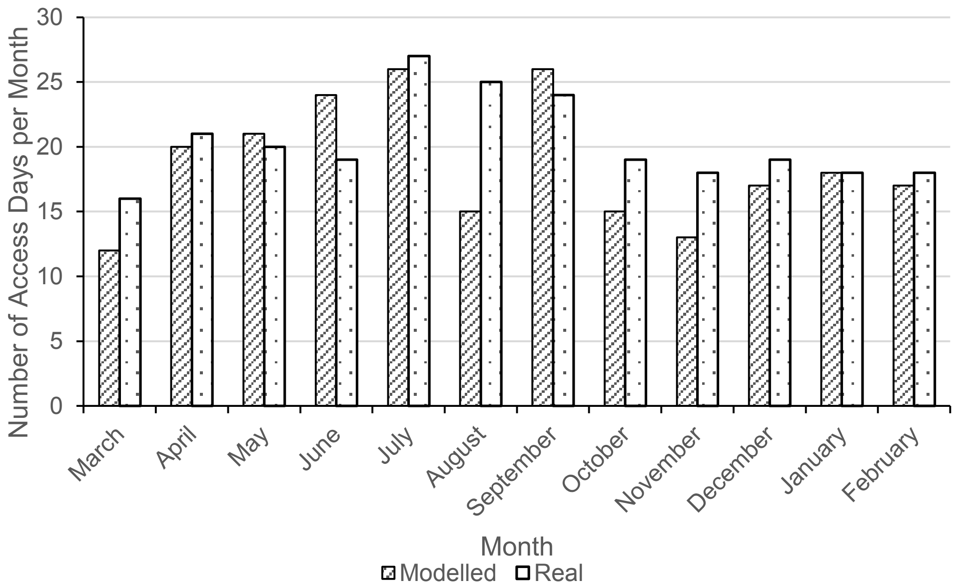


Figure 3-5: Number of vessel access days for first year of operation

Figure 3-5 shows the results of the number of vessel access day's from the model against the number of actual days accessed in the first year of operation. Between March and July there is close agreement between the results of the model and the actual days the vessels went out. The mean absolute error between the estimated and the observed for the year is 3 days per month. The dissimilarities between the results may be due to no work being required on a particular day, therefore no transfers took place. Also, the decision to launch a vessel is dependent on the wind and waves, but also the wave steepness and direction, parameters which can be localised. The reliability data is from a similar time frame as the meteorological data, except for the couple of months missing of wave data as described above.

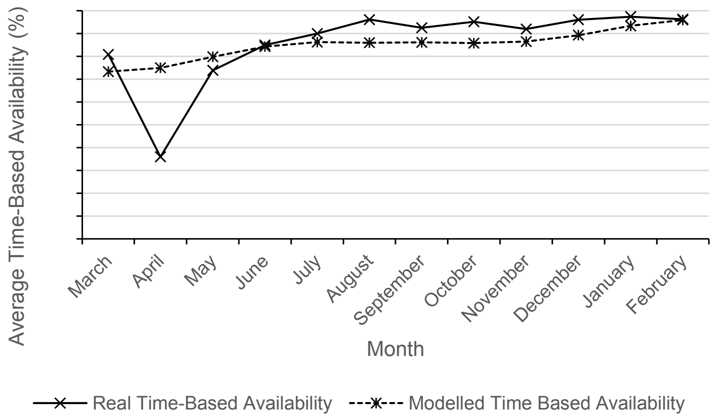


Figure 3-6: Real time based availability and the modelled time-based availability

Figure 3-6 shows the modelled and the observed time-based availability from the first year of operations at the wind farm. The availability in the graph has been hidden as this is commercially sensitive information. The real monthly time-based availability encounters a severe drop in April due to the investigations into the serial problem where as in the model, it is not possible to replicate it. However the modelled average is within 0.8% of the real availability.

The true OPEX from the site is held in commercial confidence but in conversations with the operators, the modelled costs are in agreement with the accounted costs from the first year of operations.

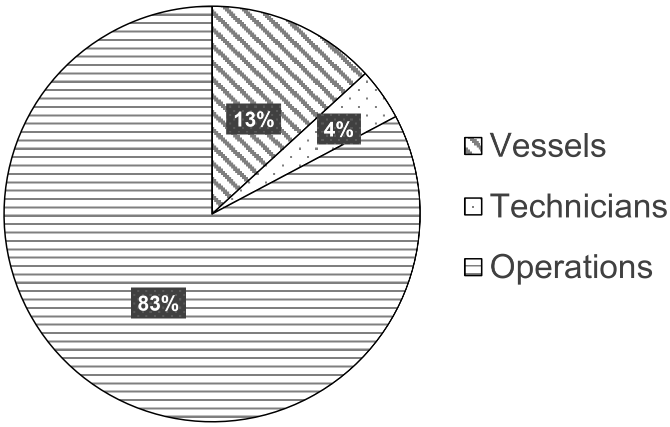


Figure 3-7: Distribution of costs from model of first year of operation

The distribution of costs is shown in Figure 3-7. The fixed service fee is part of the operational costs along with the onshore operations costs and therefore the materials and consumable costs are minimal. The technician's costs are one of the salaries of employed technicians. Vessels include the annual charter rates the fuel.

After the model has been applied to the first year of the real operations it can be used to consider the rest of the operational years. The information found in the previous study has been used to extrapolate out across the 20 year project lifetime.

The same reliability statistics are used for warranty period and five years after that. Major replacements, which require the use of a HLV, are introduced after year 10, according to the major failure rates recorded in (Carroll, Mcdonald, et al., 2015).

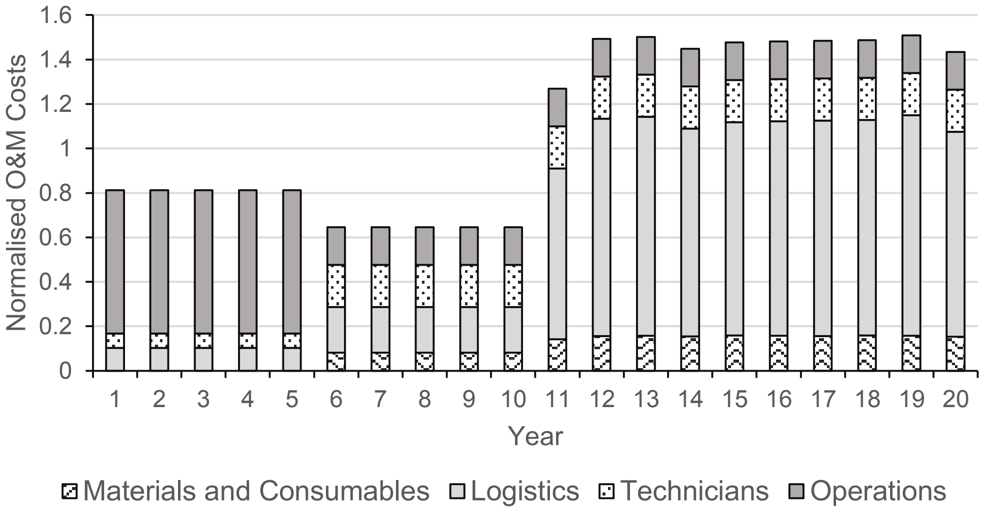


Figure 3-8: Normalised simulated costs of T1 project through 20 year project life

The costs have been normalised to the year one costs, thus Figure 3-8 shows the change in projected costs throughout the project lifetime relative to the first year. After year five, the operation moves to post-warranty. Operations costs reduce without the fixed service fee but there is an increase in materials, technicians and vessels as the operators takes over operations. The scenario modelled is that all repairs become the responsibility of the wind farm owner. Other options for the post-warranty period are to continue the service agreement with the OEM for a fixed fee or to contract a 3rd party to perform the maintenance and servicing. The model can be used to assess the opportunities for post warranty operations. For this scenario, the opportunity for major failure repair is introduced from year ten to look at the effect of wear out failures on the costs, which leads to an increase in costs relation to the logistics, i.e. vessels.

This scenario is only one possibility of how the wind farm can be managed. Considering just one scenario will not provide a full assessment of the future project profitability. To demonstrate how the model can be used, the next section provides a scenario analysis. A different OWF is chosen as T1 proved to be too small and too close to the O&M base to provide an interesting case study.

3.4.2 NB1

This section provides a case study of how the ECUME model can be used to conduct scenario analysis of defined cases. Here, an example will be presented using a proposed wind farm which has since been rejected at the planning stage. The purpose of this study is to compare the results of the ECUME model to that of a non-stochastic project lifetime cost model, which incorporates the planning, installation and decommissioning costs as well as O&M. This other model takes a "top down" approach to O&M, where a total O&M cost is taken from a completed project and scaled per the capacity of the subject OWF. This can be a misleading approach as costs and availability are affected by other input factors besides installed capacity, such as distance to shore, number of turbines and maintenance scenarios. As described in Section 3.2 to Section 3.3, ECUME takes a "bottom up" approach, where the costs are calculated through simulations.

3.4.2.1 Case and Scenarios

The case is a proposed project on the south coast of the UK. The site is part of the third licensing round of UK seabed for OWFs issued by the Crown Estate. The total capacity allowable in the license is 1200 MW.

Project developers have a choice of how many phases to build the complete project in. The options are to either build the complete OWF in one project or to build in stages; installing and commissioning each phase before moving on to the next. In this study, two options are compared; the first is that the project is split into two build phases, and the second is that it is built in a single stage.

Figure 3-9 shows a schematic of the project with relation to the coastline. The outer rectangle is the geographical extent of the entire project. The inner rectangles show the extent of the project phases, north and south. The line is the route from the O&M port on the shore line to the centre of the entire project.

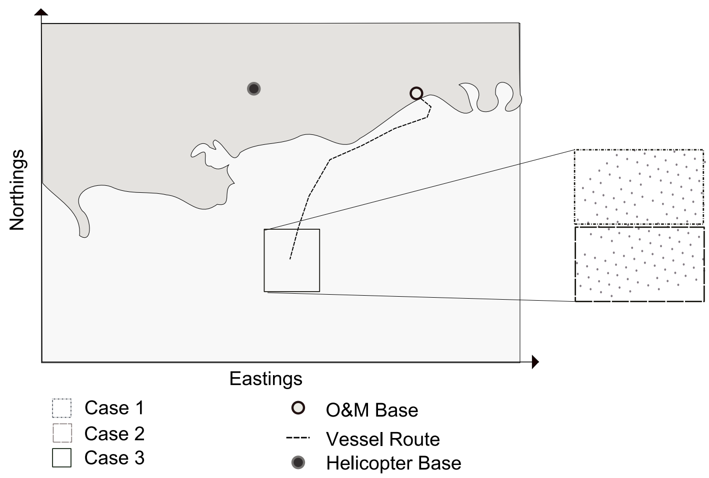


Figure 3-9: Illustration of OWF project phases

The O&M costs and availability are calculated for three cases; the northern half, southern half and the complete project. An important factor in the decision to split the construction of the wind farm in two is related to the future change to the Contracts for Difference (CFD) financial support mechanism in the UK. The Low Carbon Contracts Company pays the difference between a set strike price, a value of electricity which reflects the cost of investment, and the average market price for electricity (Department of Energy & Climate Change, 2013). The CFD is issued to eligible projects in rounds. In each round, eligible projects offer bids for the lowest guaranteed electricity price at which they can afford to invest at a range of capacities if desired. For each technology, a budget is set and the bids ordered from lowest to highest. Winning bids are those that cumulatively fall underneath that budget. They are offered a strike price which is the highest bid of winning projects (Department of Energy & Climate Change, 2014). This is done on a technological basis and the budget decreases over time. Operators will pay back any income over the strike price when required. This will last for the first 15 years of the project but the allocation budget reduces over time, incentivising cost reduction. This financial mechanism allows developers a guaranteed value for the electricity generated, making the project more financially viable and attractive to invest in, whilst pushing towards industry wide cost reduction.

If the project is built in phases then each phase will need to apply for a CFD separately, such as the East Anglia OWF, and a second phase, in all likelihood, will be allocated a lower strike price.

The first case represents the first phase: the northern half, capacity wise, of the OWF and consists of 62 x 8 MW WTGs, with a total capacity of 496 MW. The geographical extent of this case is chosen arbitrarily. The second case is the southern half of the wind farm with 59 x 8 MW WTGs and a total installed capacity of 472 MW. The complete case consists of 121 WTGs and a total installed capacity of 968MW. The likelihood is that, if built in multiple phases, then one half of the wind farm would have been built and moved into the operational phase. Soon after, the second half would have been installed, commissioned and brought into the operational phase, after which the project would be run as a complete project. In this study, it appears as though the second case would be run as an independent wind farm, which is unlikely as after commissioning it would have been run as an entire project.

As this project was in the planning stage, no decisions were made regarding the approaches for O&M. For this analysis, the access option is chosen as the scenario analysis. The possible methods are limited to use of:

- CTVs, used for the most OWFs in Europe;
- Helicopters with CTVs, currently used at Greater Gabbard in the UK and Horns Rev in Denmark;
- Mother-ship type vessel, not currently used at operational OWFs in the UK.

The WTGs are assumed to be under a service agreement with the OEM for the first five years of the WTG's operational phase, after which all maintenance switches to the owner/ operator. During the warrantee period, the cost of WTG repair, technicians, vessel transport and annual servicing is covered by a single monthly fee.

The costs taken for this study are based on experience from the offshore wind industry where available, and if that is unobtainable, then from other industries. For example, the charter and running costs for helicopters for OWFs is not available as only one UK and one Danish wind farm uses them (Bolton, 2014). Values, instead, have been taken from the annual cost for helicopter operation of Air Ambulance charities in the UK. Similarly, the costs of operating a mother-ship to serve the WTGs is unknown as they are seldom used in the UK so costs are modelled on a research ship as they have similar requirements; accommodation and facilities for technicians and also the ability to remain offshore for extended periods of time.

The technicians serving the two halves of the wind farm cases, if operated independently, work in a single 12 hour shift whereas for the complete wind farm, there are two shifts on a 15 hour work day.

The meteorological input data is comprised of four years of hourly significant wave height data from the Poole Bay WaveNet buoy, 17 km from the site (Centre for Environment Fisheries and Aquaculture Science, 2015). The corresponding wind speed at 10m above sea level is from a modelled dataset from the site from the same time period as the wave data. The mean wind speed of the dataset is 7.15 m/s and the mean wave height is 1.02 m. The mean annual wind speed is approximately 0.5m/s lower than the mean wind speed of other UK OWF sites of equivalent development stage. Likewise, when comparing the annual significant wave height of other UK OWFs from the Atlas of UK Marine Renewables (ABPmer, 2015), the site is lower than the mean by 0.47m.

There are input factors for the study that remain the same for each of the scenarios. The WTG capacity is 8 MW and hub height is 100m. The monthly capacity factor is shown in Figure 3-10, with an annual average of 0.52.

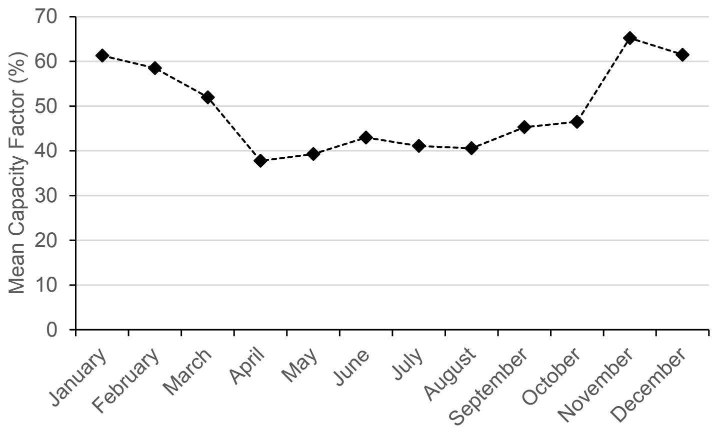


Figure 3-10: Mean monthly capacity factor for 8 MW WTG at the site with 4 years of modelled data at 100m hub height

The availability of the balance of plant (BoP) is assumed to be 100%. The wind shear factor, to convert 10m wind speed data to 100m, is estimated at 0.1.

The WTGs are considered to have seven main subassemblies:

- blades and pitch systems,
- generator,
- electrical system,
- control system,
- mechanical braking system,
- yaw system,
- gearbox,

The costs of technicians are on an annual basis of £40,000, based on details in potential salaries posed in job advertisements. Extra training costs of £1,600 every five years to keep certificates up to date, based on quotes from companies that provide training programmes. The technicians have a 15 minutes break per operation conducted. The sum of all technician salaries is multiplied by 1.65 to account for technician down time, holidays and sick days.

The vessels modelled are based on standard vessels used for crew transfer (CTV) in the industry in 2015. The CTV type can be seen in Figure 3-11.

Figure 3-11: Photo of CTV at T1 OWF with technician transfer, summer 2014

The input factors used for the vessels in these cases is shown in Table 3.2. The information on vessels is taken from vessel technical specification documents, industry fuel prices and information provided by the operators at an operational OWF. The rental cost for such a vessel includes the vessel and crew, but not fuel. This vessel can serve most routine repairs and maintenance activities, with technicians accessing the vessel via the ladder, as seen in Figure 3-11. Components weighing up to approximately 1000 kg can be transferred to the WTG via the Davit crane. The vessel has imposed limitations on the maximum wave height and wind speed it is allowed to operate in and to transfer technicians for safety reasons.

For failures which result in a major replacement of a component in the nacelle, a vessel with a greater lifting capacity than the davit crane is required. These speciality vessels are usually chartered for the tasks ad hoc. In these cases, the specialist vessel is based on a self-propelled jack up vessel. The daily rate for the vessel includes crew.

Five repair types are defined, similar to those defined by the Reliawind project (Wilkinson et al., 2010). They are remote resets, minor repairs, small parts replacements, medium repairs and major replacement.

Table 3-2: Vessel Input Factors Used for NB1 Cases

	CTV	HLV
Passenger Capacity	12	-
Fuel Consumption (tons/hour)	0.2	1.8
Average Speed (Knots)	20	12.8
Fuel Oil Price (2014) (£/ton)	590	590
Annual Cost (£)	400,000	-
Mobilisation Cost (£)	-	3,000,000
Day Rate (£)	-	100,000
Mobilisation Time (days)	-	90
Operation Wind Limit (m/s)	20	30
Operational Significant Wave Height Limit (m)	1.5	1.83

The table below shows the assumed failure rates for each of the repair types. As little information exists in how failure rates can be broken down into repair types, the results from the failure rate table in Appendix Bare divided into four and assigned to each of the four least severe failure types. This results in an average of 6.09 maintenance visits each WTG per year. This value has been verified with a number of industry experts though unstructured interviews, although the true value is said to be anywhere between two and ten per year. A major failure rate is estimated to be 0.025 for each of the large nacelle components. The electrical system, control system and mechanical brakes are not considered to have single components over 1000 kg in the nacelle requiring a HLV.

The input factors used to define the cases, are WTG number and the distance from the O&M port to the geographical centre of the different phases of the wind farm in reality. The actual O&M base for the real project is yet to be decided, however there are several possible bases that could be used. The port chosen for this study is the one that is most developed in terms of facilities but is also the busiest and furthest from the wind farm, therefore acts as a worst case scenario.

Table 3-3 : Assumed failure rates (annual failures per turbine) for different repair types for offshore WTGs

Component	Remote Reset	Minor Repairs	Small Parts Replacement	Medium	Major Failure
Blade/ Pitch	0.1725	0.1725	0.345	0.08625	0.025
Generator	0.0175	0.0175	0.035	0.00875	0.025
Electrical System	0.55	0.55	1.1	0.275	
Control System	0.45	0.45	0.9	0.225	
Mechanical Brakes	0.175	0.175	0.35	0.0875	
Yaw System	0.225	0.225	0.45	0.1125	0.025
Gearbox	0.15	0.15	0.3	0.075	0.025

As it will be shown, this has implications on the results. The distance to the centre of the first case is 56 km, to the second case is 62 km as it is further south, and to the complete wind farm is 59 km.

A potential helicopter base is identified at the closest airport facility. For the scenarios that utilises a helicopter, the distance between the helicopter base and the three wind farm centres are 33.1 km, 38.5 km and 35.8 km. The helicopter is deployed when the CTVs are limited by meteorological conditions.

The sale price of electricity changes for the different phases due the CFD mechanism as mentioned above. Prior to the first round of bid announcement in February 2015, the estimated value of strike price is £140 /MWh to steadily reduce with subsequent rounds. For the first case the CFD is estimated to be £140 /MWh produced. It is then assumed that the next phase would have been bid in the subsequent round for CFDs and the fixed price will be reduced to £135 /MWh. This analysis is done before the most recent CFD round where the final strike price for offshore wind technology is significantly less at £119.89 /MWh (Department of Energy & Climate Change, 2015).

Two of the input factors are linked to the capacity of the wind farms. Costs for onshore facilities includes office, workshop, dock rental and the wages of onshore staff. For the first case the annual onshore costs are £1,240,000; for the 2nd case it is £1,180,000 and £2,420,000 for 3rd case. The costs for the service agreement in the first five years of operations is dependent on the number of WTGs. This is based on industrial experience and is commercially sensitive so the values are not given here. For the scenarios including the mothership, the accommodation vessel returns to the base every 14 days for resupply.

The number of technicians that are available for annual service and corrective maintenance are based upon analysis of current OWFs, and more information is available in Section 5. Each team consists of two technicians as this is the minimum number to conduct work on the WTG. For the annual service, the available number of teams for the Case 1 and 2 is two and for Case 3 is three. For corrective maintenance actions, the number of available two person teams is three for the Case 1 and 2 and seven teams for Case 3.

The repair costs for components comes from the mean values of NREL's survey of onshore wind component costs in the USA (Musial & Ram, 2010). The repair costs are included in total costs for failure events when outside of the service agreement. The results of the three cases and their scenarios are shown in Figure 3-12 to Figure 3-14. The annual costs of the WTG spare parts, logistics, technicians, onshore facilities are provided as well as the production-based availability.

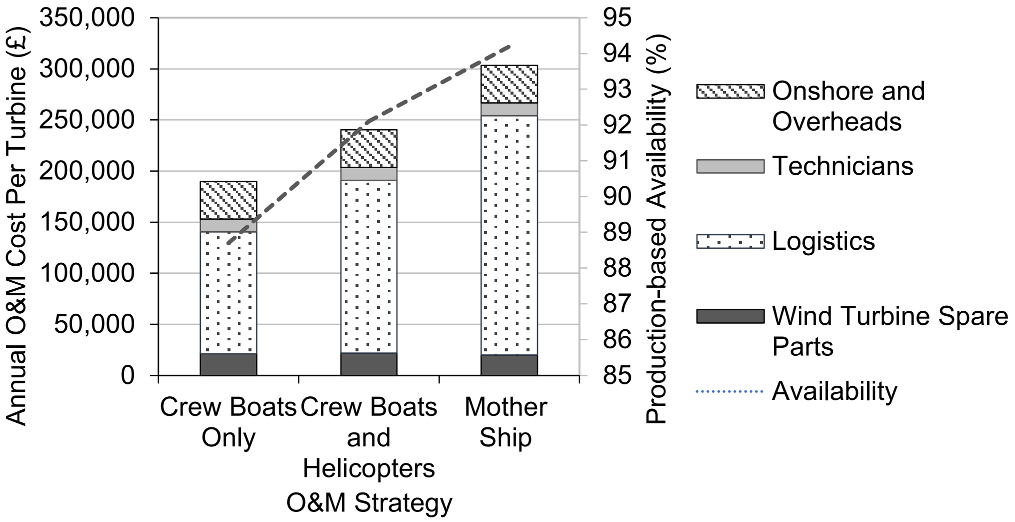


Figure 3-12: Direct costs and availability results for three access scenarios for the first case

The term direct cost is used for total costs and indirect costs for lost production revenue due to unavailability.

3.4.2.2 Results

Crew Boats

For the Case 1 (62 WTGs with 56km between the O&M port and the centre of the wind farm), the estimated annual direct cost per WTG is £189,700 when using crew boats only. This increases to £191,000/ WTG with the Case 2 as it is located further away from the O&M port. Also, with a lower number of WTGs, the expense is higher on a per WTG basis whilst using the same number of vessels and technicians. As there are fewer WTGs to the same resources, there is a slight increase of average production based availability for the Case 2 at 89.1% compared to 88.7% for Case 1. Both of these availability estimates are low compared to the industry averages of over 97.1% for onshore and over 90% for offshore, as shown in Section 2.2, and an operator would be seeking to improve on these values. This relative under performance is due to the length of time the CTVs have to travel from the port to reach the wind farm, and the number of repairs which require HLVs and the resulting long operation time. The average number of mobilisations of HLVs occurring for the Case 1 and Case 2 is approximately two per year.

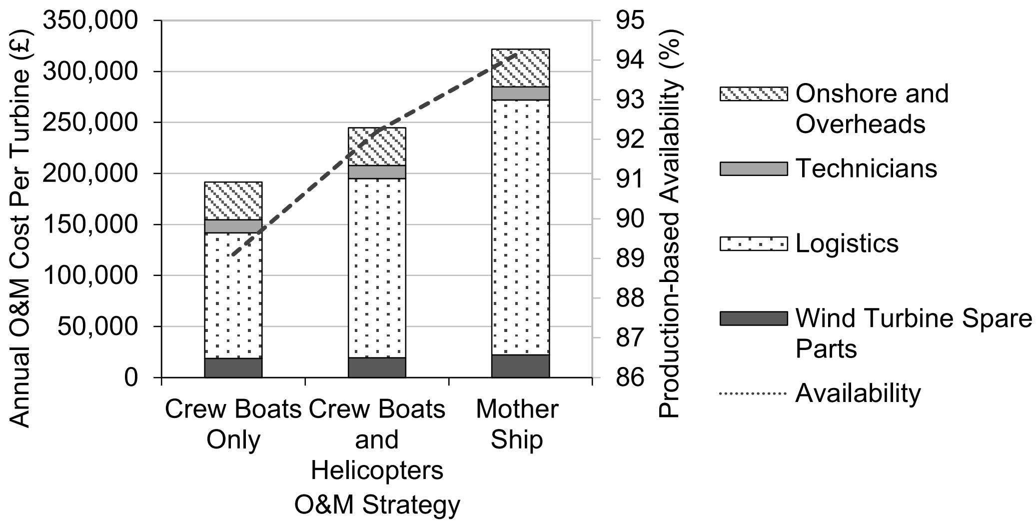


Figure 3-13: Direct costs and availability results for three access scenarios for the 2nd case

Whilst this may be possible for the early years or wear out period, it is unlikely to be consistent for the entire lifetime of the project. There is a weakness in using a consistent failure rate as this is simplistic analysis. For the Case 3, (121 WTGs and 59 km from the O&M port) there is a reduction in the direct costs /WTG /year to

£157,000 due to a reduction in logistical costs and also the increase in WTGs sharing overheads and onshore costs.

As before, the failure rate for components that require heavy lifting is high through the project lifetime. In both Case 1 and Case 2 the number of repairs requiring a HLV is on average 5.5 a year but because of the 90 day lead in time for a specialist vessel, it is probable that a similar failure would occur before the vessel arrived. As up to four WTGs can be bundled into the same operations and the vessel has deck capacity for five WTGs, only two mobilisations are required. For Case 3, the average annual number of mobilizations of HLVs is three with double the number of WTGs and the same failure rate. The case with more WTGs benefits more for the bundling of major replacement activities into one operation. The model has the option that if several failures occur at the same time and require HLVs, then all the WTGs can be repaired under one mobilisation of the vessel. To benefit from this bundling, a high enough number of major replacement failures is required, suggesting at interaction between the effects of the inputs on the outputs. This will be developed further in the SA of the model.

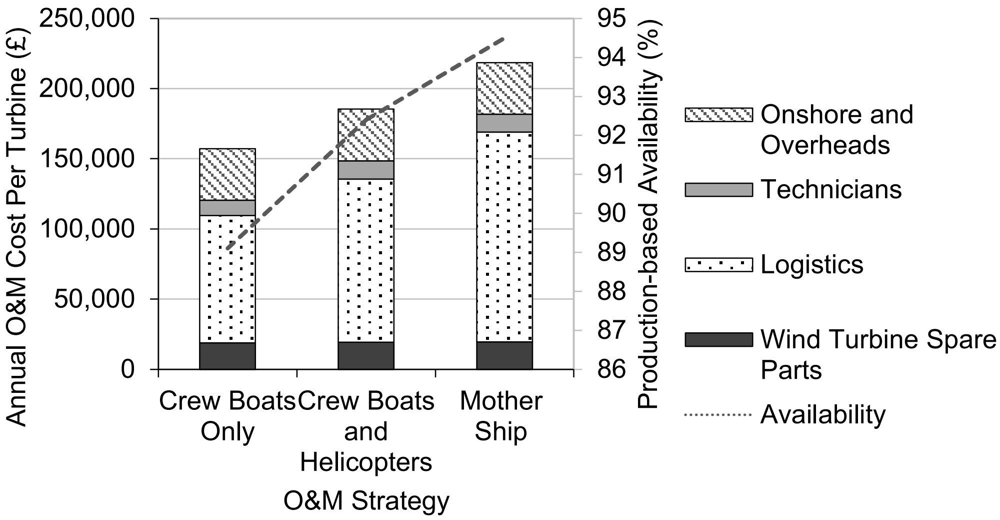


Figure 3-14: Direct costs and availability results for three access scenarios for the total case

<u>*Crewboats and Helicopters*</u>

For the scenario where both CTV and helicopters are used, there is an increase in direct costs across all cases. For Case 1 and Case 2 the direct annual costs are £240,000 and £245,000 respectively. This is due to the increase costs related to the use of a helicopter to access the WTGs. The same is true for Case 3 where the annual direct cost per WTG increases from £157,000 to £185,000. A feature of the model is that the helicopter is not limited by wave heights and, in reality, a helicopter is faster to reach the WTG and is less limited by wind speed than a CTV. This results in the available time for maintenance being increased when helicopters are used. For Case 1 and Case 2, the production-based availability is 92.1 % and 92.2% respectfully, and for Case 3 it is 92.4%. This is still on the comparatively low side for OWFs.

Mothership

For the mothership scenario, again there is an increase in the direct annual costs per WTG; up to £321,000 for Case 1 and Case 2, and £218,000 for the Case 3. This is due to the increase in logistical costs from addition of a mothership. As expected, the availability also increases to 94.2% and 94.5%. This still remains below the average of operating OWFs due to the high major failure rate, which is not effected by the presence of a mothership as it is tended by the HLV only.

3.4.2.3 Discussion

If considering direct annual costs only, the cheapest option is the use of crew boats only as each of the other possible access methodologies brings additional cost. However, if the cost of lost production is considered, the reverse is true, as the inaccessibility becomes highly important in the total costs. Figure 3-15 combines the direct and indirect costs for each scenario. They show that the loss due to unavailability is actually higher than the direct costs due to the high strike price assumed and low availability. The conclusion is that the best scenario for the Case 1 and Case 3 is to use a mothership. For Case 2, the difference between the use of CTVs / helicopters and motherships is minimal.

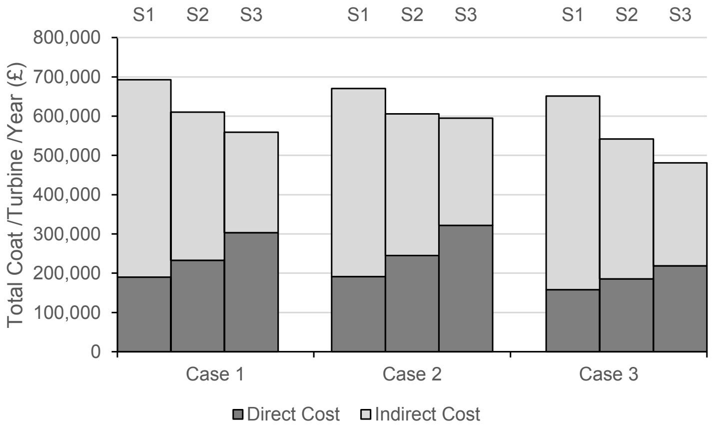


Figure 3-15: Direct and indirect costs of three cases with three scenarios

3.4.3 Input/ Output Model Comparison

The lack of historical data is an industry wide issue, with model developers from different research institutions finding it problematic to validate models. For this reason a code to code comparison is conducted with four independently developed offshore wind O&M models with the intention of checking that the assumptions made by ECUME are reasonable. This approach is reasonable given the hypothesis that multiple researchers will come to reasonable conclusions independently. A code to code comparison has been used for offshore wind applications for comparison of codes for development of floating WTG structures and for aero-hydro elastic codes (Jonkman & Musial, 2010; Karimirad, Meissonnier, Gao, & Moan, 2011) as part of IEA Tasks 30. A direct code to code is not possible in this instance. Therefore an input /output model comparison is conducted instead.

The following work has been conducted in collaboration with other model developers from SINTEF Energy Research, University of Stavanger and University of Strathclyde. The reference cases are developed collectively and the models run by each of the model developers. The results are also reached collectively. The work is presented in Dinwoodie et al. 2015. The models compared with ECUME in this work are NOWIcob, UiS Sim and the Strathclyde University Offshore Wind OPEX. Along with the execution of the cases with the ECUME model, personal participation in this comparison investigation was discussion of the case studies inputs, the differences in the models and the implications on the results.

3.4.3.1 Test Case

A base case of input parameters is devised to represent a generic Round 3 UK OWF. Details of all the inputs are given in Dinwoodie et al. 2015. The source of data for the base case originates from collective knowledge of the members of the group and indirect consultation with Statoil and SSE; NOWITECH's and University of Strathclyde's industrial partners.

The fixed wind farm and scenario inputs are as follows:

- Number, capacity and cut in/ out wind speeds of WTGs
- Distance to the wind farm
- WTG failure rate
- Wind speed and wave time series
- Day rates of the vessels
- Vessel speed and operational limits
- Technician costs
- Mobilisation time and costs
- Daily shift
- Price of electricity
- Repair time and costs

The scenario inputs are as follows:

- Vessels number
- Technician number
- WTG failure rate
- Operational limits
- Failures types occurring

Five failure categories are employed; manual reset, minor repair, medium repair, major repair, replacement. Additionally, an annual servicing is scheduled for each WTG.

The metrics chosen for comparing models are time-based availability and annual direct O&M costs.

As mentioned in Section 2.6, each model usually has its own unique features, but for the purposes of this analysis they have been restricted to a "minimal" core of features that all models share. This allows as close as possible comparison of the developed models while still being sufficiently complex to be representative of the operational reality.

After this base case is established, a range of other scenarios are created around it. The details of the scenarios are seen in Table 3-4.

The weather data used in this study comes from the FINO 1 (BMU & PTJ, 2012) offshore research platform which is situated approximately 45 km off the coast of Germany. The data set used for this analysis covers the years 2004-2012 and is pre-processed into hourly resolution and gaps are filled using a cubic spline interpolation.

Table 3-4: Definitions for different cases

Case	Case description
Base case	Defined in Dinwoodie et al. 2015
More CTVs	The number of CTVs is increased from 3 to 5 and the number of technicians is increased from 20 to 50.
Fewer CTVs	The number of CTVs is reduced from 3 to 1.
More technicians	The number of technicians is increased from 20 to 30.
Fewer technicians	The number of technicians is reduced from 20 to 10.
Failure rates down	All failure rates are 50% of base case failure rates (only corrective maintenance; annual services remain unchanged).
Failure rates up	All failure rates are 200% of base case failure rates (only corrective maintenance; annual services remain unchanged).
No heavy-lift vessels	Failure rates for failure categories requiring heavy-lift vessels (major repair and major replacement) are set to zero.
No weather limits	Weather limits for operation of all vessels are effectively set to infinity.
Historical weather data	An 8-year time series for the weather data is used instead of synthetic weather time series (for models using such).
<*Failure category*> only	Failure rates for all failure categories are set to zero except for <*Failure category*>. There are no annual services.
Annual services only	Failure rates for all failure categories are set to zero, making annual services the only form of maintenance.

3.4.3.2 Results

The results for the average time-based availability are illustrated in Figure 3-16, and for 10 year O&M costs in Figure 3-17. The results from each of the models is shown for each of the cases run, starting with the base case.

For each experiment ECUME is set to run for 1000 iterations in order to ensure that it is close to the convergence criteria. The other models ran between 50 and 100 iterations with no convergence criteria and no precision indicator other than the standard error of the model results.

Table 3-5: Average model run times

Model	Average Iterations	Average Seconds	Iterations rate (iterations/s)
ECUME	1000	400	2.5
UiS model	48	120	0.4
Strathclyde model	100	250	0.4
NOWIcob	100	20,000 – 80,000	0.005 – 0.00125

The statistical uncertainties in the results as quantified by the estimated absolute standard error of the sample mean are of the order of 0.2 % for the base case time-based availabilities.

The difference between the highest direct O&M costs out of a model and the lowest cost are in the order £0.5m–£2m for the base case and for the other reference cases where HLV are needed. When no HLV is needed, the range in the direct O&M costs are reduced from of the order £100m - £200m to circa £40m.

For the cases where the modelled system is not under stress, i.e. there are adequate resources to attend to the failures, the resulting availability from ECUME is lower than the other models.

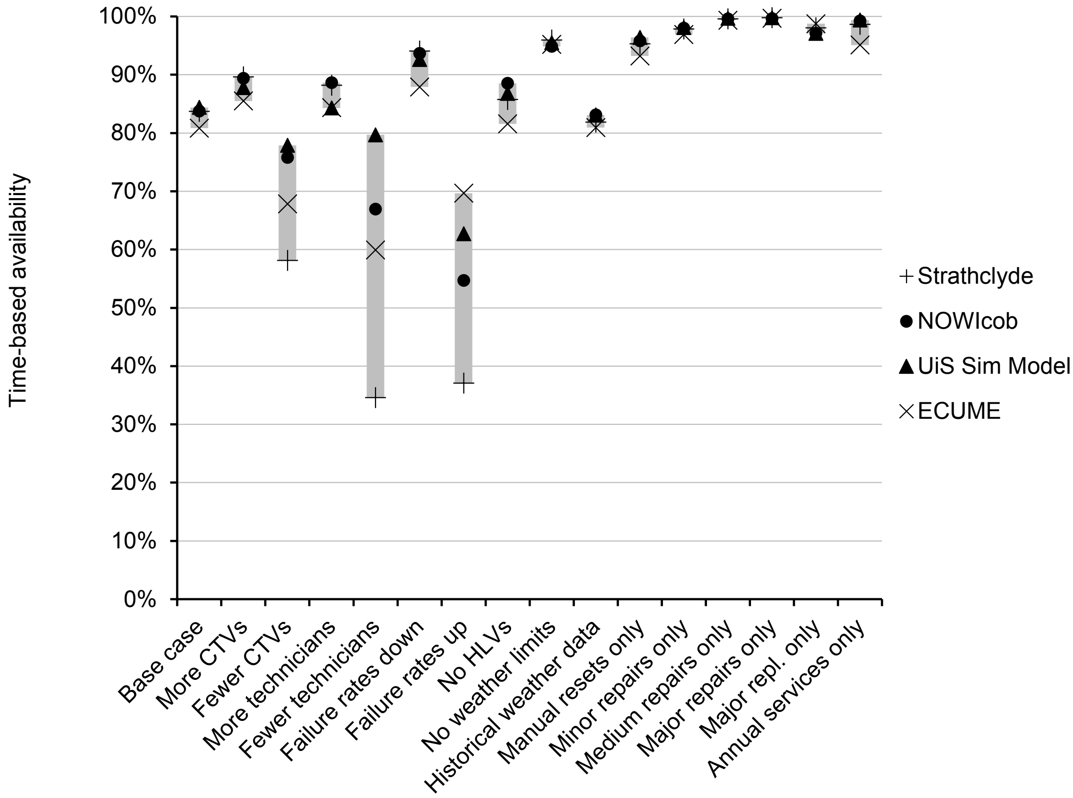


Figure 3-16: Average Annual Time based availability across all cases (Dinwoodie et al., 2015)

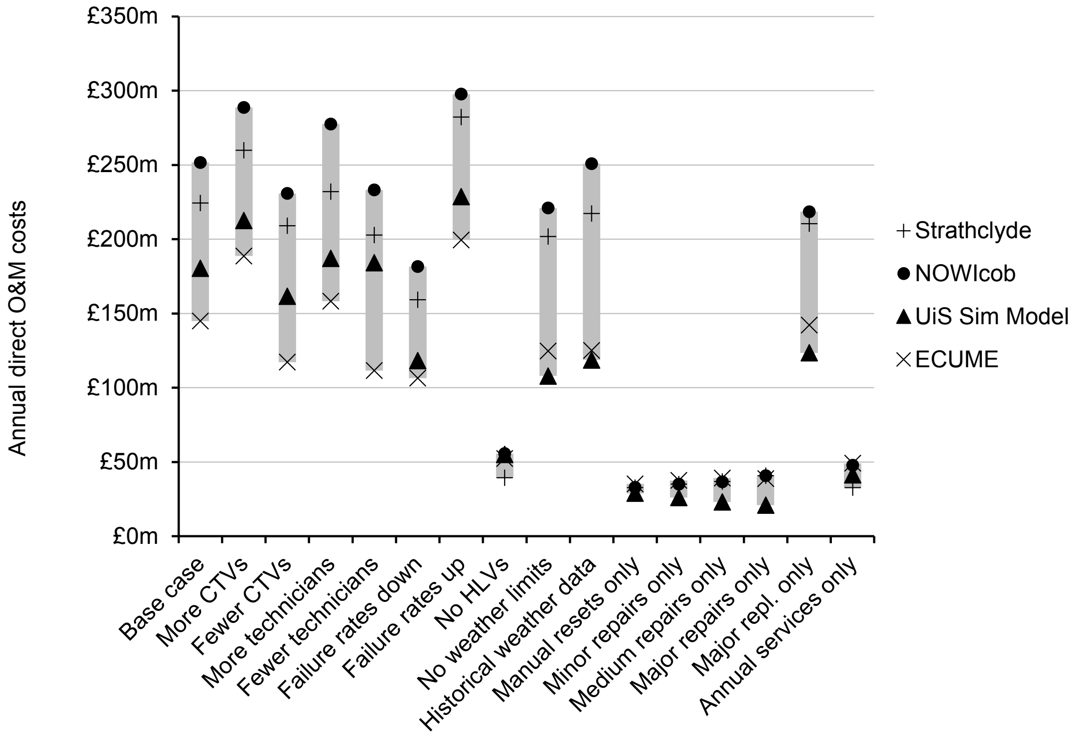


Figure 3-17: Direct O&M for 10 year project across all cases (Dinwoodie et al., 2015)

3.4.3.3 Comparison and Discussion

Considering the base case results in Figure 3-17, the generic wind farm generated low availabilities in all models, around 82%, which is a low number for OWF in the North Sea. The low availability can be explained by the relatively harsh weather data, with an annual average wind speed of 9.8m/s, annual average wave height of 1.4m. Additionally, the distance to shore (50km) is long when compared to most existing wind farms.

All four models work with weather data differently, from using historical time-series to generating synthetic time-series with different methods. This can be one of the reasons for the differences in output among the models.

Through discussion between the model developers, a lot of the variance between the model outputs can be attributed to internal model assumption and logistical choices.

HLVs

NOWIcob and the Strathclyde model enforces a minimum charter length of one month whenever a HLV is chartered, whereas ECUME and UiS model charter a HLV for the minimum required period, which is the summation of the mobilisation time, travelling time operational and weather delay. The small spread in the availability and cost results in the "No HLVs" case also supports this conclusion.

The model results show that major replacements needing HLVs account for the majority of direct O&M costs, but only make a moderate impact on availability. On the other hand, small failures only needing CTVs account for a small part of O&M costs, but have a large impact on availability.

Parallel Maintenance Tasks

The capability and number of parallel maintenance tasks accounted for much of the differences in the time-based availability results of the "Fewer CTVs" case, where the ability to conduct parallel tasks becomes more important. The Strathclyde model can accommodate three parallel tasks, which represents the lowest result in Figure 3-16. While on the other hand, the NOWIcob model in principle has the possibility for an unlimited number of parallel tasks, which represents the highest result in Figure 3-16. ECUME is limited in the number of parallel tasks by the number of teams available and time and UiS model can perform four parallel tasks per vessel. It is easy to understand that maintenance activities in a model with no limitation on the number of parallel tasks will be more efficient if there is a maintenance task backlog. Whether or not parallel tasks are realistic for a real wind farm depends on several factors such as safety regulations and maintenance strategy. However, it is a crucial assumption to be aware of when developing and using O&M simulation models.

Modelling of Failures

In the "Failure rates up" case, the large differences can be explained by different assumptions in how failures are generated with respect to the entire period. The Strathclyde model generates failures without considering if WTGs have failed or not, and the actual average annual failure rate in a simulation will therefore be very close to the average annual failure rate which is an input into the model. On the other hand, the UiS model and ECUME only generates a failure if a WTG is operating; hence, the actual average annual failure rate will be lower than the user defined annual failure rate and are consequently less sensitive to increased failure rates.

Assigning Maintenance Tasks to Vessels Offshore:

In the "Fewer technicians" case the assumption that maintenance tasks can be assigned during a working shift to vessels that are already offshore is important. In the UiS model a maintenance task can be assigned to a vessel during a working shift while it is offshore. Furthermore, because several small maintenance tasks (which have a large impact on availability) can be performed in series during a shift, this assumption results in a weaker sensitivity to a decreased number of technicians and higher availability for this case.

Technician Pooling

ECUME is the only model to split the workforce into sets for corrective maintenance and preventative maintenance, according to the O&M workforce structure of the company who commissioned the model. This significantly affects the availability and the cost as the number of preventative maintenance technicians could not keep up with the annual services required through the year when the work force is split equally. A limitation in the analysis is found that this type of simulation is not suited to the design of ECUME, which normally calls for more systematic refining of resources until local optima is found. In order to make ECUME perform similar to the other models for comparison; the technicians are all allocated for corrective maintenance and the annual servicing modelled as a failure with an annual rate of one. This decision provides a number of explanations of ECUME's difference with the other model outputs. As discussed above, there is a slight reduction in the amount of events compared to other models, however it is found, in most years that the full complement of WTG did require an annual servicing. Also, there is a change in prioritisation of events; the other models prioritised corrective maintenance over preventative maintenance whereas, when ECUME models an annual servicing as a failure, it has the same priority as other failures. With the annual servicing having such a high downtime requirement, then this can account for the low availability output from ECUME in several of the cases.

3.4.3.4 Further Work

The exercise is limited to just simulating a given case of OWF and resources. Rather than finding an optimum case, a simple SA is conducted. Whilst this exercise is useful to understand how the differences in assumptions could affect the model outputs, it meant compromises in the running of the models, particularly ECUME. It also meant that an optimisation model developed by MARINTEK could not contribute. These limitations are currently being addressed in a similar exercise conducted by the group in 2014 where the optimisation abilities of the models will be compared on a reference wind farm.

3.4.4 Conclusions

The study shows that, to understand the profitability of the project, both the cost and the unavailability needs to be considered. A further step in the analysis would be to use the model to define the optimal number of technicians or vessels, or to specify an optimal fleet of vessels to conduct the maintenance.

Through this scenario analysis, several input factors could be important to the results. These are the distance from the O&M port to the centre of the wind farm, the selling price of electricity, and the failure rates of large repairs requiring heavy lifting. For this study, assumptions have been made as to all of these factors and are provided at the beginning of this section. There is already an indication from the recent bidding rounds that the strike price of the CFD may be less than assumed here. The distance to the O&M port has yet to be decided but could be closer than assumed. If this project were to continue, it is imperative that O&M studies are updated once these values are known.

The outcomes from the input/output comparison found that there are a number of internal assumptions in the models that lead to significant differences in output. The aim of the comparative study is to identify and discuss these differences. It is out of the scope of the exercise to be able to quantify the effect of each of the identified differences.

The origin of the choices depended on the nature of the model. In ECUME's case, the decision are based on the maintenance strategies of the consulted companies' onshore wind business, as in the case of the distinct sets of corrective and preventative maintenance technicians. Similarly, the choices behind the Strathclyde model originate from discussion with their industrial partners SSE and Scottish Power, whereas NOWIcob has been developed with the support of Statoil. Recently, NOWIcob, the UiS model and the Strathclyde model are being investigated for commercial use by operators so are therefore likely to reflect the decisions of these companies.

The process of validation has led to the sensitivity analysis by investigating the model response to a set of inputs. The case studies of Section 3.4.1 and 3.4.2 begins to set the base cases for the sensitivity analysis conducted.

The key outcome from the studies presented in this chapter is that the results are heavily dependent on the inputs and the internal parameters of the model. This means that the results in the following chapters and the conclusions drawn from them are applicable to the model and the assumptions made.

4 Local Sensitivity Analysis

4.1 Introduction

When designing and building a model of an organic or non-organic system the goal is to replicate the known inputs and outcomes from what happens in the subject system. To understand how accurately the designed model does indeed achieve this aim, the modeller has a number of tools at their disposal, such as comparing the model with the real system, as explored in Section 3.4.1 and 3.4.2. Another is SA, where the outputs of the model are linked to the changing of input factors, testing their influence, either singularly or together.

Application of SA methods can be found where ever there is use of a proxy model to simulate a natural system; be it biological, chemical, operational, mechanical or more abstract processes like economics and statistics. With the rise of complex computer models and simulation tools, SA methods are used to understand how models behave and compare with actual systems they are built to represent. It can also be used to understand the uncertainty associated with each input factor and identify those inputs which most greatly affect the outputs. This is of use to a model designer or user to refine the model, eliminating factors which have insignificant effect on the output or perhaps identifying an error if the influence of a factor is of a different magnitude to one experienced in the system represented.

A variety of different methods exist to explore the sensitivity of inputs factors to model outputs, each with their own strengths and weaknesses. A plethora of reviews exist to compare different methods, often through the prism of the research field; nuclear, medical, biological for example. A thorough explanation on all types of SA exists within the text book of Saltelli et al. 2008. A recent example of a review of sensitivity analysis methods with respect to building energy analysis is Tian 2013.

Many of the global and more complex sensitivity analysis methods require the number of model evaluations, n, to have an exponent of the number of input factors k (n^k). When the number of input factors is high and a single simulation is more than a few seconds then the run time for such analysis becomes unfeasible. This I sometimes called the "curse of dimensionality" (Saltelli, Tarantola, Campolongo, &

Ratto, 2004). The more simplistic designs require the number of model evaluations to be a multiple rather than an exponent ($n \times k$).

Sensitivity analysis methods are applied to OWF O&M models in Hofmann & Sperstad 2013a, Dykes et al. 2012 and Hagen 2013. In Hofmann & Sperstad 2013a a one-at-a-time (OAT) method is shown to be a useful. It is a computationally fast way to explore sensitivity in O&M cost using the NOWIcob simulation model. The main findings included high sensitivity to vessel operational wave limits, failure rate and maintenance task duration. Moreover, the O&M cost is not sensitive to fuel cost or inter WTG distance. A limitation using this method is that it only investigates local points in the global region of investigation. A simple method is opted for in this case as a more complex method requires restrictions, such as wind farm size and capacity within the region of interest.

NREL have developed a computer tool to calculate the cost of offshore wind energy. Along with the O&M costs, the tool also incorporates engineering models so that the sensitivities of the WTG technology on the cost could be analysed and optimised. The objective of the study in Dykes et al. 2012 is to demonstrate SA on key design parameters that effect the LCOE of offshore wind. The approach taken is to vary the design parameters of the rotor diameter, hub height, rated power and maximum tip speed by ± 10 %. The results are given as the direction of the change in the LCOE (down, up and no change). There is no ranking of the parameters in terms of importance or quantification. As the SA method is not explicitly mentioned in the study, it is assumed to be an OAT method.

The most complex SA on an OWF O&M computer model found in the review of the literature is the thesis for a Master's Degree undertaken by Hagen in 2013. This study conducts an SA of the input factors to the NOWIcob model on the total O&M costs. The number of input factors included in the study is 15. Two SAs are implemented; OAT and the Morris Method (further explained in Section 4.2.1.6). Hagen calls the Morris Method "a global analysis" as it explored the region of investigation however it can also be considered a local analysis as for each perturbation of input factor x, all other factors that are not x remain at their base value. The number of replications is 10. The most influential single input factors are found to be the failure rates resulting in manual resets, failure rates resulting in major replacement, the variable cost of Jack-ups, the failure rate resulting in minor repair and the wave limit of a mothership. This result is compared to those from the OAT analysis and it is found that the same top five input factors are the same but in a different order. This work is the first to empower SA methods more complex than OAT to offshore wind O&M models. The inconsistency between the results of the OAT and Morris Method shows that further global analysis is required to confirm the results. It also only considers cost.

4.2 Methods

The methods can range from simple to the complex and classed into two groups; local sensitivity analysis (LSA) and global sensitivity analysis (GSA) (Cacuci, 2003; Saltelli et al., 2008; Tian, 2013). The choice of method largely depends on the computational size of the analysis: which is dependent on the number of the input factors and the number of replications r that are needed by that method. Choice of method will also depend on the desired results. For example, screening methods can provide a ranking of the influence of the input factors but without any information of how much more important they are with respect to each other. Some models can handle interactivity between factors better than others, therefore would be more desirable to use if the model had complex interactions between input factors. This chapter introduces some of the main LSA methods.

4.2.1 Local Methods

In the early days of SA, local based methods are employed. Local SA focuses on providing a given set of values as input factors and calculating the response at the model through the partial derivative at a fixed point in the modelling space. The results of LSA are dependant on the fixed point.

The simplest and most established way to conduct a LSA is to alter one input factor at a time (OAT) and record the effect on the output. This system involves selecting a base case of values for the model, and displace each input factor individually whilst keeping others at the base case, then measuring the output and conducting a regression analysis based upon the output.

One-Factor-at-a-Time methods cannot interpret the interaction between input factors on the output.

4.2.1.1 Screening

The computational time for sensitivity analysis is dependent on both the complexity of the model with respect to the time it takes to complete one model evaluation and the number of input factors. Computer models can, in theory, have unlimited numbers of input factors, so performing some of the analysis described above with all input factors possible would be computationally expensive. Screening analysis is a qualitative type of SA, where the most influential factors are identified and ranked. A screening design gives no information on the uncertainty attributed to each factor or how much more influential the factors are from each other. If a small number of factors are identified then it allows the analyst to continue to the more computationally expensive SA and Uncertainty Analysis (UA) methods to fully understand the subject model.

There are a number of different screening methods, suitable for physical, experimental and numerical modelling. Screening designs are classed into three sets (Kleijnen, 2008):

- Classic
- Supersaturated
- Group-screening

The classic group consists of established design methods such as Frequency Domain Experimentation. The supersaturated group has experimental designs where the number of model executions is less than the factors and the group-screening designs where they are supersaturated but occur in stages (Kleijnen, 2008). This final group is commonly found in the sensitivity analysis literature. This group is also the focus of the attention of screening design in the work of Saltelli and the Joint Research Centre (JRC) group, and are applicable to computer model analysis (Saltelli et al., 2008). The most common screening methods found are:

- One factor at a time
- Morris Method
- Cotter

- Fractional Designs
- Sequential Birfurcation

4.2.1.2 One Factor at a Time (OAT)

This type of screening design is a local analysis of the simplest kind, increasing or decreasing a factor's value around a mean point whilst keeping the others fixed. A problem with this method is that the results from the analysis are dependent on where this mean value is chosen to be. Its simplicity is the reason for its popularity with analysts, however, the SA literature does warn that it is not good practise (Campolongo, Saltelli, & Cariboni, 2011).

4.2.1.3 Cotter

This method only requires $n = 2k + 2$ so satisfies the need to be computationally efficient for screening design. This method is similar to an OAT system as it requires each factor to change and the others remain fixed between a "low level" and a "high level". The sensitivity measure M for each factor is found from

$$M(i) = |C_0(i)| + |C_e(i)| \quad [8]$$

Where C is the expected value of effects and o and e denote the odd and even effects.

$$C_o(i) = \frac{1}{4}\{(y_{2n+1} - y_{n+i}) + (y_i - y_o)\} \quad [9]$$

$$C_e(i) = \frac{1}{4}\{(y_{2n+1} - y_{n+i}) - (y_i - y_o)\} \quad [10]$$

Issues with Cotter's method are that significant factors can be neutralised in the process with C_o and C_e cancelling each other out (Cotter, 1979; Saltelli et al., 2008).

4.2.1.4 Factorial Designs

Factorial designs are a well-used design of experiment, developed from OAT experimental design methods. In most cases, there are only a few factors (say less than five) and each has two predetermined levels; high and low. The model is executed for each combination. A typical design for a 2^3, i.e. a 2 level, 3 input factors full factorial design is shown in Table 4-1.

Table 4-1: Design of experiment for a 2^3 full factorial design, where + means higher level and - means lower level.

Sample	x_1	x_2	x_3
1	-	-	-
2	-	-	+
3	-	+	-
4	-	+	+
5	+	-	-
6	+	-	+
7	+	+	-
8	+	+	+

The main effect for each input factor for each level is the difference between the average value for all the outputs with the factor in question at each level and the average across all runs.

To consider the two factor interactive effects, the averages of the output when the levels are --, ++, -+ and +- (for a 2 level factorial design) are found. The interactive effect for two factors is the average of the outputs for combination, minus the main effects for the factors plus the total average.

If a full factorial design are undertaken for an entire ECUME case where $k \approx 50$ for the most simplistic case, with a high and low level (a 2^{50}design), then $n = 1.1250 \times 10^{15}$ which is unsuitable.

Fractional factorial designs are designs where not all of the samples need to be run. Enough information can be taken from an experiment with a fraction of the number of runs considering that the higher order interactive effects could be compounded with the 1st and lower order ones.

The reduced number of n in the fractional factorial design can then be grouped and regrouped as part of an iterated fractional factorial design (IFFD).

The IFFD method is designed to cope with a large amount of factors of the order of hundreds or thousands (Saltelli, Andres, & Homma, 1995), with only a relative few being significant. It also can be a super-saturated design with, $n < k$ and to some extent be controlled and adapted to the subject model, although at higher orders, there can be compounding effects. This method can also detect the quadratic effects between the factors as well as 1st order ones (Saltelli et al., 2008). For these reasons, IFFD is an applicable for factor screening. Investigations have found that IFFD has more reproducibility than other methods (Saltelli et al., 1995). The number of replications r is chosen so that the computational expense is twice the size of the FFD run, multiplied by the number of iterations. The number of iterations could be chosen to suite a computational budget (Saltelli et al., 2008). Notice how for this method the value of n is a multiple of k rather than being its exponent.

4.2.1.5 Sequential Bifurcation

Like IFFD, the sequential bifurcation method splits the factors into groups and investigates them to see if a group is influential. The process happens in steps and if a group is deemed to be non-influential then it is eliminated from the process. The process continues until the most influential factors have been found, for this reason the computational cost is an unknown (Kleijnen, 2008; Saltelli et al., 2008). Another drawback is that judgement is needed at the end of each iteration to eliminate groups. Other methods can be executed automatically with a fixed number of samples.

4.2.1.6 Extended Morris Method

The Morris method is developed in response to the increased use of computer models and a desire to identify input factors that do not have an influential effect on the outputs. It is a type of LSA and it measures the effect of changing the input factors, x_i, throughout the region of investigation Ω and is first described by Morris (Morris, 1991). The first column of the sample matrix is an initialising vector of x_i, the values of which are randomly chosen from the input distributions and is not used in the analysis but is a starting point for translating x_i to a predetermined distance away Δ. The distance Δ is found from a predetermined multiple of $\frac{1}{p-1}$ and p is a value of discretization of the input factor distribution. The effect of the change on the output due to the input is found through, what Morris calls, the Elementary Effect. The Elementary Effect (EE) is determined from each trajectory for each input factor using:

$$EE(\boldsymbol{x}) = \frac{[y(x_1, \ldots, x_{i-1}, x_i + \Delta, x_{i+1}, \ldots, x_k) - y(\boldsymbol{x})]}{\Delta} \quad [11]$$

Where if Δ is increased:

$$EE(x^l) = \frac{[y(x^{(l+1)}) - y(x^{(l)})]}{\Delta} \quad [12]$$

And if Δ is decreased:

$$EE(x^l) = \frac{[y(x^{(l)}) - y(x^{(l+1)})]}{\Delta} \quad [13]$$

Where y is the output of the model l and l+1 denote the perturbed points in the region of experimentation (Morris, 1991). If using the design matrix by Morris, then for each input x_i there are r EEs from which a distribution is sampled.

In order to ascertain the relative importance of each input factor to each other, two sensitivity indices are calculated. The first is calculated from the distribution of sampled EEs. It indicates the main or 1st order effects of the input factor (Campolongo et al., 2011):

$$\mu^*{}_i = \frac{\sum_{i=1}^{r} |EE_i|}{r} \quad [14]$$

The higher the μ*, the more influence on the model output. Note, μ* is used here to reflect the notation used in Campolongo et al. 2007, which is an adjustment to the original method in Morris 1991. The adjustment prevents the effects with positive and negative values from cancelling each other out.

The second index is an indicator of the interaction or non-linear effects of an input factor or a combination. A feature of this method is that the interaction with other inputs and non-linearity cannot be distinguished from each other in this analysis. It is calculated from the standard deviation of the EE distribution (Campolongo et al., 2011): Ideally, it would be advantageous to distinguish these two but for the sake of screening, it is not necessary.

$$\sigma_i = \sqrt{\frac{\sum_{i=1}^{r} (EE_i - \mu_i)^2}{r}} \quad [15]$$

The extended Morris Method has been presented as a suitable method to initially identify the most influential main, interactive/ non-linear and negligible effects on the model output. There has been some criticism of the method's ability to truly identify the most important effects adequately when compared to the results of a more sophisticated design. Additionally, an investigation into the number of replications required indicates that r may need to be much greater than ten suggested by other authors. It may need to be of the order of hundreds instead (Cosenza, Mannina, Vanrolleghem, & Neumann, 2013).

4.2.1.7 Applications of Screening Design

The methods summarised here are not the only ways to conduct screening analysis on computer models. Different approaches are also demonstrated in the literature. In a recent analysis on a human reliability analysis model (Bedford, Bayley, & Revie, 2013) the authors has access to a simplified version of a full model in order to conduct a SA and uncertainty analysis that acts like a screening process. However, it is found that the basic and extended versions differ too much in their construction and additional weightings need to be implemented. This option only works when a fully functional, but simplified, model is available, but the work of Bedford et al. 2013 shows that care is needed in order to verify that the basic model will behave the same as an extended one.

It is found, in other studies, that the approaches described above are not guaranteed to be applicable, as in Auder et al. 2012. The author's objective is to produce a metamodel of a thermal shock analysis model in a nuclear power station. Initially, the number of factors are reduced through a screening process in order to implement a metamodel. An OAT analysis is conducted to get an initial understanding of the most influential factors. This identified 14 out of the 32 factors as influential. The model produced outputs at discrete time steps and the authors use Lamboni's generalised sensitivity indices to measure the effect on outputs at each time step (Auder et al., 2012). This is, itself, an extension of a multivariate sensitivity analysis proposed by (Campbell, McKay, & Williams, 2006; Lamboni, Makowski, Lehuger, Gabrielle, & Monod, 2009).

4.2.2 Review of LSA Applied to External Models

Overviews of the models in the review are shown in Appendix C according the model classification outlined in Section 2.6.1. Many of the models are deterministic, continuous and numerical. Application of SA to stochastic models is a new field and there is less published accounts of implementation available. Local sensitivity analysis are often used in conjunction with global sensitivity analysis in the same manner as this thesis, where a LSA precedes a GSA. Many of the papers have both LSA and GSA, and these of which are reviewed in Chapter 5.

In Troche & Malone, 2000, an overview of screening methods and the possible pitfalls are provided. It also provides the features of screening designs and a decision tree based on the number of input factors to be evaluated. The original tables have been adapted for the methods described in Section 4.2.1 and the ECUME model.

Table 4-2: Comparison of the Effectiveness of Screening Methods, adapted from Troche & Malone 2000

	n	**Number of Input Factors**	**Main Effect?**	**Interaction Effects?**
Desired	*Small*	*Large*	*Yes*	*Yes*
One-at-a-time	k	Small	Yes	No
Full Factorial	2^k	Small	Yes	Yes
Fractional Factorial	2^{k-p}	Small	Yes	Yes
IFFD	100 - 500	Large	Yes	Some
Sequential Bifurcation	-	Large	Yes	Some
Morris Method	$r(k+1)$	Large	Yes	Yes

Table 4-2 condenses the choice of which screening design into two issues. The first is the number of model evaluations needed (n), which is linked with the second column, the number of factors with which the model can effectively handle. The second issue is the type of information you get from the analysis, only main effects or interactive as well.

The Morris method was deployed on a model for urban water supply systems by King & Perera, 2013. The input factors understudy were climate scenarios and measuring the effect on the volume of water from the system. The REsource ALIocation Model (REALM) is a linear programming algorithm based model for simulation of Australian water systems. Twenty climate sequences were the used in the sensitivity analysis with the Morris method. The most important variables found in the study, on the water yields was the security criteria and restrictions. The most relevant outcome to this thesis is that using a single climate scenario can present unrepresentative water yield results (King & Perera, 2013).

4.2.3 Discussion

The sensitivity analysis methods presented here are only a selection of the possible ways in which to investigate models with regards to inputs and outputs. The variance based methods are commonly used. Similarly, the review of published literature is only a sample of the investigations with different methods but is representative of the comparative style of studies conducted.

In many cases, investigators have chosen to employ several methods for comparison in order to identify the most appropriate technique to the model of interest and the type of result required. In order to increase the confidence in results, bootstrapping techniques are used and the experiments are repeated but with different number of model evaluations are changed to identify at which point the results become stable.

An observation from the review is that there is a strong core of research on SA methods centred at the Joint Research Centre of the European Commission, although the methods are used all over the world in a variety of different research fields. This centre, through textbooks (Saltelli et al., 2008, 2004) and peer-reviewed papers (Campolongo et al., 2011; Campolongo & Saltelli, 1997; Saltelli et al., 2010, 1995) have preference for the variance based global methods such as Sobol' indices, eFAST and the screening method of Morris.

4.2.4 Conclusions

Key conclusions from this review are that, there is no one obvious method to be applied to a stochastic O&M cost model for OWFs in order to complete a full sensitivity analysis, demonstrated by the broad range of methods available. Most methods are designed for deterministic models and applicability to stochastic models require building meta-models. Most GSA methods require large number of model evaluations. The number of ECUME input factors needed to effectively model a real life wind farm is variable but a minimum number of around 50 is required. A typical process to handle a high number of factors is to conduct a screening analysis to identify inputs that have a negligible effect on the output. The most appropriate screening methods are Morris and IFFD, as demonstrated by the number of method abilities in Table 4-2 . Then a full global variance based analysis is conducted and this can help bring confidence to the screening process.

Once the factors with negligible effect are identified, the value of k is reduced to a number of the order of 10s, rather than 50 or 100. Then GSA techniques can be implemented. Therefore to fully understand the effect of the input factors on ECUME, first a screening experiment using Morris Method is conducted to reduce the number of important factors to a number that can be handled with by the computer resources available and the GSA method that requires the fewest number of model executions. The choice is then to use a joint meta-model to incorporate the stochastic model parameters. As the LSA is deterministic, the deterministic version of the Sobol' indices is calculated. This is to allow for comparison between the LSA and GSA and provides the basis for further work conducting stochastic elements.

A number of sensitivity analysis packages and toolboxes available to implement the techniques exist. The most common are within existing statistical and computational frameworks such as R and MATLAB® (Pujol et al., 2015; Tian, 2013; Zhang, Trame, Lesko, & Schmidt, 2015). Standalone frameworks also exist, such as SimLab, which is a purpose built executable for generating sample files and calculating sensitivity measures, developed by the Joint Research Centre of the European Commission. These options generally offer a choice of method to implement and the resolution of the experiment. SimLab is used in combination with MATLAB® to conduct a screening process and full global, variance based analysis on ECUME.

4.3 LSA applied to the model using Morris Method

This section provides the methodology and results of a screening design applied to a set of cases introduced in Section 3.4.2.1. The same methodology is used on a set of generic cases and the results are published in (Martin, Lazakis, & Barbouchi, 2014), which is also available in Appendix G.

4.3.1 Choice of Method

Throughout the review of application of sensitivity analysis, many different methods were found to be employed. However, no clear formulation of how to choose a method was found for the entire LSA to GSA process. To summarise the conclusions from the review of literature, the best way to choose is to consider the features of the methods, selecting the one that corresponds closest to the desired results. For example, the ability to extract information of the effects within a reasonable number of computational simulation. By engaging one of the most active sensitivity analysis research communities, through attendance of conferences and through the literature review, there was indeed a small selection of methods that are conducted routinely. As one might expect, these corresponded with the methods that have useful features such as being able to extract from the results the different effects from the 1st order and those higher orders or integrative effects. Table 4-2 shows, for methods where the desired result is to reduce the number of factors, so-called screening process, there are three that fulfil a high number of the desired features; IFFD, Morris and sequential bifurcation. All three these methods would have provided 1st order and higher order effects and are suitable for a large number of factors. A short feasibility test was conducted on a simple, three input factor example with the ECUME model. After which, the Morris method was chosen to conduct the complete screening. This is because a fixed number of interactions can be deduced from the outset, whereas, for the sequential bifurcation, the number of iterations is unknown. Using the Morris method also allowed for the use of parallel computer and each sample run is, in effect, independent of the results of the other. Therefore autonomous analysis can be run. For sequential bifurcation, the sample runs are dependent on the results of the previous simulations and therefore not applicable for parallel computing. As the length of the each simulation can be up to a minute long and with the limitation of the computing power, the ability to parallel compute made the Morris method the better choice. The capability to show interactive effect was greater in the Morris than IFFD whilst remaining within a reasonable amount of computation simulations.

With a greater amount of computing resources, the method choice could be different, however, the computing resources utilised in this analysis reflects the kind available for industry, who possible do not have access to large sever arrays or cloud computing applications.

The offshore wind model has a considerable number of factors, and computational execution time can be between one to 30 minutes long for each model execution. For this reason, a screening design is chosen as this approach allows for the most important factors to be found with a certain amount of computational efficiency, i.e. the information obtained for the least computational effort. The reason why the Morris method is often presented as best practice for screening design is because it has the ability to apply to identify the most important input factors for main effects and interaction between effects, which separates it from IFFD as a method . It can also cope with the amount of input factors that are needed to run a reasonably complex case with ECUME and it is applicable to most models (i.e. it is model independent) (Campolongo et al., 2011).

4.3.2 Cases

To identify the important factors in offshore O&M, the method described above is applied to the three cases introduced in Section 3.4.2.1. The input factors that define the cases is fixed and the rest are allowed to vary. Are the OWF allowed to be built, then discovering the key inputs affecting the O&M cost and production-based availability at an early stage, will allow sufficient time to conduct further analysis and inform decisions in order to manage the operation stage towards maximum profitability. The OWF could be built in two stages; therefore the cases in this investigation represent the project in its entirety and the two halves with regards to geographical extent (north and south). An illustration of the cases can be found in Figure 3-9. Two of the input factors are fixed to define the cases: the number of WTGs and WTG capacity, as shown in Table 4-3.

Table 4-3: Fixed inputs used in the three cases

Case studies	Case 1	Case 2	Case 3
Number of WTGs	62	59	121
Capacity of one WTG (MW)	8	8	8
Total Capacity (MW)	496	472	968

4.3.3 Variable Inputs

The values of the input factors are found from industrial experience, from series of meetings and discussions throughout the duration of the three year project, operational research, scientific literature and analysis. An important part is to provide the right input distribution to reflect reality as close as possible. With an industry with only approximately 12 years' experience like offshore wind it is a challenge to identify the full spectrum of possible values. Additionally, WTG manufacturers and operators are reluctant to distribute information related to reliability and cost due to intellectual property agreements and commercial sensitivity. With models that require hundreds of input factors, assigning accurate distribution factors incur a lot of unnecessary effort if the factor effect is deemed to be negligible. Therefore, uniform distributions can be used initially. When the important factors have been identified a more complex distribution is used (Saltelli et al., 2008). With this in mind, an attempt is made to identify possible minimum and maximum values and affix a uniform distribution. Where this is unobtainable, due to lack of published data or commercial sensitivity, a single value is identified and uncertainty envelope of ± 10% or 20% is applied. This is performed in order to input a known value of uncertainty proportional to the estimated value but is simplistic. Ten percent has been used when a variety of sources are available, whereas 20% is used where only a single value is found and therefore has a greater uncertainty attached to the value. This approach in assigning uncertainty to unknown parameters has been adopted by other SA practitioners and model developers (Byon, Perez, Ding, & Ntaimo, 2010; Campolongo & Saltelli, 1997; Dinwoodie et al., 2015). Once the number of factors under investigation has been reduced then effort can be devoted to attributing more accurate uncertainty distributions for further analysis.

In this section, a subset of the variable inputs is described. In order to identify the inputs in the results, abbreviations have been used between square brackets.

Other than the fixed inputs shown in Table 4-3, 115 other independent input factors in the study are varied. The majority of input minimum and maximum values are the same across all cases. Five of the inputs factors are different between the cases. This avoids the model simulating scenarios that would not occur in reality, for example ten maintenance teams but only one CTV. The factors where the minimum and maximum of limits vary between cases are:

- Number of CTV chartered to the site [MEnve]
- Number of preventative maintenance technicians teams available [MEptm]
- Number of corrective maintenance teams available [WEcmt]

- Mean inter-WTG distance [WFint]
- Distance from the centre of the wind farm to the O&M base [WFdis]

The mean inter-WTG distance [WFint] is the mean value of the distance between all WTGs from every other WTG. This is calculated from a sample of several operating and planned wind farm layouts. It indicates WTG geographical spread ensuring that, over the course of the project lifetime, cost and time taken to travel between WTGs is accounted for. This can be site-specific but the values used in this analysis are indicative as there are two likely forces governing this value. The first is the desire for a developer to maximise the total capacity in a licenced area and the second is that a minimum distance between each WTG needs to be kept for wake loss and toppling distances.

An average capacity factor for each month [WFjan – Wfdec] is found from multiplying an approximation of three WTG manufacturers published power curves (Areva, 2010; Siemens Wind Power Ltd, 2011; Vestas Wind Systems, 2011) with five years' worth of modelled wind speed data from an existing UK OWF (ABPmer, 2008) in increments of 1 m/s over 1 hour averages. Siemens and Vestas are the market leaders in installed capacity of WTGs with 65.2% and 20.5% of the share respectively in 2014 (European Wind Energy Association, 2015b). Areva represents a share of 0.9%. A spread of 10% is found and input at a uniform distribution and is shown in Figure 4-1.

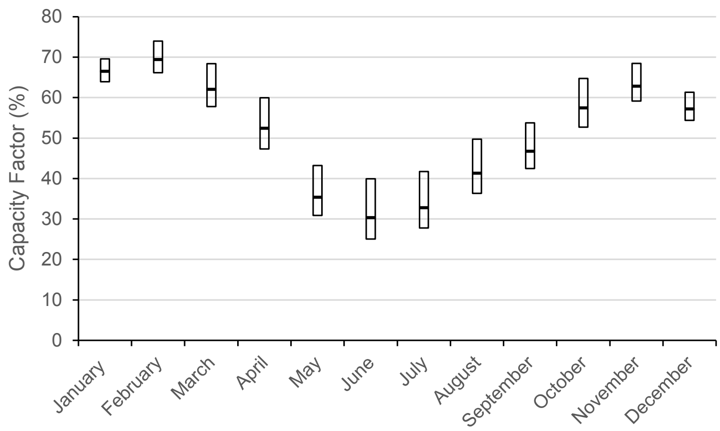


Figure 4-1: Capacity factor of three WTGs using modelled wind speed data based on 5 years of modelled data.

Balance of plant (BoP) availability [WFbop] includes downtime for the OWF not due to WTGs; such as cables, substation and grid issues. Information in the public domain on BoP availability is minimal but it is known to be quite high, between 98 % and 99% (Stevens & Graves, 2009), so a conservative margin of between 90% and 100% is chosen.

The wind speed is inputted in the time series from 10 m above ground level and extrapolated to hub height using the wind shear law (Douard et al., 2012). This allows the wind speed to be affected in the SA through changing the wind speed at hub height by varying the alpha value between 0.06 and 0.27. These values are given in Kaltschmitt et al. 2007 and Hsu 1988 for the calculation of wind speeds over open water in unstable and stable atmospheric conditions.

The fixed onshore costs for the O&M site infrastructure such as an office and staff will depend on the port location and the wind farm size. As they are foreseen to have an additive effect on OWF cost, a mean value is found based on scaling costs from an operational wind farm according to WTG number.

$$C_{st_{x(i)}} = C_{st_{x(0)}} \times \frac{N_{t_{x(i)}}}{N_{t_{x(0)}}} \quad [16]$$

In equation 28, (i) is the new cases, (0) is an existing wind farm, C_{st} is the staff cost and N_t is the WTG number.

One key input of the scenario is the technician number available to keep the WTGs operable. Information on the technician number for current OWFs is limited. Details of the technician number and total staff are available from six wind farms; from personal communication with operators and promotional literature (Dudgeon Wind Farm, 2013; Highlands and Islands Enterprise, 2010; Scrira Offshore Energy, 2012). For these OWFs, the average total staff number, including onshore staff, ranges from 0.37 to 0.75 persons per WTG. For T1and Robin Rigg, the proportion of WTG technicians to other operational staff is approximately 60% (Highlands and Islands Enterprise, 2010). From the trend found in Figure 4-2, the total staff number for the three cases can be estimated. The 60% factor from Robin Rigg and T1is applied to find an approximate technician number.

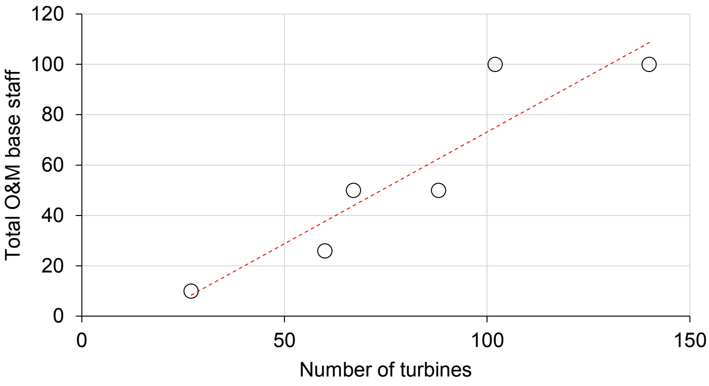


Figure 4-2: Number of total O&M based staff from 6 UK OWFs based on number of WTGs (capacity independent) and wind farm capacity. (Dudgeon Wind Farm, 2013; Scrira Offshore Energy, 2012)

The working day length [MEend] varies between 10 and 12 hours per day as a typical one shift per day strategy.

The vessel inputs are based on a typical CTV, the Ocean Wind 4, an aluminium catamaran, with ±10% uncertainty to account for fleet variation. Workboats in the UK fleet attending offshore wind O&M are similar with regards to maximum vessel speed and operational limitation. The vessel number for each case is based on a survey of CTVs working at 19 UK OWFs taken on 5th March 2014 using the Marine Traffic website (Marine Traffic Ltd, 2014). The survey criterion is to count the number of CTVs and workboats visiting OWFs within a 24 hour period.

The number of CTVs serving each case is estimated from the trend line in Figure 4-3. For Case 1, the CTV number varied between one and two, for Case 2, three and four and for Case 3, either four or six. The vessel cost is extracted from communication with operators at an operational wind farm.

For this study, the HLVs used are based on a self-propelled jack up barge and values for operational limits based on a survey of eligible vessels from the 4C Offshore Vessel Database (4C Offshore Limited, 2014a). The mean maximum significant wave height from the database is 1.83m.

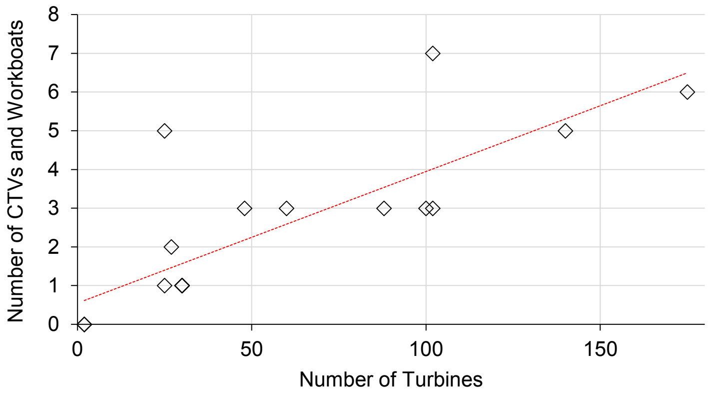


Figure 4-3: Number of CTVs and workboats used per WTG (4C Offshore Limited, 2015; Marine Traffic Ltd, 2014)

Information on helicopters is based on the Eurocopter ECN 135, used at Greater Gabbard OWF. A ± 10% uncertainty envelope is applied as this helicopter model represents the majority of those used on OWFs currently.

To limit the amount of input factors in the analysis, the number of types of repairs to be conducted is limited to two. Failure Type 1 can be considered as routine repairs, defined by the use of a CTV. Failure Type 2, however, will require the mobilisation of a HLV and will require a subcontracted workforce.

The reliability and maintenance of seven major components of a generic WTG with a gearbox have been considered in this analysis.

Failure rates and associated downtime information of modern components is a significant gap in offshore WTG performance modelling. The most complete information source in the public domain stems from reliability data in the WMEP and LWK databases from Germany (Tavner, 2012). Although failure rates may differ for larger WTGs placed offshore (Yu et al., 2013), onshore values are commonly used. To reflect this large uncertainty, an envelope of ± 20% is applied. It is assumed that the WTGs remain within the useful life region of the bathtub curve shown in Figure 2-4 and so have a constant failure rate over time. The failure rates in Tavner, 2012 are based on databases that do not distinguish between failures requiring CTVs and those that require large, specialist vessels. Therefore it is assumed that the rate of failure Type 2 (major) for each component is lower than failure Type 1 (minor), but the proportion of components to the total is consistent. As this information is not available, industry experts are asked for how many failures they expect over the course of the project lifetime and the mean failure rates tuned to that value.

It is assumed that component repair costs include all the materials and consumables to bring the component back to a functional state not including cost for labour. It is also assumed that the costs and will be similar to onshore costs and have been taken from a database of component costs collated by NREL (Martin-Tretton et al., 2012).

4.3.4 Local Sensitivity Analysis Execution

Having described the inputs in the previous section, the SA framework software SimLab (Joint Research Centre IPSC, 2008) is used to create the samples according to the Morris design outlined in Section 4.2.1.6, and to calculate the sensitivity indices. MATLAB® is used to write the input file to the model according to the sample, execute it, provide the results and save them to an output file for SimLab to read.

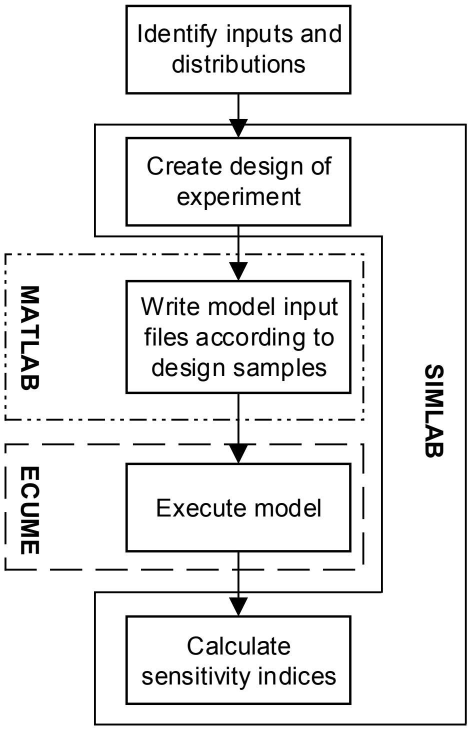


Figure 4-4: Flow chart of SA used with computational software

The flowchart in Figure 4-4 shows how the SA of the model is implemented using MATLAB® and SimLab. For Case 1, Case 2 and Case 3, the number of input factors is 115, discretization level p is 8 and the number of replications r is 10. The number of model executions is therefore $n = 1160$ for each case. The number of p and r are chosen to provide the highest number of model executions whilst remaining within the limits of SimLab software, which allows a maximum r value of 10.

The computational time is dependent on the number of WTGs in the OWF. For Case 1 and Case 2 the analysis takes several days to complete on an HP EliteBook with Intel® Core™ i5-2540M processor. However Case 3, with 150 WTGs, requires use of the parallel computing toolbox in MATLAB® and a workstation with one Xeon (R) E5620 processor with 16 logical cores to reduce the computational time down from weeks to days. If a GSA method such as eFAST is used, then the required number of simulations suggested in literature would be of the order $k \times 500 \rightarrow 1000$ (Cosenza et al., 2013), between 57,500 and 115,000 model executions resulting in computational time of several months to complete, which justifies the choice in employing a screening LSA before the GSA.

4.3.5 Results

The measures of sensitivity σ and μ* are shown for two OWF cases in Figure 4-6 and Figure 4-8 along with histograms of results from the samples in Figure 4-7 and Figure 4-9. The results from Case 1 and Case 2 are indistinguishable. The factors identified are provided in Appendix D along with a full description and the sensitivity indices results.

Each point in Figure 4-6 and Figure 4-8 represents an input factor with the coordinates provided from the μ^* and σ indices. The location of the points relative to each other provide information on the input factor interaction in the model. Factors with a negligible effect on the model have low indices values and are located in the lower left of the graph. The more important factors will have higher indices and appear depending on the strength of main or interactive/non-linear effect. The majority of factors are a mixture of the two and occasionally there will be factors with a primarily strong main or interactive/non-linear effect. A factor is classified as either a) main effect, b) interactive/non-linear or c) a mixture of the two by calculating the ratio of difference between $\mu^*$and σ and the mean value. If this value is less than 10%, the factor is considered mixed, a negative value greater than 10% is interactive/non-linear and a positive value greater than 10%, a main effect.

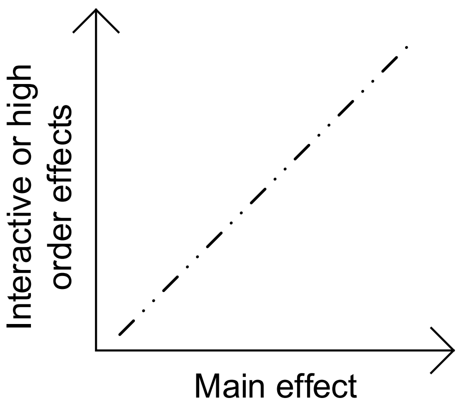


Figure 4-5: Illustration of how to interpret Morris method indices

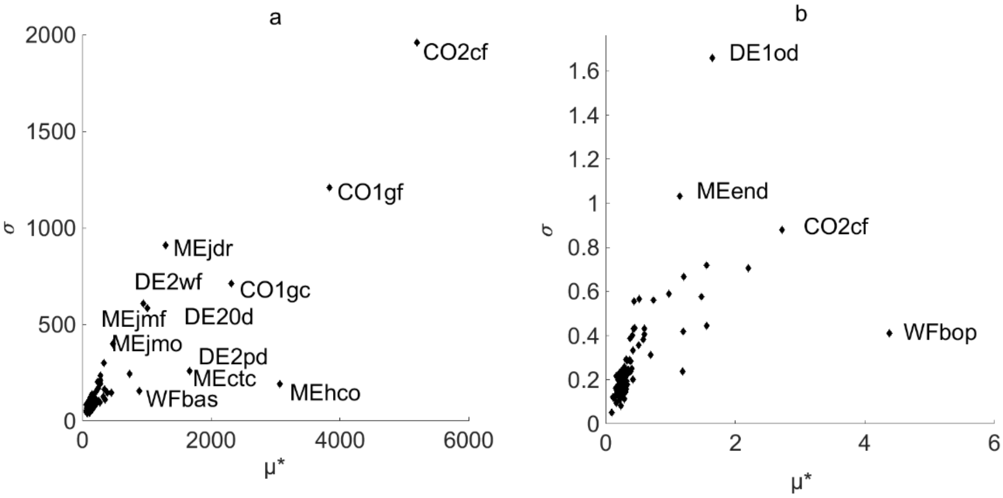


Figure 4-6: Sensitivity results for Case 1 a) operational expenditure and b) availability of the wind farm

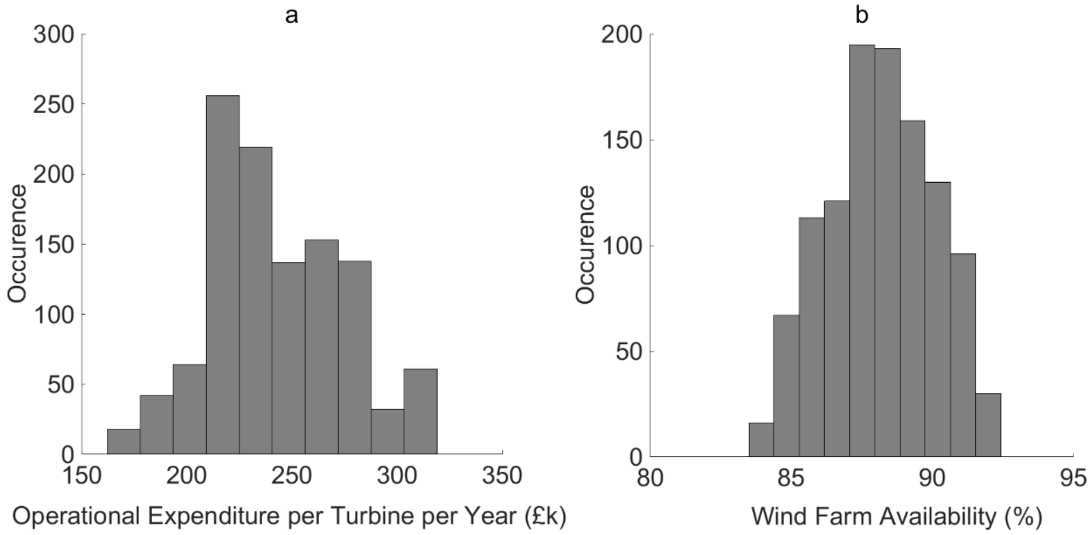


Figure 4-7: Histograms of sample results from a) O&M costs and b) availability for Case 1

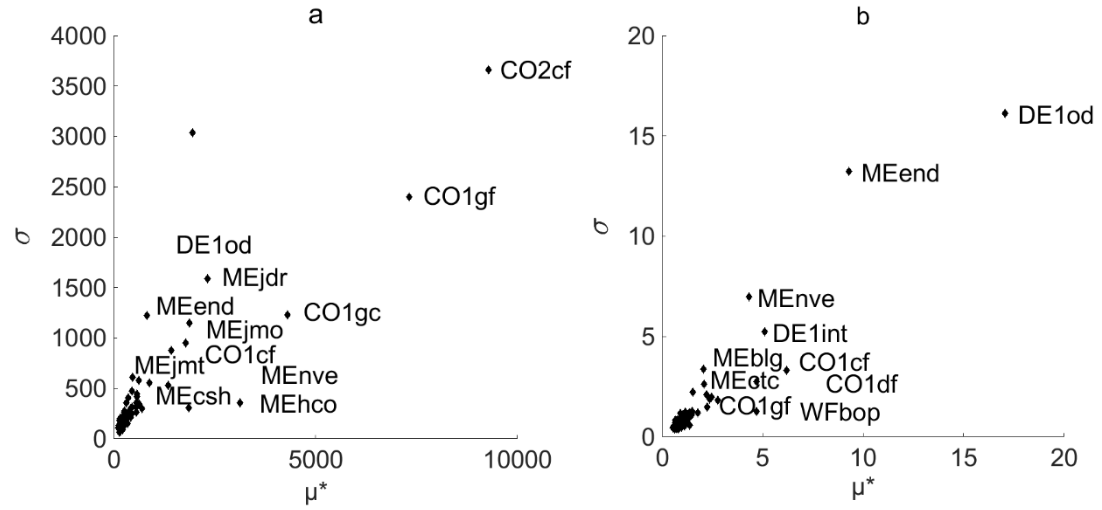


Figure 4-8: Sensitivity results for Case 3 a) operational expenditure and b) availability of the wind farm

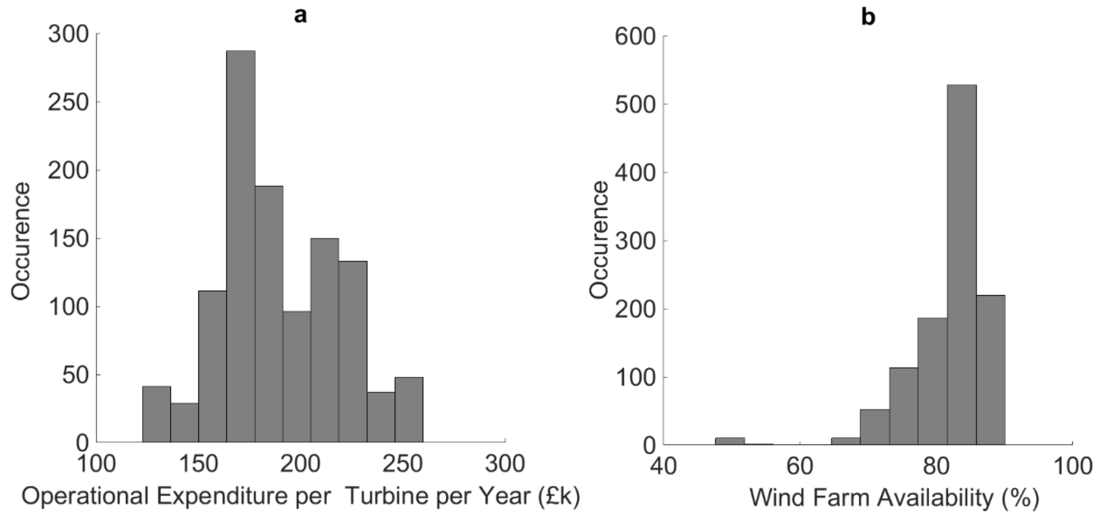


Figure 4-9: Histogram of sample results for a) O&M costs and b) availability for Case 3

Table 4-4: WTG components and corresponding label

Component	Label
Blades/ Pitch System	a
Generator	b
Electrical System	c
Control System	d
Mechanical Brakes	e
Yaw System	f
Gearbox	g

4.3.5.1 Costs

The results for the total O&M costs are shown in Figure 4-6a) and Figure 4-8a). This is the sum of technicians, materials, vessels and fixed onshore costs. A list of the important factors is seen in Table 4-5 along with the effect. From these graphs, it can be argued that the high rate of component failures for both small and large repairs is important as these factors in Table 4-5 are prominent.

For both the first phase, Case 1, and the complete project, Case 3, the component failure rates for the electrical system and the gearbox are important. The electrical system is susceptible to high rate of small failures, but has the lowest component cost. The gearbox, on the other hand has a low failure rate for repairs requiring a HLV, but has a high component cost. This demonstrates to the operators that they have to consider the frequent, low cost component failures as well as the high cost, low probability failures and take steps to reduce the failure rate and cost of both. Other important factors for cost in both Case 1 and Case 3 are the cost for HLVs and helicopters (MEjdr and MEhco, respectively).

For Case 3 the duration of smaller repairs [DE1od] and interaction with shift length [MEend] are other important factors demonstrated by the fact that [DE1od] and [MEend] in Figure 4-8a) on the left hand side of the group, indicating high interaction.

Table 4-5: Important factors for costs in both cases in alphabetical order with description and type of influence (main effect, interactive/non-linear or mixed)

Code	Description	Main, Interactive/non-linear, Mixed
CO1gc	Repair cost for gearbox for failure Type 1	Main
CO1gf	Failure rate of gearbox for failure Type 1	Main
CO2cf	Failure rate of electrical system for failure Type 2	Main
DE1od	Operation duration of repair for failure Type 1	Interactive/ Non-linear
DE2od	Operation duration of repair for failure Type 2	Main
DE2pd	Planning delay to conduct failure Type 2 repair	Main
DE2wf	Cost of subcontracted workforce to conduct failure Type 2 repair	Interactive/ Non-linear
MEctc	Number of technicians per corrective maintenance team	Main
MEend	Work end time	Interactive/ Non-linear
MEhco	Annual fixed cost of helicopter	Main
MEjdr	Day rate of HLV	Main
MEjmf	Maximum number of failures before mobilization of jack up vessel	Main
MEjmo	Time to mobilize HLV	Main
WFbas	Distance to O&M base from OWF centre	Main

Component cost and failure rates are assumed to be the same as those for onshore wind farms. Therefore, it can be concluded that the influence of those constituents would also be non-negligible for onshore wind. Especially as the same conclusion cannot be made for the access vehicles for onshore wind projects, where helicopters are not used and the cost implications of lifting heavy components is much larger in an offshore context. The length of shift and operation duration would similarly affects costs for onshore wind farms as offshore. However, they are unlikely to be the same magnitude. Fixed costs associated with each visit to the WTG, if the operation is more than one shift length, would be higher offshore as vessel daily rates are greater than vehicles used to access onshore farms.

The results demonstrate that the access strategy may need to look beyond just CTVs and helicopters to provide enough time to conduct necessary repairs. This analysis shows that, other than the access and duration of small repairs, the important factors related to costs are the same for the Case 1 and Case 3.

4.3.5.2 Availability

For Case 1, the most important factors are the small repair duration [DE1od], working day length [MEend], failure rate of the components requiring a HLV [CO2cf], BoP availability [WFbop] and personnel transfer time from vessel to WTG [MEblg].

For the Case 3, the top factors are the same as for Case 1. Additional factors are the vessel number [MEnve] and number of teams required in order to complete small repairs [DE1int].

Table 4-6: Important Factors for availability in alphabetical order with description and type of influence (main effect, interactive/non-linear or mixed)

Code	Description	Main, Interactive /non-linear, Mixed
CO1df	Failure rate of control system for failure Type 1	Main
CO2cf	Failure rate of electrical system for failure Type 2	Main
DE1int	Number of teams required to repair failure Type 1	Mixed
DE1od	Operation duration of repair for failure Type 1	Mixed
MEend	Work end time	Mixed
MEnve	Number of type CTV	Interactive/ Non-linear
WFbop	Average BoP availability	Main

The histograms in Figure 4-7 and Figure 4-9 show the results from the samples. The range of availability generated for the first case is between 84% and 92%, with an average of 89%. With Case 3, there is a dramatic reduction in project availability which sometimes can be as low as 50% and an average of 82%. The maintenance strategy for this study is limited to only an onshore O&M base, with transfer via either CTVs or helicopter and a single 12 hour shift. In this case, this is the limiting factor of the availability. Employing an offshore base in a mothership or permanent structure might lead to increased availability for Case 3.

4.3.6 Discussion

The factors that affect costs are similar for different cases of the same OWF. There are additional important input factors concerning the failure rates and operation duration of routine repairs.

For the first construction phase, Case 1, it is WTG reliability and speed at which repairs can take place that primarily affects farm availability. This is true for the complete farm, Case 3, but the repair strategy also becomes more prevalent.

There is minimal information available in the public domain on the frequency of major component failures. The input distribution of failure rate is taken from onshore reliability databases from smaller WTGs a decade ago.

The OWF performance in Case 3 is limited by having only an onshore O&M port strategy, where as other options include using offshore bases such as motherships or fixed platforms to reduce CTV travel time. In the same manner, a single shift per day scenario is modelled, which can be extended to consider 2 or 3 shifts per day as well.

Prior to the LSA being conducted, there was a supposition that key project characteristics, such as number of turbines and distance from the O&M port would have large effect on the resulting cost and availability. This supposition stems from general use of the model for analysing costs, as demonstrated in the case studies in Section 3.4. These two inputs were thus fixed to create the cases for the LSA and subsequent GSA. Even with these fixed inputs and conducting separate sensitivity analyses, it has been found that there was a difference in the key input factors identified, as shown above in Section 4.3.5. In the studies of T1 and NB1, it is found that the input variables needed to change to reflect the different O&M practises for different sized wind farms. For example, the use of helicopters and mother vessels for wind farms further from the O&M base, where a more coastally located wind farm would not need such provisions. It was expected that, by introducing different input factor variables to the analysis for Case 1 and Case 3, different results in the sensitivity analysis would be found. It was also expected that the different case characteristics (number of turbines and distance to O&M base) would themselves effect the results between the cases in some manner. From the results shown in Section 4.3.5, the list of top important factors are not exactly the same between cases and that the pre-analysis suppositions were correct.

As each analysis was done independently of each other, it is not possible to measure the effect of the change caused by the different input variables or the case characteristics. The results, at this stage, are comparable. That is to say that it is possible to say the outcomes from Case 1 and Case 2 are different. But due to the lack of quantitative result using the Morris method, it is not possible to investigate the reason for the differences in more detail.

4.3.7 Conclusion

Fourteen inputs are found to be important in calculating O&M costs; including failure rates, component cost and repair duration interacting with the shift length. For availability, seven important factors are found, components with both low and high failure rates the maintenance resources availability and shift length. In a comparison of two cases of a single OWF, it is found that the larger OWF had the same important input factors as the smaller phases plus additions. This indicates to operators, building wind farms in multiple phases that the sources of uncertainty are subject to change between the different build phases and that focus of consideration for reduction in costs and increase availability should be reconsidered when commissioning subsequent phases.

The LSA has provided the most influential factors but what is still absent is the quantification of their relative importance to each other. Now that the non-influential input factors can be fixed, a more complex, global method can be used. It also means that the input distribution of those input factors can be investigated.

5 Global Sensitivity Analysis

5.1 Introduction

This section describes the approach and the results of application of Sobol' method for sensitivity analysis to the offshore wind model. In the first section, the possible GSA methods are introduced along with explanation of the method choice.

The GSA cases are based on the same cases in Section 5.3 except Case 2, which is found to produce similar results as Case 1. Case 1, with 62 WTGs and Case 3, with 121 WTGs, are taken forward for the GSA. To broaden the scope of the analysis, a third case is introduced from the results of Martin et al., 2014 and in Appendix G, a "generic" case with a WTG population of 30.

5.2 Global Methods

Global SA techniques attribute the uncertainty in the inputs through to the uncertainty present in the outputs. They generally have a sampling based approach from the probability distribution functions (PDFs) of the input factors. These methods have a wider applicability to models but can also be complex and computationally expensive.

Some of the most commonly used GSA methods are variance based, where portions of variance in the output variable are attributed to variance brought by the input variables. Variance based methods provide quantitative results and consider the interactive effects as well as linear ones. Another property is their general applicability to models. The drawback with variance based methods is that they can be computationally experience, using a Monte Carlo aspect, therefore more suitable when the number of impact factors are of the order of 10's rather than 100's or 1000's (Saltelli et al., 2008, 2004). Two variance based methods are considered here, Sobol' indices and extended Fourier Amplitude Sensitivity Test (eFAST).

5.2.1 Definitions

X is the set in input factors

Y is the set of model outputs

$$Y = f(X)$$

k is the number of input factors, therefore X is a vector of k input factors. Individual input factors are identified by x_i where $i = [1, \ldots, k]$. Likewise, l is the number of outputs, and individual outputs are identified as y_j where $j = [1, \ldots, l]$.

5.2.2 Sobol' Indices

One of the most regularly used sensitivity measures in the variance based classification is the Sobol' indices, employing Monte-Carlo analysis. It provides two indices for the sensitivity of each x_i on each y_j; the main effects (S_i) and the total effects (S_T). The indices are first introduced in Russian by Sobol' in 1990 (Sobol', 1990). A summary in English has since been provided in 2001 (Sobol', 2001).

For models where the inputs are orthogonal, that is to say, unrelated, then the calculation of measure is relatively straight forward. The following outline is adapted from (Quaglietta, 2013; Saltelli et al., 2010).

The effect of the variance of x_i, on y_j, can be expressed as

$$V_{x_i}(E_{x_{\sim i}}(y_j|x_i)) \qquad [17]$$

Where $x_{\sim i}$ is the matrix for all factors other than x_i. So the sensitivity measure of the main effect is found from:

$$S_{ij} = \frac{V_{x_i}(E_{x_{\sim i}}(y_j|x_i))}{V(y_j)} \qquad [18]$$

Where $V(y_i)$ is the variance of the output. The total effect measure is given as:

$$S_{T_i} = \frac{E_{x_{\sim i}}(V_x(Y|x_{\sim i}))}{V(Y)} = 1 - \frac{V_{X_{\sim i}}(E_{x_i}(Y|x_{\sim i}))}{V(Y)} \qquad [19]$$

Therefore the main effect is the direct effect of the x_i and the total effect is the sum of the effects that are not due to x_i.

Another of Sobol''s decomposition scheme follows. For this description, the input values are assumed to be uniform between 0 and 1. It begins with the Analysis of Variance (ANOVA) representation of the form, (Sobol', 1990):

$$f(x) = f_0 + \sum_{s=1}^{n} \sum_{i_1 < \cdots < i,}^{n} f_{i_1 \ldots i}(x_{i_1}, \ldots, x_i) \qquad [20]$$

Table 5-1: Overview of common SA methods

Class	Method	Features	Strengths	Weaknesses
Local	One Factor at a Time	Simple Well Established	Does not reflect the interaction between factors	Only suitable for linear and additive models. Does not reflect the interaction between factors
	Morris Method	Identifies factors with: a) linear influence b) interactive or higher order influence c) negligible effects Is a qualitative analysis	The replications value suggested in literature may be too small	Can produce erroneous results when compared to more sophisticated method. The replications value suggested in literature may be too small
Global	Standard Regression Coefficients	Identifies linear effects but not interactive effects. Suitable for linear and non-monotonic	Simple implementation	Does not provide interactive effects
	eFAST	Inputs are identified by a set of sin curves at different frequencies from which variance is decomposed Suitable for non-linear and non-monotonic models	One of the most accurate methods Both linear effects and total effects can be found from one analysis	Can require high number of model evaluations, at least k x 500
	Sobol' Indices	Identifies main effects and interactive effects. Suitable for linear and non-monotonic models. Uses a function decomposition scheme.	Straight forward method if the inputs are orthogonal Provides a quantitative measurements	Can be complex when inputs are non-orthogonal and results in high number of required model evaluations

Where $f(x)$ is the model (computational or numerical) under study and x are the set of inputs. If $f(x)$ is considered a random mean then f_0 is the mean. The variance of the model is decomposed into summands of increasing dimensionality as in:

$$f(x_1, \dots, x_k) = f_0 + \sum_{i=1}^{k} f(x_i) + \sum_{1<i<m<k} f_{im}(x_i, x_m) + \cdots + f_{1,2,\dots,k}(x_1, \dots, x_k) \quad [21]$$

Where m is an input that is not i.

Each term of the decomposition is:

$$f_i(x_i) = -f_0 + \int_0^1 \dots \int_0^1 f(x) dx_{\sim i} \quad [22]$$

$$f_{im}(x_i, x_j) = -f_0 - f_m(x_m) - f_j(x_j) + \int_0^1 \dots \int_0^1 f(x) dx_{\sim i,m} \quad [23]$$

Where:

$$f_0 = \int f(x_{ij}) dx_{ij} \quad [24]$$

From this the total variance of x can be found:

$$D_j = \int f^2(x_j) dx_j - f_0^2 \quad [25]$$

Sobol''s sensitivity indices, for each output, are:

$$S_{i_{1,\dots,i_j}} = \frac{D_{i_{1,\dots,i_j}}}{D} \quad [26]$$

$$S_{im_{1,\dots,i_j}} = \frac{D_{ij_{1,\dots,j}}}{D} \quad [27]$$

And the total order effects found from:

$$S_{T_{ij}} = S_{ij} + S_{im_{i \neq j}} + \cdots + S_{1\dots i\dots k} \quad [28]$$

(Saltelli et al., 2010; Sobol', 2001).

In order to produce the sampling matrix to evaluate the model and calculate the sensitivity measures, two matrices are generated: **A** and **B**. These matrices are the size of N by k, where N is the number of Monte Carlo simulations and are quasi-random numbers. A set of matrix is generated from **A** and **B**, which are identical to matrix **A** but except for the ith column which is equal **B**, so the number of new matrices ($A_{B,i}$) equals the number of k inputs. At this point the model can be evaluated $n = N \times (k + 2)$ times. A satisfactory value of N is an unknown quantity. One approach taken by (Saltelli et al., 2008) it to conduct the experiment with increasing values of N until the results is stable, which $N > 1000$. However this will increase the total time to reach results.

For models where the inputs are non-orthogonal, the decomposition is not as simple as the total order effects are not a sum of the main effects of factors plus interactive effects ($S_{T_{i,m}} \neq S_i + S_m + S_{i,m}$). In this case the integrals for the decomposition need to be estimated from Monte Carlo methods with r replications and are therefore more computationally expensive and can be up to $\frac{1}{2}k(k-1)Nr$ times where r can be 100 and N can be 1000s.

5.2.3 Fourier Amplitude Sensitivity Testing (FAST)

This method, developed by Cukier et al in the 1970s (Cukier, Levine, & Shuler, 1978), is variance based, using curves to originate the inputs into the models. The classical version of FAST is developed to provide first order sensitivities and extended in 1999 by Saltelli to provide the total effects as well and is often referred to as eFAST. The frequencies of the input curves are the identifiers for the analysis, with the transform of the input parameters taking the general form:

$$x_i = G_i(\sin \omega_i S) \tag{29}$$

Where s is a scalar variable between $-\pi$ and π and ω_i is a frequency chosen in order to identify i. A version of G_i is proposed (Saltelli et al., 2008) in which provides uniformly distributed samples. In eFAST, the choice of ω_i is required to be high compared to the other input factor frequency set $\{\omega_{\sim i}\}$. The variance of the input and output factors are calculated from Fourier analysis and the variance decomposition is determined the same way as equations 17 and 18. The number of model evaluations is dependent on $k \times N_c \times N_s$ where N_c is the number of curves employed and N_s is the number of points chosen. In the literature, the value of $N_c \times N_s$ should be greater than 500 (Cosenza et al., 2013).

5.3 Review of Application of GSA methods to external models

Three GSA methods are compared using an integrated membrane bioreactor model for waste water applications (Cosenza et al., 2013). Cosenza et al conduct an eFAST analysis and compare the results of rank of sensitivity indices with analysis conducted using Standardised Regression Coefficients (SRC) and Morris Method. There are 79 input factors and 21 model outputs. The number of model evaluations for each followed suggestions in literature. The analysis with eFAST has 395,000 model evaluations and both SRC and Morris call for 800 simulations. Seven different criteria are applied to investigate the sensitivity indices and ranking from each method. The eFAST is the reference method so the SRC and Morris results are compared to these results. The SRC method can only provide the linear effects and is unable to consider the interactive effects. It is found, however that the SRC results performed outside of the range of applicability with regards to R^2 values but still offers close correlation to the eFAST results, even though it can only offer non-linear results. Whilst requiring less model evaluations and being able to at least provide indices for interactive effects, the Morris Method correlated poorly with the reference method. This is attributed to the lack of convergence due the suggested r value being too low. The author indicates that even using an r value of 60 is not enough to gain satisfactory results, and that instead of the suggested r value between 10 and 20, it should be more than 100 according to analysis. This has serious implications for use of the method as a principle way to screen out non-important factors where the limited number of simulations required is seen as a benefit. The number of model evaluations required is been, if the author is using the design matrix plan described by Morris, as $n = r(k + 1)$. With an increasing r value, then the attractiveness of Morris diminishes. Perhaps this paper takes the values from the Morris Method too literally, in which case, the main criticism of the method would be the over estimation of the non-important factors.

In work done on SA on multivariate outputs, three methods of SA are combined with principal components analysis to measure the sensitivity of an output to input factors over time (Lamboni, Monod, & Makowski, 2011). A wheat crop development simulation model, AZODYN, has outputs which are time-based functions rather than discrete outputs at determined time steps. One of the outputs, the nitrogen nutrition index, is used and three classical SA methods are implemented;

Sobol-Saltelli (with random latin hypercube and Monte-Carlo sampling), eFAST and fractional factorial design of resolution six. To understand the variance in the results, the sensitivities are subject to a bootstrapping method. The principal components are computed using the three methods with 13 inputs, reduced from 69 after a screening process. It is found that eFAST and Sobol-Saltelli methods provided very similar results. The multivariate analysis allows for more information on the time-varying sensitivity of the inputs to be revealed. The conclusion of the paper is that each method had its own strengths depending on the desired focus of the analysis. The eFAST method provides more "coherent sensitivity indices" with small number of model evaluations. The FFD method provides reliable information on the indices but can be prone to bias due to discretisation.

In another comparative investigation between different models, a marine atmospheric model is subjected to a screening analysis through the Morris method, then a full analysis with and calculated with Sobol' indices and SRC (Campolongo & Saltelli, 1997). For the full sensitivity analysis, Monte Carlo sampling is used. As well as application to the model, a test is done with an analytical test case with regards to a G function. In this paper, the SRC analysis is used as the reference analysis. The conclusion of this analysis is that Morris Method, with bootstrapping, can quantify results. However, it is found that Morris method under performed with regards to identifying all of the influential factors. In many cases, the ordinality of the input factors is in agreement between all methods, however, Morris Method failed to identify several factors as important.

The methods described here have been built to test the sensitivity of deterministic models. In recent years, there has been development of techniques to conduct the same tests on stochastic computer models. An example of which is outlined in Marrel & Iooss 2012. The approach is to establish the mean and the dispersion caused by, what the authors call, the random seed variable through joint meta-modelling. Three joint meta-modelling approaches are compared; joint generalised linear model, generalised additive model and the Gaussian process model. After building these models, the same methods of GSA can be applied but the total effect of the dispersion of the random seed variable can be quantified along with other variables. The benefits of this are that, for ECUME, the random seed of the failure rates can be considered. For subsequent versions of ECUME, which may have stochastic elements in the meteorological model, this can be incorporated as well. The drawbacks are that, as classical GSA techniques are required, a deterministic screening experiment still needs to be done to reduce the number of input factors. For example, the illustration provided in Marrel & Iooss 2012, the PUNQ model has only eight input factors. It is found that the generalised linear model are not applicable for complex models, and that the Gaussian process is more accurate than the generalised additive models but required more research.

5.4 Method choice

For the GSA, again there is a choice of methods to choose. These are all more complex than the screening ones. The choice of method is dependent on the required information whilst being able to be conducted on the available computing resources within a reasonable amount of time (for example, not greater than 2 weeks on a standard workstation computer). The foremost methods found in common use in the literature analysis was eFAST and Sobol'. Both these methods provide a sophisticated way of ascertaining the effect of factors on the outputs, with the Sobol' indices requiring, notionally, fewer number of runs. However, in reality, because of quality issues of the results, during that actual experiments the number of simulation required for the Sobol's indices ranged from 4,000 to 7,000, which is similar to those required for eFAST (500 multiplied by the number of input factors). Therefore, even though Sobol' was used for this analysis, eFAST presents an alternative. Because the Sobol' method uses a Monte Carlo sampling approach, it is more suitable for input factors with discrete distributions than the eFAST method, which uses a sine function instead (Tian, 2013; Zhang et al., 2015).

For the GSA, Sobol' indices are chosen as this is a robust method that has been commonly applied to a range of complex models (Campolongo & Saltelli, 1997; Quaglietta, 2013). As outlined in Section 5.2.2, the method allows quantification of the both the main and interactive effects and is model independent. The input factors are orthogonal so the method as described in Section 5.2.2 is used.

This method is designed for deterministic models. As with the LSA, the stochastic nature of the model has been reduced to pseudo-deterministic by taking the mean value of cost and availability from the internal iterations of the model. This is the value that is then compared with the input to then calculate the sensitivity indices.

5.5 Input Distributions

5.5.1 Introduction

This section will detail the processes and approaches of how the input distributions are estimated for the GSA. The input distributions chosen are those found from the results of the screening analysis in Section 5.3. There are originally 115 inputs tested which have now been reduced to 21 unique input factors across three cases. The description of the generic case and results from the LSA is presented in Martin et al., 2014 and the two project-specific cases are presented and results given in section 4.2.3. This reduction of inputs allows for a more focused study into collecting the data required and defining the probability distributions key inputs.

For the GSA, more effort is focussed on identifying the type and probability distributions from the information available, principally, from the first years of operation experience at the T1 OWF. If this is not available, information from literature and industry is used.

As shall be seen in this section, there are multiple sources of information used to find input factor distributions. Using a decision tree, each input distribution can be graded, qualitatively, based on the quality of the source of information. Figure 5-1 to Figure 5-6 show the decision tree used to arrive at 10 grades. Grade one means that the source of information is primary data with enough of a population to make reasonable assumptions. The decision process prioritises primary data. If that is not available, the process moves to publically available secondary data and then results of analysis information from peer-reviewed journal papers. If this cannot be found, then on to privately available secondary OWF industry data and, finally, data or peer-reviewed literature from other related industries. This order is chosen as it prioritises data where background of how that data is collected, categorised and analysed is known. The process then ensures that all potential sources of information have been pursued.

The contribution of using this framework, along with the results of the sensitivity analysis, allows for the prioritisation of the inputs to consider for further investigation. It allows for the identification of which of the inputs, resulting from the GSA, have the most quality at the front end of the analysis. For example, if an input with the lowest desirable grades (8 -10) are identified as key inputs in the sensitivity analysis, then these are prioritised for further investigation.

The limitation of this framework is that the grading value is linked to the source of data (real operating data, public domain, private domain, literature and related industries) rather than the quality of the uncertainty analysis. It also does not consider the amount of data used in the uncertainty analysis. The reason for this is so that the framework is, chiefly, a communication tool best suited for simplification.

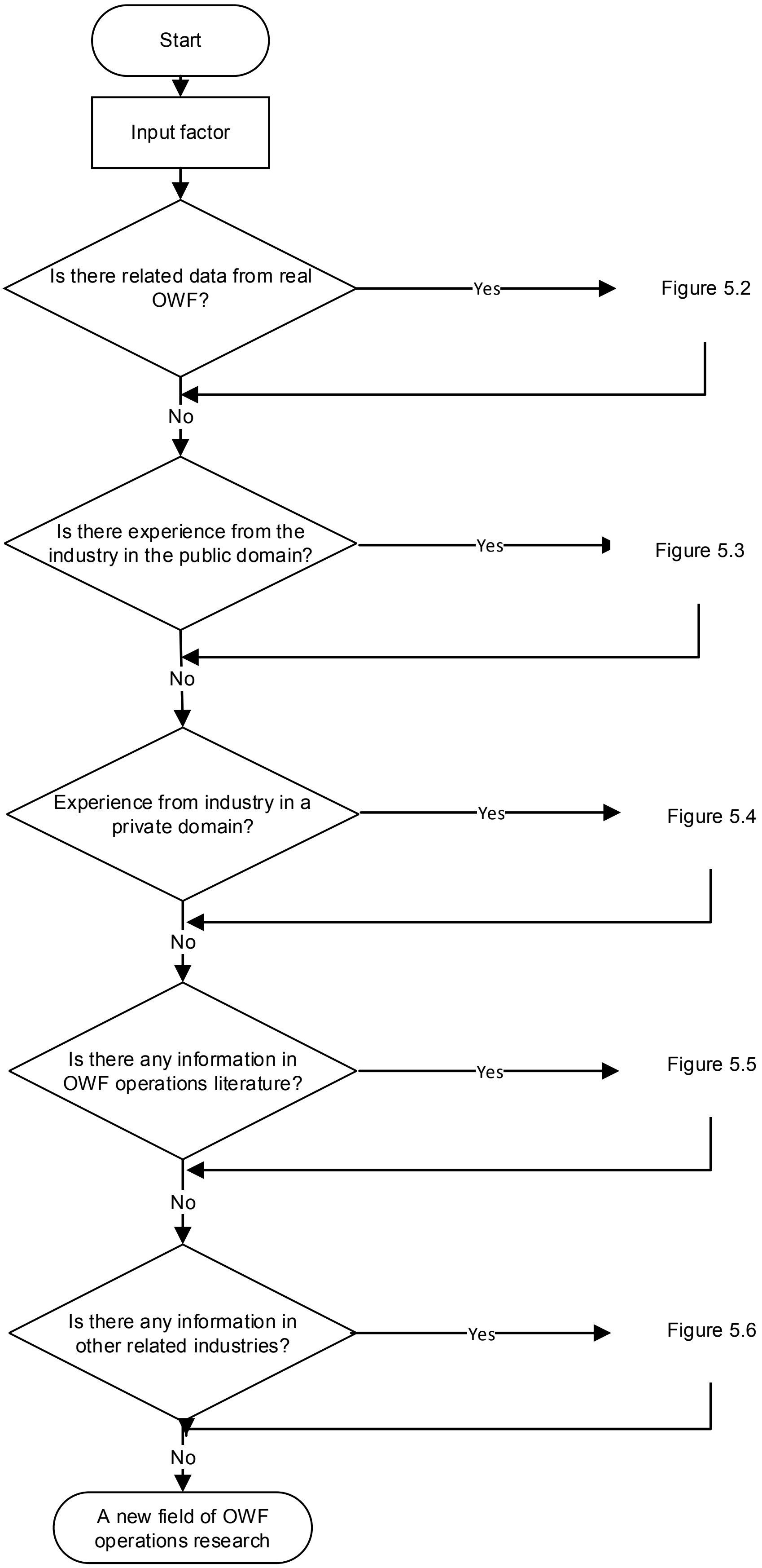


Figure 5-1: Main structure of input factor distribution grading decision tree

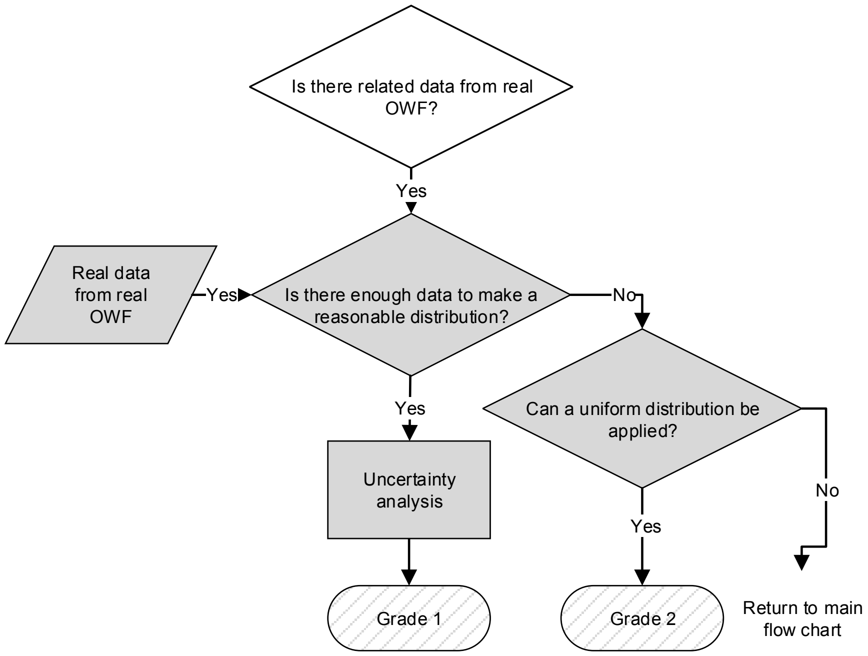


Figure 5-2: Part two of grading decision tree for input factor distributions

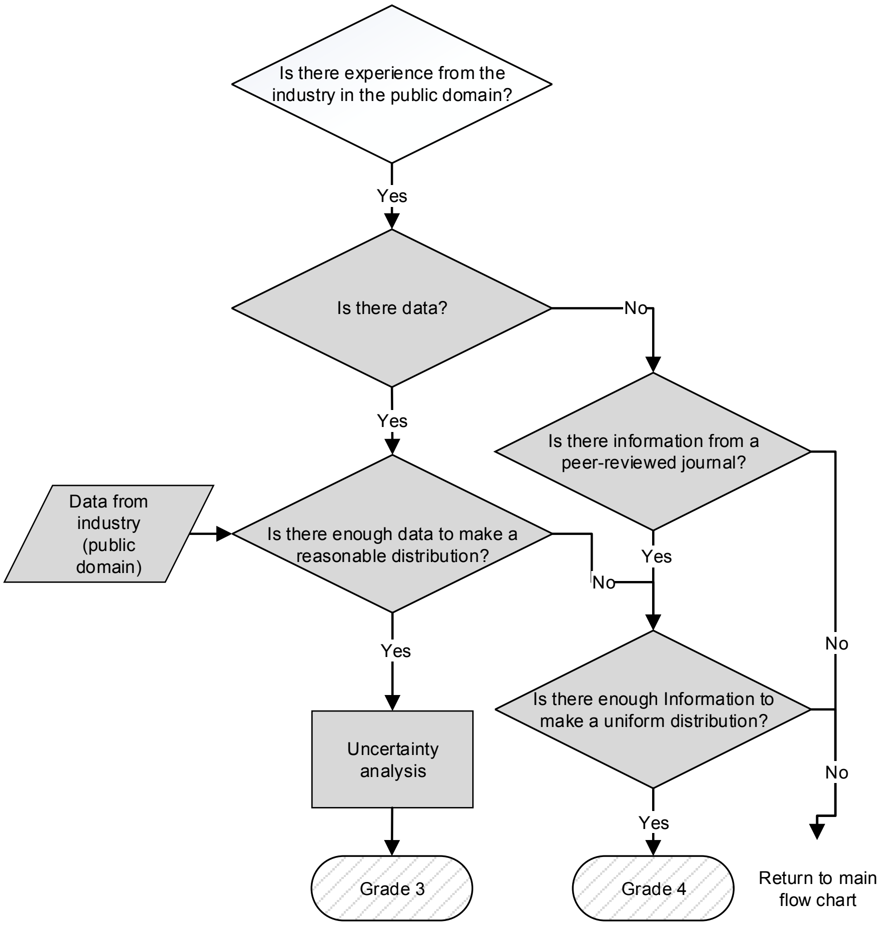


Figure 5-3: Part three of grading decision tree for input factor distributions

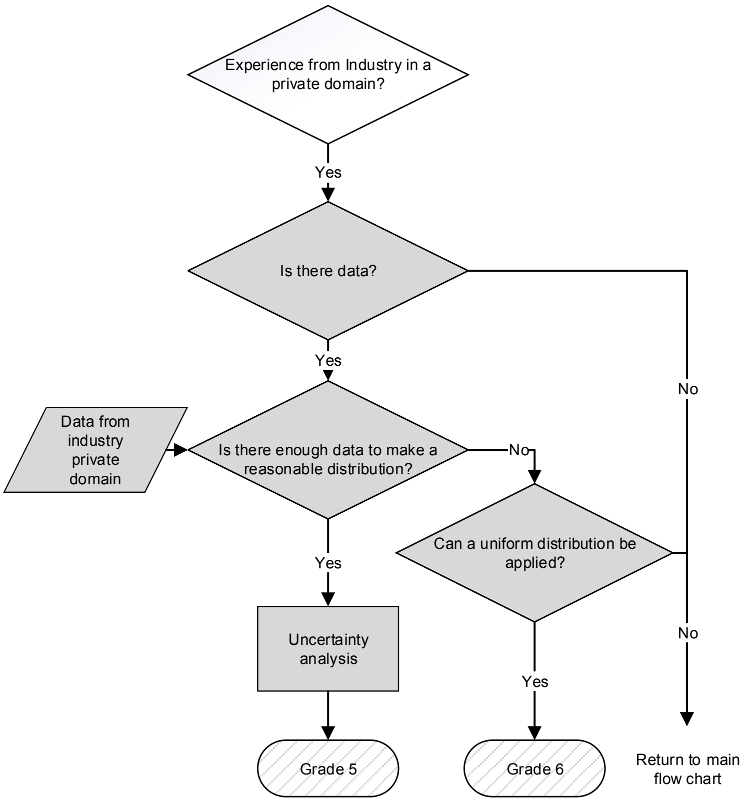


Figure 5-4: Part four of grading decision tree for input factor distributions

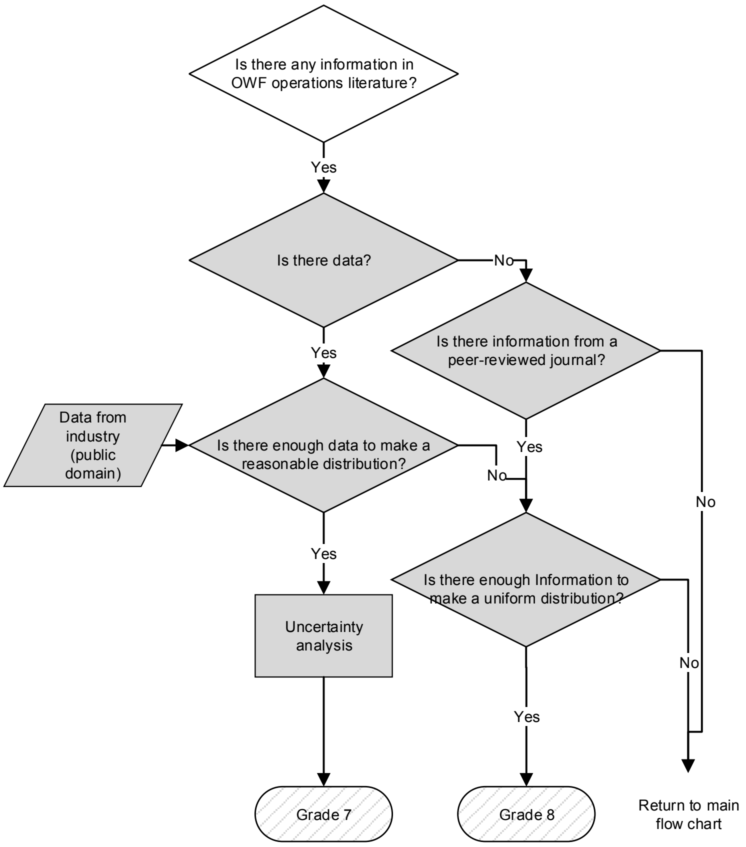


Figure 5-5: Part five of grading decision tree for input factor distributions

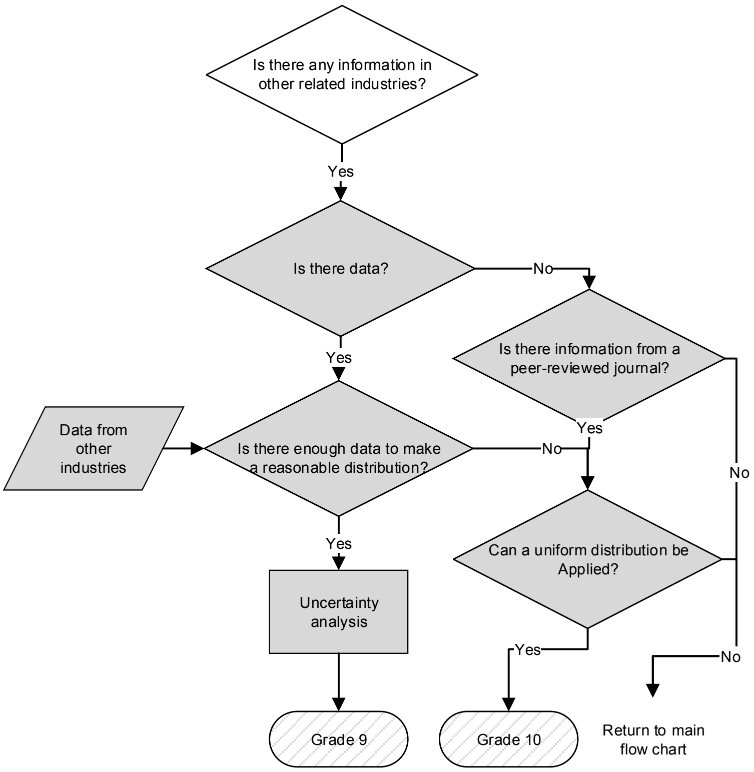


Figure 5-6: Part six of grading decision tree for input factor distributions

5.5.2 Primary Offshore Wind Operational Data

Operational data from the T1 OWF has been crucial for some of the inputs. The wind farm has been in the operational phase since 2013, however, data management systems have taken time to be established and operational data on repair actions and technicians transfers has only been made available since summer 2014. This results in one year's worth of operational observations. The main sources of operational data have been

- Daily maintenance logs from OEM
- Supervisory Control and Data Acquisition system (SCADA)
- Transfer Log Database

The daily maintenance logs of the WTGs are produced by personnel working for the OEM. These logs record WTG stoppages, the cause and the repair actions that have been conducted. They also record the running faults on WTGs and the total time frame for annual servicing. The data availability for these logs is 92%. They are generated and issued manually.

The location of technicians and other personnel on the site is a record of when a person moves between onshore, vessels and WTGs. It is logged by the operational manager at the O&M onshore base. This is so that the location of everyone onsite is known at any given point. This database is maintained by hand and is subject to human error but is generated in real time. Data availability is 100% and data accuracy is estimated to be 98%. An erroneous data entry can be detected when, over a given period, the number of transfers on to the WTG does not equal the number of transfers off. The data accuracy is calculated as the total number of transfers (on and off) minus those that are incomplete (i.e. when a technician is mistakenly put on a WTG or has not been removed) over the total transfers. The selected period is during the annual servicing time frames for each WTG on a daily basis.

As in the LSA, the inputted meteorology data time series is the same throughout the analysis, i.e. the same time series is used in each sample. In the LSA, the wind input was varied by changing the wind shear exponent but it was not identified as one of the top most important input factors in the results. This is not to say that in real life, the overall cost and availability would not be affected by the wind and wave regime. Through reducing the meteorological data down to a single input and nullifying that stochastic input, it allows for the investigation of the other input variables. Whilst this important aspects of the model has been isolated at this stage, the results from the GSA can be used in studies (beyond this thesis) to fully understand the effect of the meteorology.

5.5.3 Number of Teams for Repair Type 1: Grade 1

The number of teams for repair Type 1 is taken from the experience of corrective maintenance actions at T1 in the first year of operations. For each of the 33 corrective maintenance actions that occurred in the time period, the average number of technicians working on that repair is logged. The actual number of technicians working on a single repair operation varied between two and four on a daily basis. For the model, the number of technicians visiting the WTG is the product of two input factors fixed throughout the project lifetime; the number of technicians per team and the number of teams required for each failure type. As it is shown that the number of technicians visiting a WTG can be odd, the number of technicians in each corrective team is one and the input distribution for the number of teams required is two, three and four at the same probability shown in the table below.

Table 5-2: Number of Corrective Maintenance Teams for Repair Type 1

Number of Teams (1 team = 1 technician)	Probability of Occurrence
2	47%
3	41%
4	12%

5.5.4 Time Taken to Conduct Annual Servicing. Grade 1

The time taken to conduct the annual serving of the WTGs at T1 is calculated in a similar way to the number of teams required. The daily maintenance logs prior to July 2014 are not available for six turbines so it is unknown how much of the time spent in the annual service time frame is spent on corrective actions for these turbines. It is assumed that technicians began work as soon as they are transferred to the WTGs. As there is some time delay between the first technician transferring to the WTG and the last, normally a couple of minutes, the total time on the WTG is counted from when the first technician to when the first technician transfers. The time is calculated on a "technician hours" basis, so the time on the WTG is multiplied with the number of technicians. This is summed over the days of the annual service time frame to reach a total "technician hours" per WTG. The results of which can be seen in Figure 5-7. The figure shows count of the total personal hours needed for each WTGs, the results are binned into 10 hour long discrete periods and the x axis shows the middle of the bins. The minimum amount of technician hours is 74 hours and the maximum is 470 hours. The WTG with the maximum technician hours is one of the WTGs where no information on corrective actions during the annual servicing time frame is available. Therefore it is possible that corrective maintenance actions account for this extended period of time.

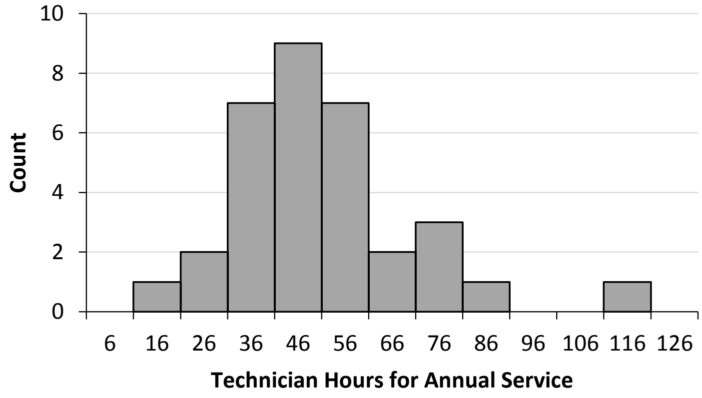


Figure 5-7: Histogram of technician hours for annual servicing

Again, as with the number of teams, the model requires a fixed time duration of the annual servicing for all WTGs throughout the lifetime of the project. The variability of the time it takes to conduct the annual service may depend on the experience of the technicians conducting the maintenance. Figure 5-8 shows the cumulative time per WTG number when ordered by start date. At the beginning of the service cycle in April, the time per WTG increases and is unstable until September 2014, after which there is a steady decline in the time to conduct the annual service. This could be attributed to a learning curve as this is the first annual servicing cycle, however, further data on the length of other wind farms may be needed to verify this. The dotted line shows a linear fit.

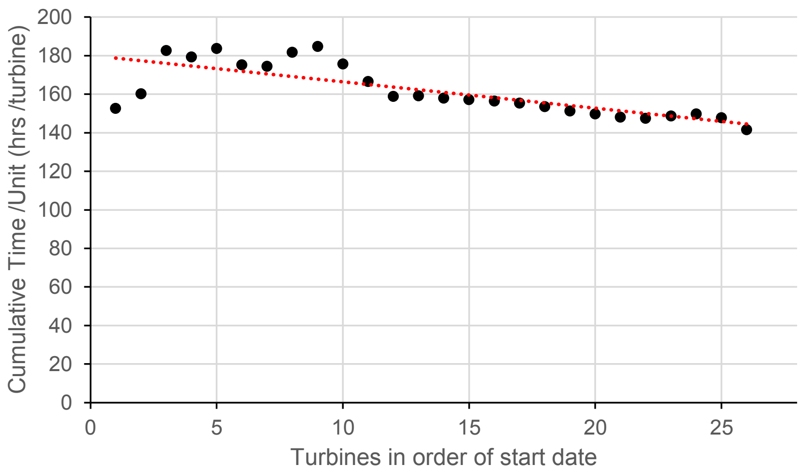


Figure 5-8: Cumulative time of technician hours for annual service per WTG number in order of start.

For the operation duration time, a continuous log normal distribution is fitted to the distribution shown in Figure 5-7.

5.5.5 Number of CTVS: Grade 1

The number of CTVs used is based on the information available on vessel tracking websites and from privately held information from the SPARTA project. All vessels over 300 gross tonnage have a GPS system allowing their location to be tracked in order to avoid collisions. This information is made available via the Automatic Identification System and the Marine Traffic Project website (Marine Traffic Ltd, 2014). This gives the current position of the vessel as well as allows the viewer to look at the location of the vessel in the last 24 hours. Using this information, a survey of the number and type of vessels used at operating OWFs is conducted. The number of vessels working on a single wind farm may fluctuate on a daily and seasonal basis, however the model only allows for a fixed number of vessels to be available. The actual number deployed on a given day depends on the weather conditions and work demand. The day chosen for the survey is a week day in March. March is chosen as a time when, after the winter period, the weather conditions across the UK were mild, with low winds and low wave heights so no area had any particularly adverse weather limiting operations. March is also chosen as there is likely to be work demand with corrective maintenance after the winter period but also the start of the period of annual servicing. The vessels in this database cannot be filtered to only vessels working on OWFs and there is no meta-data available to link the vessel to the OWF it is working on. Therefore, the following process is used to count the vessels:

- Identify all the OWFs in the UK that are, or have some part, in the operations stage.
- For each wind farm, select the main O&M base. This information is available from the operator themselves or from a third party source such as the 4C Offshore online database.
- For each wind farm, identify likely vessels that are CTVs from a vessel profile by looking at the all vessels that have visited the site in the previous 24 hours or are stationary at the O&M base.

The vessel profile is categorised as a “high speed vessel”, “uncategorized” or “work boat” in the online database. Also it has enough seats for technicians. Through the course of the industry, there have been vessels made specifically for WTG transfers which makes it easier to identify these vessel separate from other marine traffic.

Table 5-3: Table of CTV number results (Marine Traffic Ltd, 2014)

Offshore Wind Farm Name	Number of WTGs	Number of Vessels	Year of Commissioning
Barrow	30	1	2006
Beatrice	2	0	2007
Blyth	2	0	2000
Burbo Bank	25	1	2007
Greater Gabbard	140	5	2013
Gunfleet Sands 3 Demo	2	0	2013
Gunfleet Sands I and II	48	3	2010
Inner Dowsing, Lyncs and Lynn	102	7	2009 - 2013
Kentish Flats	30	1	2005
London Array	175	6	2013
North Hoyle	30	1	2003
Ormonde	30	1	2011
Rhyl Flats	25	5	2009
Robin Rigg	60	3	2010
Scroby Sands	30	1	2004
Sheringham Shoal	88	3	2012
T1	27	2	2013
Thanet	100	3	2010
Walney 1 & Walney 2	102	3	2012

The results from the survey are shown in Table 5-3. The average ratio of CTVs per WTG is 0.03 however there are a few exceptions: T1 Rhyl Flats, Gunfleet Sands, Lyncs, Lynn and Inner Dowsing, which all have higher CTVs per WTG. Barrow, Beatrice and Gunfleet Sands 3 projects are demonstrations of project, and with their low WTG population, are likely to skew the results so are removed. Whilst a population of 18 OWFs is small, there is enough to fit a log-normal distribution to it using the fitting tools in MATLAB®. The model accepts discrete integers for the number of vessels. The input distribution is a probability of discrete number of vessels from 1 to 10.

5.5.6 Operation Duration for Repair Type 1: Grade 1

The duration for repair is the time the technicians will take, from transfer to the WTG, to perform the necessary tasks to make the WTG operable after failure. It contributes to the downtime of the WTGs, so is a crucial factor in OWF availability. In reality, the length of time for repairs will depend on the accessibility of the component that needs to be repaired and the complexity of the repair. Also, the repair time may involve time for diagnosis and plan a suitable course of action.

In the model, this is all combined in one value. For the purposes of this analysis, all repairs not requiring a HLV are treated as one repair type. The first year of repair actions from the T1 OWF is used to base the input distribution on. Between November 2014 and June 2015, 33 corrective maintenance actions are recorded in the maintenance logs. Twenty six repairs are in response to a failure that had caused the WTG to stop. Seven are conducted to fix running faults, where problems are detected but did not interfere with the WTG operation. For each repair action, the operations logs are used to find the length of time that technicians are present. Similar to the preventative maintenance time; it is assumed that once the technicians are on the WTG, they are working. The technician hours are found by multiplying the time from when the first technician transferred to when the first technician transferred off, by the number of technicians who entered the WTG that day. This is calculated on a daily basis. The shortest repair time is 25 minutes and the longest time is 22 hours and 45 minutes. This high variability will result in high variability in the input function of the SA. Each repair is categorised into components according to the RDS-PP designation.

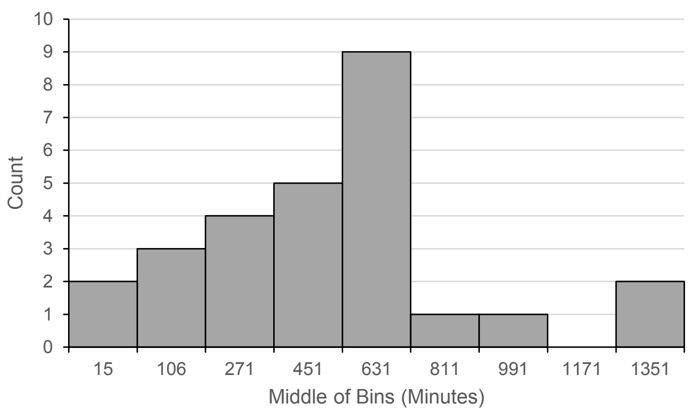


Figure 5-9: Histogram of operation duration for corrective maintenance

A histogram of the repair times can be seen in Figure 5-9. As the model accepts discrete integers for the number of hours taken for repair actions, then the closest integer to the middle of the bins is taken. The probability is entered as the input distribution.

5.5.7 Number of Teams for Annual Servicing: Grade 2

The number of teams that are employed to conduct preventative maintenance is based on the number of technicians used for the first year of routine campaign at T1. The first year of annual services began in April 2014 and are completed in March 2015. For each WTG the overall period of planned annual service is identified using the daily maintenance logs. The technicians have a set procedure for annual servicing, so this timeframe is started from the day they begin this routine to the day they complete the tasks. The operational database of technician locations is taken from the servicing timeframe for each WTG. This list is cross-checked with the daily maintenance logs to ascertain whether any other maintenance actions occurred that are not related to the annual servicing. If present, these actions are removed from the list. For each day that annual servicing operations occurred, the number of technicians transferring to the WTG are counted. It is assumed that all technicians entering the WTG are there to conduct the servicing routines, rather than tasks not directly related to the annual service, such as supervising. It is found that the average number of technicians entering the WTG per day is 3.2. The value of number of technicians in the GSA has to be an integer. During the first year of annual servicing, 55.9% of the days, no visits to the WTGs for annual servicing occurs. This could be due to limitations on access due to weather or that other corrective maintenance actions are given priority. Of the days that annual service took place, on 52.8% of them, only one WTG is subject to service activities. The percentage of days where two WTGs or more have simultaneous annual servicing is 47.2%. The figures below show the distribution of number of WTGs simultaneously worked on for annual service as well as a radial graph of time. The graph shows each day in the total annual servicing campaign cycle. It begins mid-April and, up to mid-September the technicians visited either one or two WTGs for annual servicing activities daily. From October there is three, four and, on one day, five WTGs having maintenance activities conducted. The reasons for this could either be a desire to complete all the annual services by a certain time, an increased availability of technicians, or a combination of both. As it is approaching the winter season, there could be a drive to complete as many of the annual services before bad weather. A delay to the annual services being completed earlier in the year may have been due to the long time it took to complete the first 11 WTGs, as shown in Figure 5-8, causing a backlog. It also could have been delayed by corrective maintenance actions being given priority over annual servicing. Linked to this, when the serial corrective maintenance tasks have been completed, this would result in technicians being available for annual services, allowing for simultaneous annual servicing visits.

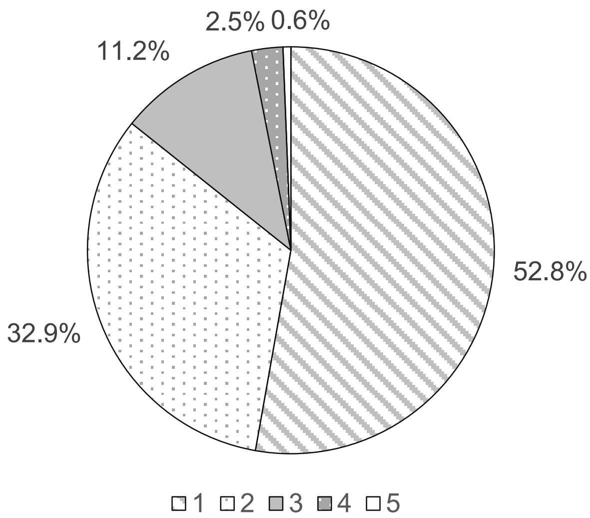


Figure 5-10: Distribution of the number of WTGs that are simultaneously worked on for annual servicing

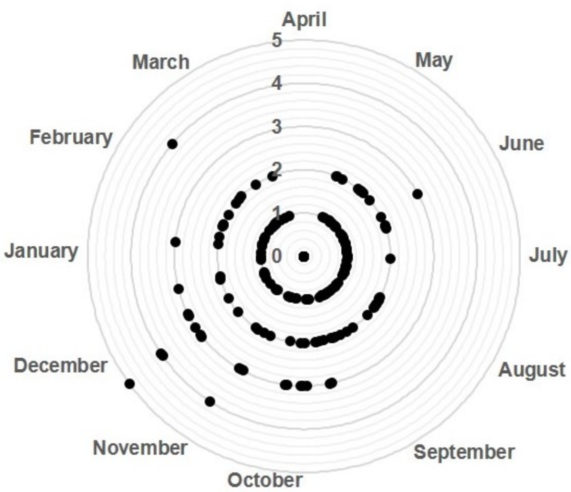


Figure 5-11: Number of WTGs worked on a daily basis for annual servicing

Whilst in reality the number of technicians is flexible, as shown, the model requires a fixed number. For the GSA, it is assumed that a team consists of two technicians. Multiple teams can be sent to work on different WTGs simultaneously or multiple teams sent to one WTG. With this in mind, of the 161 days that annual servicing took place at T1, the distribution of number of two person teams deployed (to either the same WTG or multiple WTGs) consisting of 1 team (10.6 %), 42.9% with two teams and 46.6% had 3 or more teams deployed in one day.

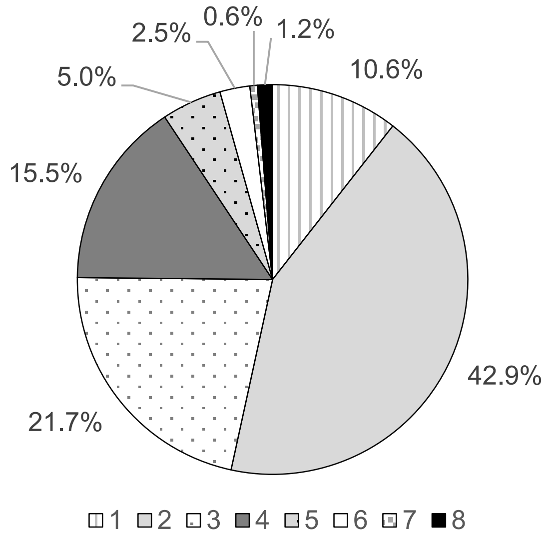


Figure 5-12: Distribution of the number of deployed two man teams in one day for annual servicing

In terms of most occurring number of teams sent to a single WTG for annual servicing within the year, 20.9% have one team, 54% have 1.5 teams sent and 25% have two teams or more.

This analysis shows that the number of teams deployed for annual maintenance activities fluctuates on a daily basis, as can be seen in the figures above. The way the ECUME model is built is that there is a distinction between technicians who perform corrective maintenance and those who perform preventative maintenance. As there will not be the same pressure for preventative maintenance technicians to perform corrective actions in the model, the numbers that are deployed will be more stable than in real life. Therefore the numbers for the analysis is fixed to 1, 2 or 3 teams required.

5.5.8 Work End Time: Grade 2

The work end time dictates the length of time available for each shift in order to travel to the sites and to conduct the repair operation. Longer allowed time for repair work to take place results in reducing downtime, but also requires more technicians when increasing the amount of shifts in place. It is likely to affect the costs, through increased technician salaries, but simultaneously increase availability. For the larger wind farms, the length of the shift becomes crucial due to the increased time in travelling to the wind farm and also the number of WTGs. For the large case studies, the work end length shift is changed between a 12 hours and a 24 hours shift when two shifts will be required. Therefore, if there are two shifts working, the number of available technicians is doubled.

In reality, most operating OWFs work on a single shift per day basis as there are relatively close to shore with a moderate amount of WTGs. Specific operations, such as oil changes, may require a 24 hour period as the task requires more than a single shift uninterrupted. However, normal corrective tasks are within this period.

5.5.9 Component Failure Rates: Grade 3

In the LSA, the range of failure rates is taken from the component failure rates and then adding an uncertainty range of 20 % based on examples given in previous SA studies. For the full GSA, the distribution of possible failure rates is investigated by using the failure rates in Appendix B. Using the information from the original WTG failure rate studies, the distribution of time to failures is replicated using a Poisson distribution random number generator. With these pseudo-observations, the possible distribution of failure rates for each components can be estimated.

Onshore turbine failure modes and the frequency of failure may be different to those experienced by offshore ones. The causes of these differences are given in Section 2.2 but those that affect the measured failure rates can be summarized to:

- Environmental:
    - Increased moisture ingress into nacelle housing from more humid environment.
    - Increased corrosive atmosphere from maritime climate
    - Presence of wave and tidal loading on structure
    - Increased wind loading on structure and drive train from higher wind velocities.

- Operational:
    - Higher limitations on access from environment, resulting on delayed scheduled maintenance operations

An extra dimension of this issue is that, because of the remoteness of offshore wind farms, there may be extra condition monitoring provision and better operation, leading to lower failure rates. No information on the level of CMS use on onshore turbines is provided so it is impossible to quantify any effect of this.

In section 2.5.1, eight sources of onshore WTG failure rates are identified. Table 2-3 provides details on the country of origin and frequency of reporting. These are:

- Driftuppföljning av vindkraftverk, årsrapport (Operation monitoring of wind WTGs, annual report)
- VTT (Technical Research)
- Windenergie Report (Wind Energy Report)
- Danish Energy Agency
- Betriever-Databasis/ IWET (Betriever database)
- Scientific Measurement and Evaluation Programme (WMEP)
- LWT (Chamber of Agriculture)
- Electric Power Research Institute (EPRI)

The list of components that data is available for, in at least two of the databases, is:

- Hub
- Blades
- Generator
- Electrical System
- Control System
- Drive Train
- Sensors
- Gears
- Mechanical Brakes
- Hydraulics

- Yaw System
- Structure
- Axle
- Air Brake
- Gearbox
- Meteorological Instrumentation
- Inverter
- Instrumentation
- Entire Unit

For each database the sum of all failure rates is called “Total”. As with the LSA, two types of failure are simulated. The first (failure Type 1) requires the technicians and a CTV. This makes up the majority of the failures. The second is a failure requiring a specialised HLV with an external sub-contracted workforce to repair the failure (failure Type 2) and is a smaller proportion of the total failures. At this point, it is necessary to consider what proportion of the failures are Type 1 or Type 2. Industrial experience is lacking of the proportion of failure rates that result in repairs requiring a HLV. It is found in a study data of 1500 WTGs in the WMEP database that the division between major failures and minor failures is 75% to 25% (Faulstich et al., 2011). The definition of major failure is one where the associated downtime is greater than a day. This result is similar to assumptions of major /minor split made in the DOWEC concept study has been made (Van Bussel & Zaaijer, 2001). The split is assumed to be 75% of failures result in minor repairs and 25% result in major repairs. The results of a recent study into approximately 350 offshore WTGs support this assumption (Carroll, Mcdonald, et al., 2015). The research finds an average number of failures per WTG per year of 8.3 failures, 76% of which results in minor repairs, 13% results in major repairs and the remainder is unclassifiable. For this study, the difference between major and minor is based on costs.

The failure rates are transformed to MTBF so that a random sample using the Poisson distribution can be generated using the MATLAB® Poisson random number function *Poissrnd* (MATLAB, 2015). This function generates a vector of random numbers of size m according to the Poisson distribution with a mean parameter of λ.

The value λ is the MTBF and m is the size of the population and is equal to original database population. These randomly generated populations are called “pseudo-populations”. Using the Poisson distribution, it is assumed that all failure events that occur within the population are independent events. This provides a weighting to the size of the databases and a view of the level of agreement between the databases. Figure 5-13 to Figure 5-17 show the histograms of the random populations generated by the *Poissrnd* functions. Each component is shown on a figure and each database shown in different colours. Figure 5-13 to Figure 5-17 show the failure events for failure Type 1 but failure Type 2 results are generated in the same way. The histogram of yaw system time to failure, Figure 5-13, shows that the LWT, VTT, Betriever Databasis, and Wind Energie databases agree on a mean time to failure of approximately 10 years, which overlaps the lower tail of the Danish Energy Agency databases and the upper tail of the WMEP database. The early WTG models from the Californian EPRI database are less reliable; a trend seen for all components. The Driftuppföljning database has more reliable yaw system than other databases.

The gearboxes in the EPRI database, again, are the least reliable WTGs. The Wind Energie and Danish Energy Agency database stand out with the largest population and the population mean time to failure differing by 10 years.

The electrical system in all of the databases, the mean time to failure is 10 years or below. For the populations of the yaw systems and gearboxes, whilst the mean time to failures are different, the pseudo-distributions overlap to some degree. There are a few components that result in disparate populations. There is broad agreement between the Betriever database and Danish Energy Agency database at 32 years MTBF but these are separate from the WMEP, LWT and Windenergie databases where the mean of the mean time to failure values are 7 years, 10 years and 12 years respectfully.

For some of the components, the resulting distributions are different between the databases; particularly for the control system. This may be because of the inconsistency of how the data is collected or how it is categorised into different components. See Section 2.5.2 for information on this issue.

For the control system, there is agreement between the LWT and the Windenergie population. As with the other components, the Driftuppföljning provides higher MTBF. But the results from Danish Energy Agency are significantly more reliable, with a higher mean time to failure. For the other components, whilst the mean time to failure are separate, the population tails tend to overlap somewhat. However, for the control system, there is a 50 year gap. Interestingly, some of the trends that have occurred between the databases for other components have not occurred here. In other components, the Driftuppföljning database has the highest mean time to failure. However for the control system, the highest mean time to failure is provided by the Danish Energy Agency database.

Similar to the control system, the majority of the databases report mean time to failure below 50 years and a significantly different result from a different database, however, unlike the control system, it is the Driftuppföljning database that provides this result. The pseudo-population generation is done similarly for failure rates requiring major repairs.

The TTF events from all of the databases are combined into one population for each component, and converted back into failure events on a failure per year basis. Here the distributions are provided for the components that the screening analysis has concluded are important and for failure Type 1:

- Yaw System
- Control System
- Gearbox
- Electrical System
- Blades

For these populations, the log-normal fit function from MATLAB® is used to get an estimated distribution of the component failure rates.

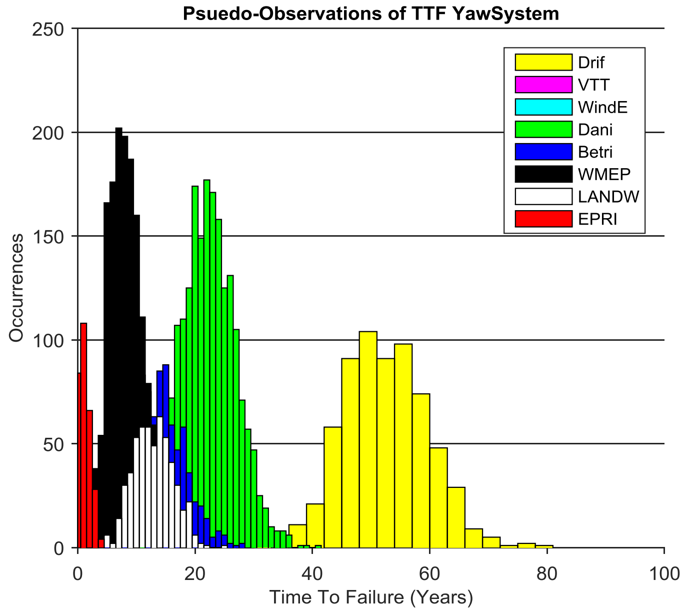


Figure 5-13: Histogram of pseudo-observations of time to failure of Yaw System

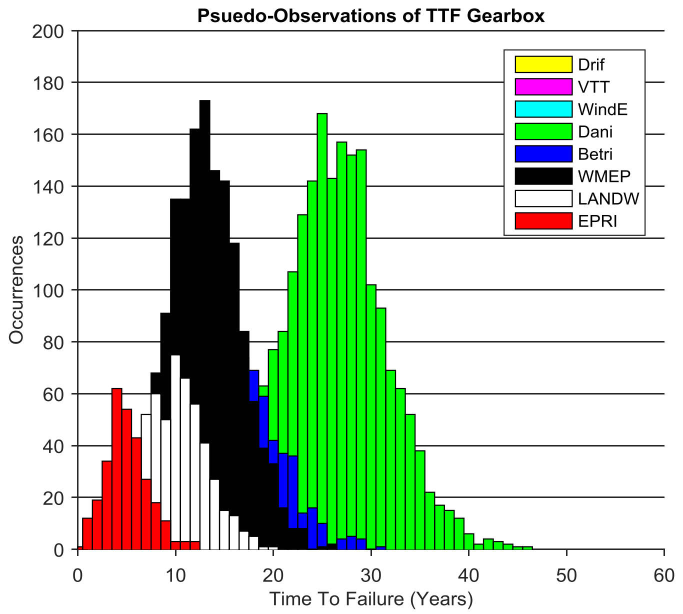


Figure 5-14: Histogram of pseudo-observations of time to failure of Gearbox

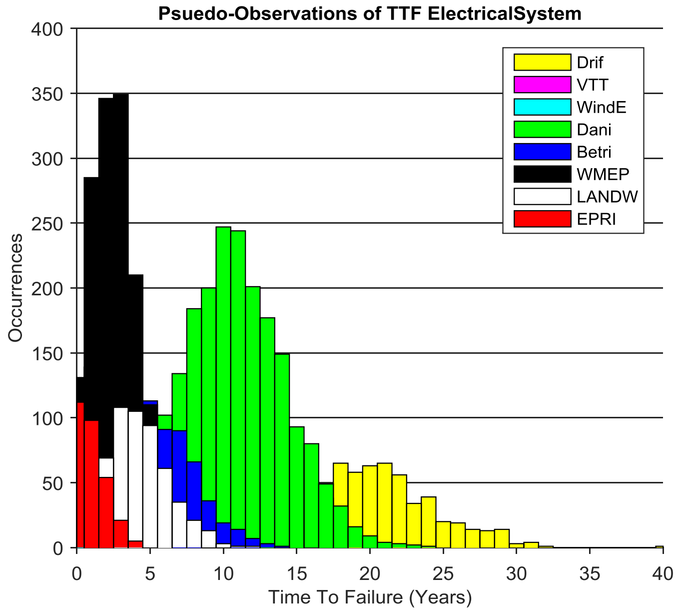


Figure 5-15: Histogram of pseudo-observations of time to failure of Electrical System

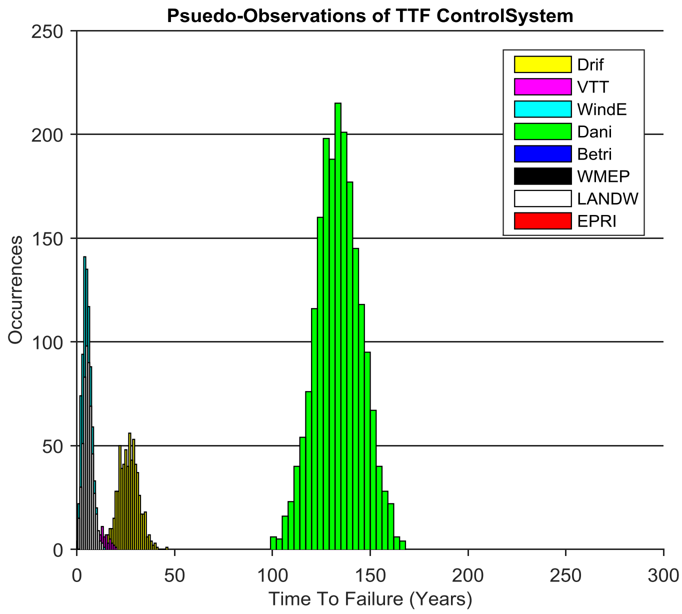


Figure 5-16: Histogram of pseudo-observations of time to failure of Control System

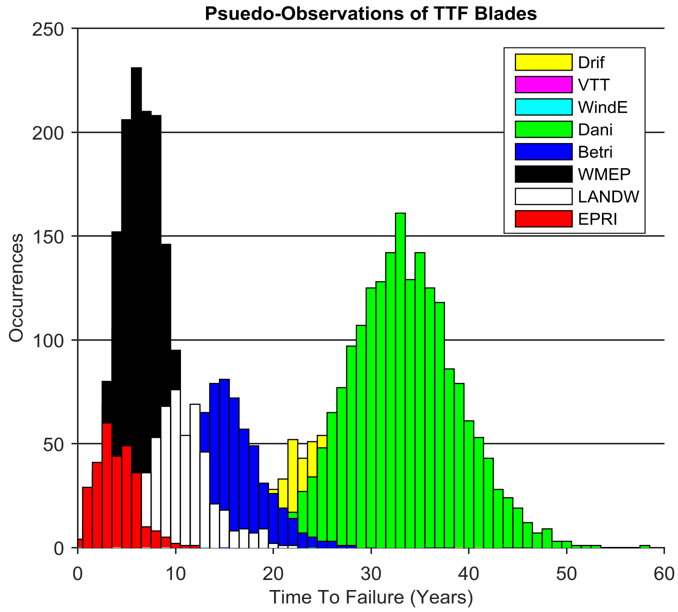


Figure 5-17: Histogram of pseudo-observations of time to failure of Blades

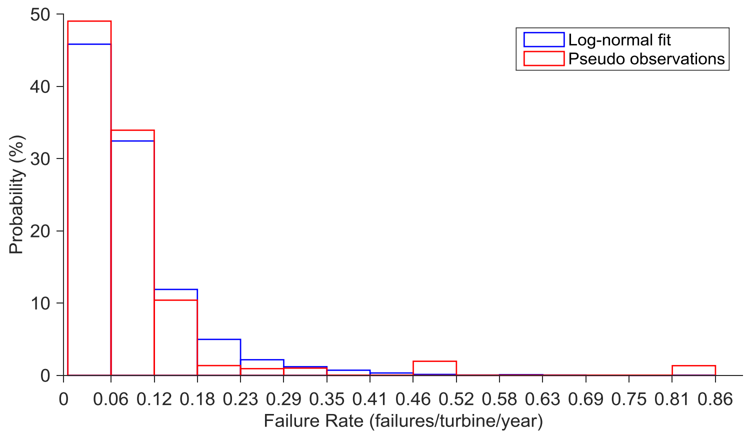


Figure 5-18: Distribution of failure rates for yaw system from combined pseudo-observations and log-normal fit.

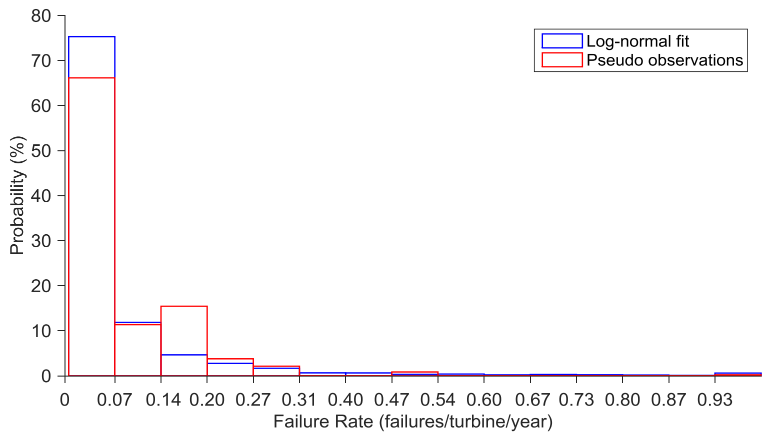


Figure 5-19: Distribution of failure rates for control system from combined pseudo-observations and log-normal fit.

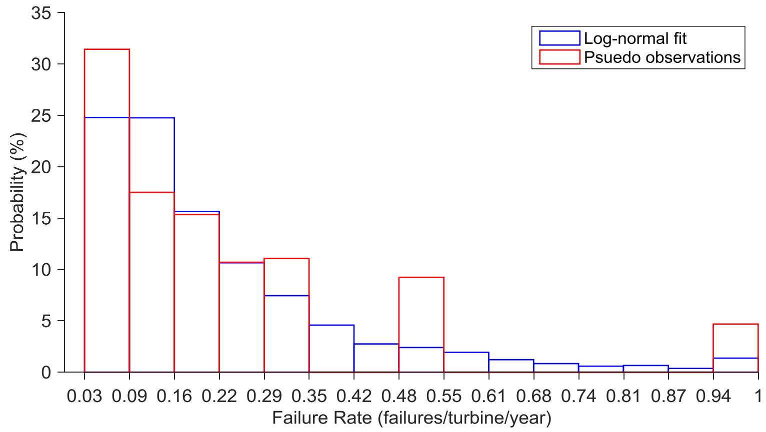


Figure 5-20: Distribution of failure rates for electrical system from combined pseudo-observations (red) and log-normal fit (blue).

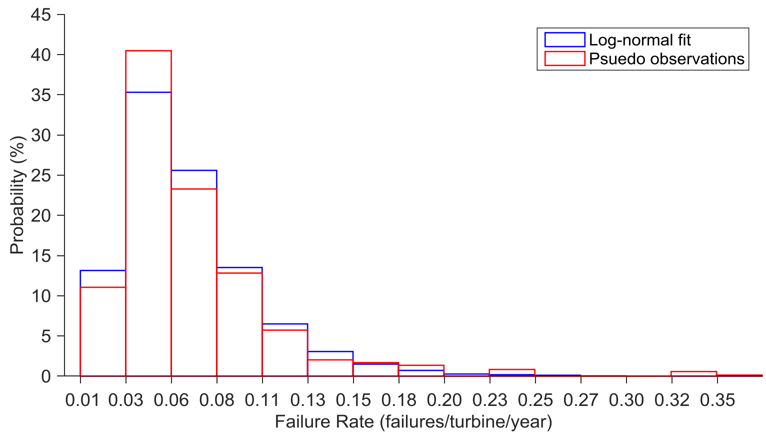


Figure 5-21: Distribution of failure rates for Gearbox from combined pseudo-observations and log-normal fit.

For the yaw system of failure rates of Type 1, there is a reasonable amount of agreement between the two. The original pseudo-population is shown in red and the randomly generated from the μ and σ of the log-normal fit is shown in blue. This fit may underestimate the failure rate, particularly above 0.2 failures per WTG per year.

For the control system, the wide expanse between the database populations means that the log-normal fit may underestimate the failure rates from 0.1 but overestimate the failure rates that occur between the two distinct distributions and the very lowest failure rates.

The distribution of the electrical failure rates from the pseudo-population is very discrete beyond failure rates greater than 0.24, from which the log-normal distribution does not fit very well.

The log-normal fit for the gearbox approximated the distribution well but again underestimates the higher failure rates due the discrete nature of the higher pseudo-populations.

5.5.10 Gearbox Repair Costs: Grade 4

The costs for repair of WTG gearboxes cannot be taken from real experience as T1 is still in warrantee so no repairs have been conducted by the consulted operator. Thus, information of repair costs needs to be found from industry. In the LSA, the repair cost for failure Type 1 is identified as influential for the total cost of both cases. The repair costs for Type 1 failures are spent on subcomponents and consumables, in order to bring the component back to a functional state. These subcomponents are bearings and ancillary systems for lubrication and cooling (Burton et al., 2011). As with the LSA, the best source of information on gearbox repair costs is the report for onshore winds farms compiled by DNV Renewables for the NREL in the United States (Martin-Tretton et al., 2012).

The cost data is from the component parts list supplied by the WTG manufactures supplying to the US market. The data is split between two classes: 1.5 MW to 2.0 MW, and 2.1 MW to 3.0 MW. The capacity of the WTG in the GSA is 8 MW. As these machines are produced in lower volumes than the 2 MW to 3 MW WTGs, they may have a disproportionally high unit cost for repairs and replacements. As there are very few 8 MW capacity turbines currently operating, how the repair costs increase with capacity is unknown so the cost information from the 2.1 MW – 3 MW WTGs is used. The data is compiled between the years of 2005 and 2010. The contributing manufacturers are GE Wind, Vestas, Siemens, Mitsubishi, Gamesa, Suzlon, Nordex and other smaller manufacturers. There is no information on the probability distribution but the survey does provide the mean, highest and lowest value. The uniform distribution is taken for 2.1 MW to 3 MW WTGs using the minimum and maximum values. The gearbox costs are broken down to:

- Gears and bearings
- Bearings
- Lube pumps
- Cooling fans and gearbox cooling systems

For the failure Type 1, where repairs are conducted on small sub-components such as the pumps or cooling system, the costs are \$1,000 to \$9,000. Converted to pounds and from 2010 prices this is between £644 and £5,800. The wind operator company consulted is asked to verify this range as likely.

5.5.11 Balance of Plant Availability: Grade 6

Very little information is available on the possible distribution of BoP availability of OWFs at this time. The SPARTA project has begun to collect and consolidate data from UK OWFs on the number of repair actions of BoP on a monthly basis however no information has been reported on the length of downtime associated with those repairs. As detailed analysis is unavailable, a uniform distributions between 95 % and 100 % availability of the BoP is chosen. This is a reduction from the inputs for the screening as the BoP availability had a very strong main effect on the output, a result expected by the model developers. This value is revisited after discussions with operators, and the original 90 % to 100 % is considered too conservative in the LSA. The range is reduced to better reflect reality. To sense-check between this assumption and reality, the corresponding MTTR for given BoP MTBF is found at different availability levels. The MTTR is considered to be all downtime after the failure, including repair times and waiting for weather windows.

The SPARTA project has 12 months' worth of monthly failure rates for the BoP of UK OWFs that have been contributing to the database. This value is the number of repairs conducted to the foundations, inter-array cables, offshore and onshore substation facilities divided by the total number of WTGs contributing to the population that month. The drawbacks of using these values is that the population is unknown, can vary over the months according to the wind farms contributing data and the result is a single statistic which represents different technologies. The average value in terms of MTBF is 27.9 months for any of the BoP components (when considering them a single component type). Using the definition of commercial availability:

$$A_{time} = \frac{MTBF - MTTR}{MTBF} \qquad [30]$$

The MTTR required to reach that availability level for a given MTBF can be found from:

$$MTTR = -1 \times (A_{time} \times MTBF) - MTBF \quad [31]$$

A selection of MTBF is taken from the SPARTA database, the minimum, maximum and mean, and the availability levels of 95 %, 96 %, 97 %, 98 % and 99%. Using the mean MTBF value, the MTTR to reach availabilities of 95% - 99% would be between 43 days to 9 days. For the maximum MTBF, the estimated MTTR would be between 127 days and 26 days and for the minimum MTBF, the range of expected MTTR is 13 days.

Whilst it is hard to use these values for developing a distribution of possible BoP availability values, it can be seen that, using the very small amount of data available, the assumptions used are appropriate, i.e. that for 95% availability, a long period of downtime (between 14 and 127 days) is expected, and for high availability, shorter down time (3 days to 9 days) is expected.

5.5.12 Operation Duration for Failure Type 2: Grade 8

As with previous inputs related to requiring HLVs, as there is no experience with operations of these vessels yet, so there is no basis from which to establish a distribution from. An example of one operation, the time taken for lifting a nacelle during the installation of a WTG, is provided by Thomsen 2014 as an estimation of five hours, the preparation time before the lifting operations is one hour, and jacking down is 30 minutes.

For this input a discrete set of operation times is defined as 10 to 40 hours in intervals of 10 hours. It is assumed that the sequence of events for replacement of a failed component is similar to the installation of the component as noted by Thomsen 2014, but the time duration is approximately doubled:

1. Vessel arrives on site and positions next to the WTG
2. Jacking up if using a jack-up vessel
3. Attaching the crane hoist to the components
4. Unbolting the damaged component from the nacelle
5. Lifting and hoisting down of damaged component
6. Fixing of damaged component to the deck
7. Securing new component to crane
8. Hoisting and positioning of new component

9. Bolting new component
10. Commissioning of new component
11. Jacking down of vessel (if using a jack up vessel) and removal from WTG vicinity
12. Re-energising of WTG.

5.5.13 Daily Charter Rate of HLV: Grade 8

The daily rate of the HLV vessel is taken from analysis of jack up vessels for offshore wind according to the type of charter market by Dalgic et al 2013. Three charter periods have been identified; in the spot market (1-3 months), short term charters (3 months - 1 year) and long term charter (1 year - 20 years). It is assumed that a HLV is only chartered for the time it takes to mobilise the vessel and complete the task rather than a fixed period. As no information is available on the distribution of charter costs, a uniform distribution is assumed between the estimated charter jack-up vessel charter rates on the spot market; £93,000 to £280,000 per day.

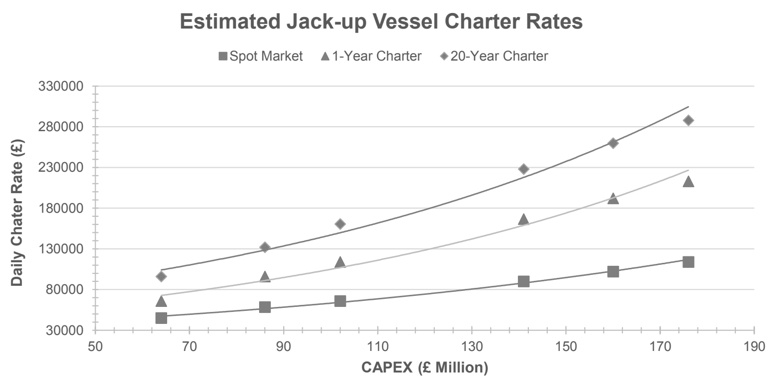


Figure 5-22: Estimated jack-up vessel charter rates for different vessel capex (Yalcin Dalgic et al., 2013)

5.5.14 Fixed Annual Helicopter Costs: Grade 9

There is one OWF in the UK that regularly uses a helicopter to transfer the technicians to the WTGs. This is the Greater Gabbard OWF, operated by Scottish Power Renewables. Other OWFs in Europe also use helicopters, Horns Rev I, Alpha Ventus and Global Tech 1 (Drwiega, 2013). Other than these, the majority of OWFs do not use helicopters as their part of the daily maintenance strategies. Therefore there is not enough information to put together a probability distribution. The source of information used to devise a distribution is taken from UK Air Ambulance charities as the helicopter type is the same used for OWF; the Eurocopter EC-135. Charities are required to publish annual accounts on the Charity Commission website (Charity

Commission, 2015). Between 2010 and 2013, there are 17 air ambulance charities operating in the UK. Helicopter costs are not described in detail. It is assumed that all operating costs for the helicopters; fuel, maintenance, staff, licenses and hangarage is included as well as costs for the specialist paramedic staff and equipment. The average call out across all the charities is two to three times per day. The average distance travelled is unknown. The figure below shows the annual operating costs for a single air ambulance helicopter. The minimum cost is £472,000 per year and the highest is £2,924,000. There is a mean increase in annual operation costs of £189,000 from 2010 to 2011, £146,000 from 2011 to 2012 and £151,000 from 2012 to 2013.

Figure 5-23 shows the distribution of the annual operating costs across all of the years. From this distribution, the probabilities are entered as discrete values and weights according to this distribution.

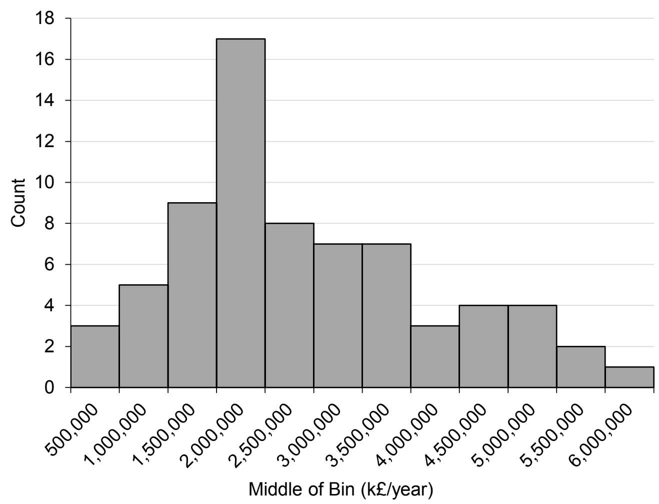


Figure 5-23: Distribution of annual helicopter costs

5.5.15 Planning Delay for Failure Type 2: Grade 10

The planning delay for the repair operations where a HLV is required, is usually longer than the repair operation time itself. In reality, it may take time for technicians to diagnose a failure type and recognise that a major replacement will need to take place. This could mean weeks of testing and failure analysis. There are not many records available in the public domain, of the breakdown of failure downtime in to the constituent parts including planning. However, one example is provided by DBB Jack-Up Services Ltd, where the time from diagnostics to the end of the planning and preparation stage is approximately 83 days (The Crown Estate, 2014).

Once a course of repair action is decided upon then the planning can begin. Incorporated into repair planning is the identification and chartering of an adequate vessel; identifying and ordering the replacement component; identifying any other expertise that is required to complete the repair. The choice of vessel will depend on the weight of the component, the height at which it needs to be lifted to, the vessel deck capacity if more than one replacement is taking place, the water depth at the WTG and what vessels are available. The repair action may be delayed until the meteorological conditions are more tenable so that there is lower probability of incurring weather delays. The Crown Estate, in their report on jack-up vessel optimisation (The Crown Estate, 2014), have defined the process further to:

- Project planning
- Project consent
- Contract negotiation
- Technical information exchange between the operators and the vessel supplier
- Contractor audit and inspection of the vessel
- Detailed planning
- Final project approval

This planning component can contribute to the majority of downtime, hence why it is selected in the results from the screening analysis.

For the purpose of the model, the diagnostic period is combined into the planning stage so the total planning delay for each failure begins from when the fault occurs up to the point of departure for the vessel to the site for the maintenance operation. This means that the mobilisation time for the vessel runs concurrently to the planning stage, as well as the lead time for the component. This planning delay is constant throughout the year, each year of the project and insensitive to external factors such as demand. Without further information, the input distribution applied is uniform around this value from 60 days to 90 days.

5.5.16 Maximum Number of Failures Allowed Before Mobilisation of HLV: Grade 10

The model allows for a maximum number of failures allowed before automatic mobilisation of a HLV to be defined. This feature allows for the bundling of repairs requiring heavy lifting capabilities in case of multiple failures. This circumnavigates the planning stage for each failure as it is assumed that planning activities would be the same for multiple WTGs. No information is available on what the maximum number of WTGs could be as there is no experience of this situation within the operations company consulted. Therefore, it is assumed to be proportional to the number of WTGs. The total number of WTGs is multiplied by 0.05 to 0.25 (5% to 25% of the WTG population) in 0.05 steps and rounded to whole WTGs. Each of these values has an equal probability of being in any given sample and is therefore a discrete distribution.

5.5.17 Time to Mobilise HLV: Grade 10

Similar to the maximum number of failures, the distribution of times to mobilise a HLV is unknown as there is no experience of this situation at the operations company consulted, therefore a discrete distribution between 1 day and 5 days is used. This is considered the time, once it has reached the O&M base, to configure the vessel deck for transporting the components, preparation and obtaining provisions. The vessel chartering period and movements are counted in the repair planning factor, which is discussed above.

5.5.18 Subcontracted Workforce Costs: Grade 10

A large operation to remove and replace a component may require extra costs on top of the vessel and component costs. The exact nature of this cost will be heavily dependent on the type of failure. After a component has failed, there will usually be time when diagnostics will take place in order to conduct failure mode analysis and prescribe the course of action. If the WTG is within the warranty period, then this will be conducted by the OEM. However, out of warrantee, it is possible that the operator may use subcontractors with specific expertise, for example, those who have experience in drivetrain components. A subcontractor could also be employed to oversee marine operations for the replacement of the component. Again, there is no experience of this at T1 wind farm. However, a quotation for engineering expertise for drivetrain failure analysis has been provided for other investigation types. The source of this information needs to remain undisclosed as it is commercially sensitive information. The quoted day rate of a lead engineer is £800 per day. For this analysis, it is assumed that three engineers would be required. The total cost of subcontractors depends on the length of time they are engaged on the project so is a factor of the severity of the project. The total subcontractor cost is linked to the repair operation time.

5.6 Results

5.6.1 Introduction

The following are the results of the GSA using the Sobol' method for providing the sample matrix and calculation of the sensitivity indices S_{ij} and $S_{T_{ij}}$. An overview of the input factors values used in the analysis are given in Appendix F. The results are Case 1 from the set of generic wind farms, describe in Martin et al., 2014 and Case 1 and Case 3 as described in Section 3.4.2.1. The cases here identified as Case 1, Case 2 and Case 3. For clarity, Case 1 from the LSA is now Case 2.

Table 5-4: Reminder of Case Names, WTG Number and WTG Capacity for GSA

Case Name	WTG Number	WTG Capacity
Case 1	30	3.6 MW
Case 2	62	8 MW
Case 3	121	8 MW

The sample plots in Figure 5-24, Figure 5-29 and Figure 5-34 show the relationship between the different input factor distributions. These figures can be used to give an overview of the distribution types and how it translates into the sample data. The samples are generated using the SimLab software as specified by the distributions detailed in Section 5.5.

5.6.2 Case 1

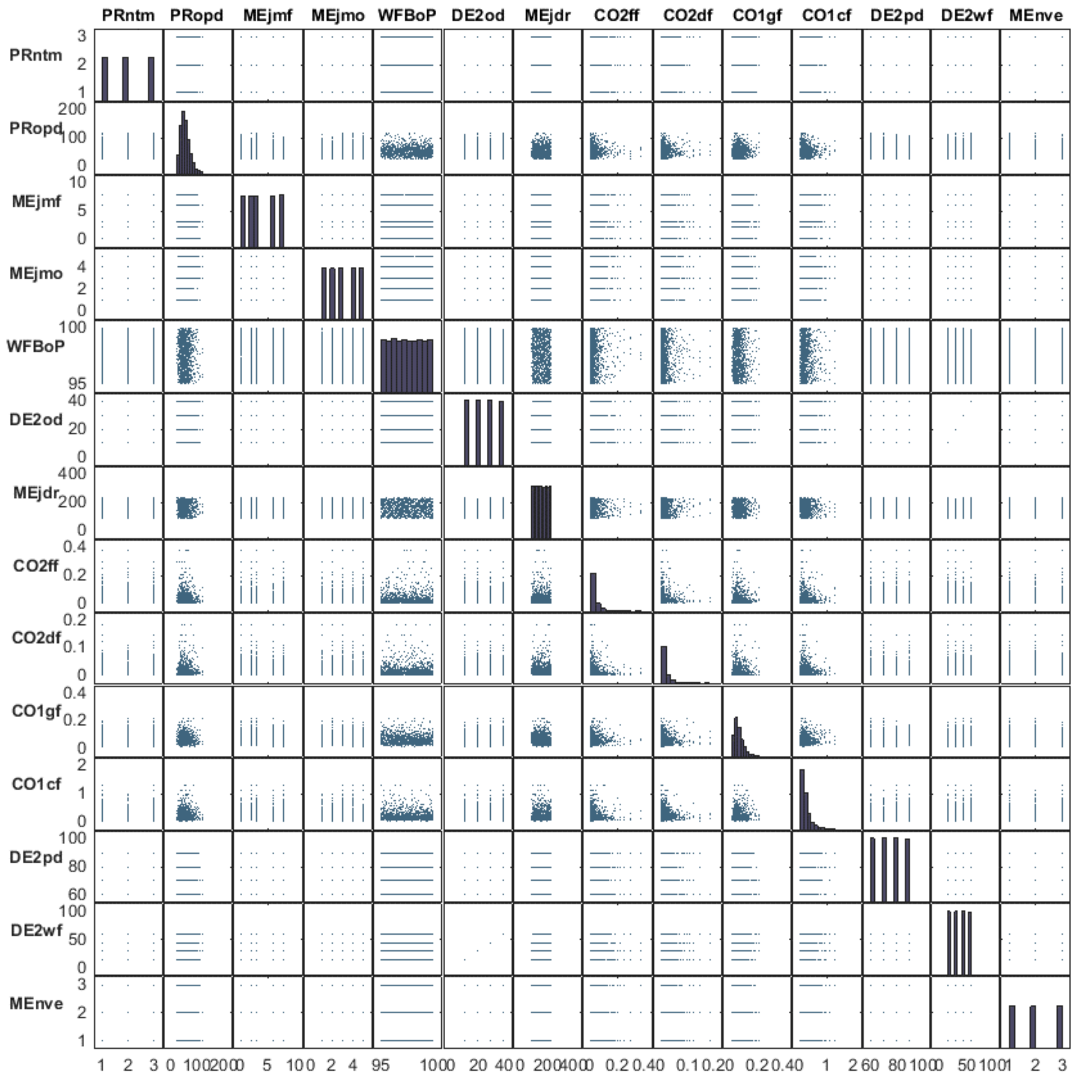


Figure 5-24: Sample distributions of inputs for Case 1

Figure 5-24 is a matrix of scatter plots showing the correlation between all of the inputs used in Case 1. The sample is generated using SimLab framework software and the number of executions set so that $n > k \times 500$. The sampling technique used by the SimLab program is summarized in Section 4.2.3. As $k = 14$, the resulting sample size n is 7168. The distributions in Figure 5-24 are derived from the investigations explained in Section 5.5. The names of the factors are given on the left hand side and also along the top. Eight of the inputs have discrete and/ or uniform inputs, giving rise to a limited set of sample values. The remaining five have more continuous log-normal distributions.

The samples are run through ECUME model through the same methodology as for the LSA; writing the input text files via MATLAB® and calling the model executable. The resulting sample results are stored in MATLAB®. The computations are conducted in parallel on a single laptop. The run-time for this case is approximately 62.4 hours.

Availability

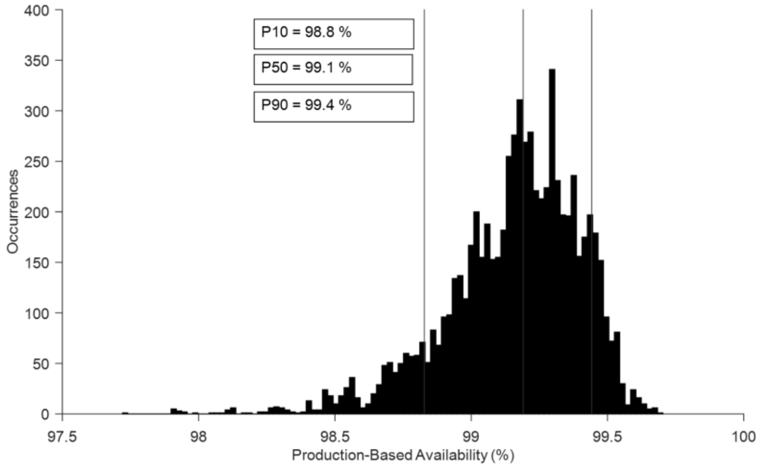


Figure 5-25: Histogram of production-based availability of Case 1

The production-based availability sample results are shown in the histogram in Figure 5-25. The minimum result from the model is 97.7 %, the maximum is 99.7 % and the median is 99.1 %. These values are reasonable for an OWF that is located near to the O&M base.

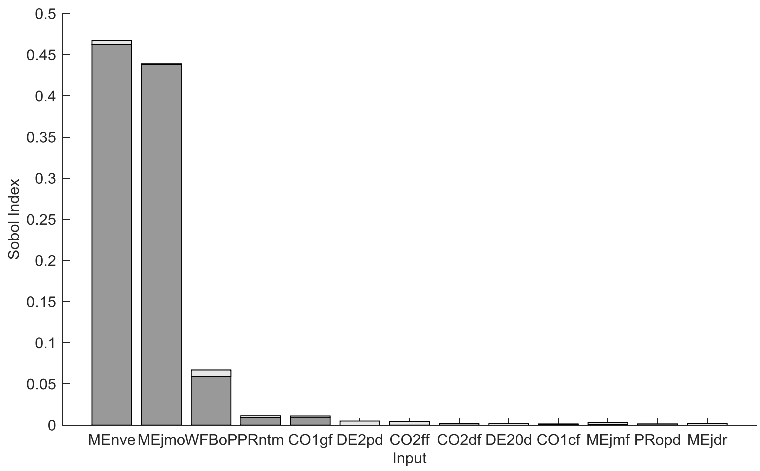


Figure 5-26: Sobol' indices of production-based availability for Case 1, dark grey is 1st order effects and light grey as higher order effects

The calculation of the Sobol' indices are summarised in Section 5.2.2. The indices are calculated using the SimLab software framework and are shown in Table 5-5. Some of the indices result in negative values. This is a result of the choice of sample size (Saltelli et al., 2008). A limitation of the SimLab software is that the maximum number of samples that can be generated is predetermined. In the case of negative values, the indices have been given a zero value.

Table 5-5 shows the Sobol' indices for the 13 inputs on the production-based availability for Case 1. The results are displayed graphically in Figure 5-26. The 1st order effects, S_i, are the main effects of the each input on the output. It is calculated as the fractional contribution to the variance (Chan, Tarantola, & Saltelli, 2000). The second index, S_{T_i}, is the total effect, which is a sum of all the variance contributions of the factor on the output. The difference between the total effect and the 1st order effect is caused through interactions with other factors. The SimLab framework provides S_i and S_{T_i}. The dark grey bar shows S_i and the lighter grey shows the interactions $S_{T_i} - S_i$. The factors are then ordered, left to right, in descending order according to S_{T_i}. The contribution of each input factor to the total S_T is given as a percentage in the far right column.

Table 5-5: Sobol' indices of availability for Case 1

Factor Names	S_i	S_T	$S_{T_i} - S_i$	S_T (%)
MEnve	0.4627	0.4671	0.0044	46.6%
MEjmo	0.4381	0.4390	0.0009	43.8%
WFBoP	0.0669	0.0592	0.0000	5.9%
PRntm	0.0093	0.0113	0.0020	1.1%
CO1gf	0.0097	0.0111	0.0014	1.1%
DE2pd	0.0000	0.0050	0.0050	0.5%
CO2ff	0.0000	0.0042	0.0042	0.4%
CO2df	0.0000	0.0018	0.0018	0.2%
DE20d	0.0000	0.0017	0.0017	0.2%
CO1cf	0.0012	0.0013	0.0001	0.1%
MEjmf	0.0029	0.0006	0.0000	0.1%
PRopd	0.0013	0.0001	0.0000	0.0%
MEjdr	0.0019	0.0000	0.0000	0.0%

Of the 13 inputs, the highest index is provided by the number of CTV vessels available to transport technicians and equipment to the WTGs. For Case 1, the number of vessels is varied between one, two and three. From Figure 5-25, the O&M system does not appear to be under stress in terms of production-based availability. By this it is meant that the availability of the system does not go below a limit to indicate that the OWF is performing unsatisfactorily. The high S_i for number of CTVs indicates that, for this case, increase in performance of the wind farm is directly linked to the number of vessels. So the more vessels that are available to provide technicians to the wind farm, the more failures that can be fixed in a given period of time.

The second most important effect is the mobilisation time for a HLV when a severe failure occurs. The factor is varied between one and five days. There is a little interaction between this factor and the rates of the Type 2 failures.

The third important factor showing a significant effect on the production-based availability is the BoP availability. The reduction of the effect of the BoP availability when compared to the results from the LSA is due to the revision of the input distribution from between 90% and 100% to between 95% and 100%. Even with this revision, there is a notable effect on the end availability. There is a part of S_T that cannot be explained by the first order effects.

In the LSA, there is an indication of the importance of factors but no quantification of how important those factors are in relation to each other. With the Sobol' indices, quantification is now possible. The LSA can be compared to the Sobol' indices with regards to the ranking. For Case 1, the top list of importance factors (Martin et al., 2014) are identified as:

- PRntm	Number of teams required to conduct annual service
- PRopd	Operation time for annual service
- MEjmf	Maximum number of failures before the mobilisation of a HLV
- MEjmo	Time to mobilise a HLV
- WFbop	Availability of BoP

The number of CTV vessels is not highlighted in the results of the LSA. However, the Sobol' indices shows that it is, in fact, the most important input factor. The reasons for its inclusion in the LSA is because of its clear importance on the cost output, rather than the production-based availability. This demonstrates a possible weakness in the arbitrary nature of the Morris Method for selection of important input factors. The number of teams required to conduct the annual service is actually the fourth most important factor in production-based availability as opposed to the main one detected in the LSA. Similarly, the operational time to conduct the annual servicing has been reduced from one of the most important factors to a minimal effect. This, maybe, in part due to the revision in the input distributions between the LSA and GSA.

What is consistent between the analyses is that the effect of the variance of component failure rates for both failure Type 1 and failure Type 2 are minimal. For OWFs that are close to the O&M port and have relatively few WTGs, 30 in this case, the availability is much more affected by the operators response to failures rather than the frequency of failures themselves.

The input factors can be categorised into two sets; factors that are directly controllable by the operations team of an OWF, and those that are not. Controllable factors include number of vessels contracted, number of technicians available and deployed, and the number of failures allow to occur before the automatic mobilisation of a HLV. Those that are uncontrollable are due to stochastic processes such as failure rates, or are decisions of external contractors. Using S_T, the percentage of variance that is controllable from an operator is 47.8% and 52.2% is uncontrollable. The results of this implies that, from an operator's point of view, the operational and strategic decisions will have approximately half of the total influence on the availability.

Costs

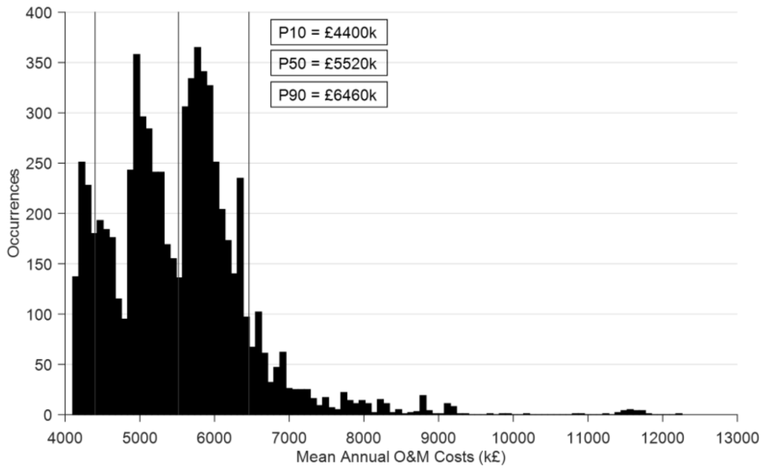


Figure 5-27: Histogram of annual mean O&M costs of Case1

The sample results for the mean annual O&M costs are shown in Figure 5-27. The range of results is from £4m per year to approximately £12m. This equates to approximately £130,000 to £400,000 per WTG per year. This result is similar to the results of the cases in section 4.3.5. There are three distinct peaks in the results. The bin centres of these peaks are £4.2m; £4.9m and £5.8m. It is likely that the cause of this is an input factor with a distribution with three discrete entries, therefore, either the number of teams conducting the annual servicing or the number of CTV vessels available, as seen by the input distributions in Figure 5-24. The results of the GSA are shown in Figure 5-28.

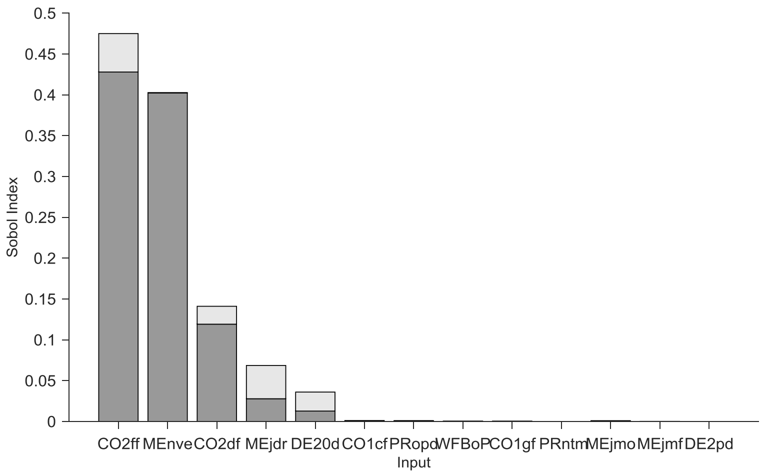


Figure 5-28: Sobol' sensitivity indices for annual O&M cost, dark grey is 1st order effects and light grey as higher order effects

Table 5-6: Sobol' indices of Annual O&M costs for Case 1

Factor Names	S_i	S_T	$S_{T_i} - S_i$	S_T (%)
CO2ff	0.4279	0.4750	0.0471	42.2%
MEnve	0.4022	0.4027	0.0005	35.7%
CO2df	0.1192	0.1411	0.0219	12.5%
MEjdr	0.0279	0.0686	0.0407	6.1%
DE20d	0.0128	0.0360	0.0233	3.2%
CO1cf	0.0000	0.0012	0.0012	0.1%
PRopd	0.0008	0.0009	0.0000	0.1%
WFBoP	0.0000	0.0005	0.0005	0.0%
CO1gf	0.0000	0.0005	0.0005	0.0%
PRntm	0.0000	0.0000	0.0000	0.0%
MEjmo	0.0000	0.0000	0.0000	0.0%
MEjmf	0.0000	0.0000	0.0000	0.0%
DE2pd	0.0000	0.0000	0.0000	0.0%

For the annual O&M cost the most important factor is the failure rate of the yaw system, resulting in component replacement. When considering the mean of the input distribution the estimated failure rates of the yaw system resulted in approximately 1.15 a year in a ten year project. The average cost from the NREL database of component costs had replacement costs for yaw systems, including motors of approximately £9,000, therefore the financial implication comes from the mobilisation cost for the vessel and its day rate, which is ranked fourth in the importance factors relating to cost. The failure rate of the control system input factor is also important but the mean failure rate is lower than for the yaw system. This is also interacting with the vessel day rate too and the mobilisation costs to effect the variance in the costs. Also part of this interaction is the operation duration to repair the yaw system or the control system, which is linked strongly to the vessel daily rate.

The second most important factor however is the number of CTV vessels. There is almost no interaction with other factors so can be considered purely additive on the costs. The fixed annual vessel cost is £750,000. This corresponds to the difference between the distinct peaks in Figure 5-27, which are £740,000 and £810,000. In terms of cost, each successive addition of vessels increases the costs. However, the availability is also affected by the number of vessels, thus a factor that has been identified as pivotal in the balance between achieving the lowest O&M costs whilst retaining the highest availability.

For the costs, this time, only 35% of the variance is due in part to controllable factors from the point of view of the operator. Whereas 64.3% of the variance is from stochastic processes or other activities out of the operators' control.

In comparison to the LSA, the results of the GSA are similar. However the ranking of the factors has changed. The HLV day rate and the operation duration still rank highly however the failure rates are higher. The workforce cost shows minimal importance after the revision of the input factors. Also the number of vessels has increased its importance.

5.6.3 Case 2

As with the previous cases, Case 2 consists of a mixture of continuous and discrete random samplings. In the LSA, Case 2 is based one half of a proposed OWF. For the GSA it is considered an independent wind farm. For this GSA, 15,360 model executions are performed.

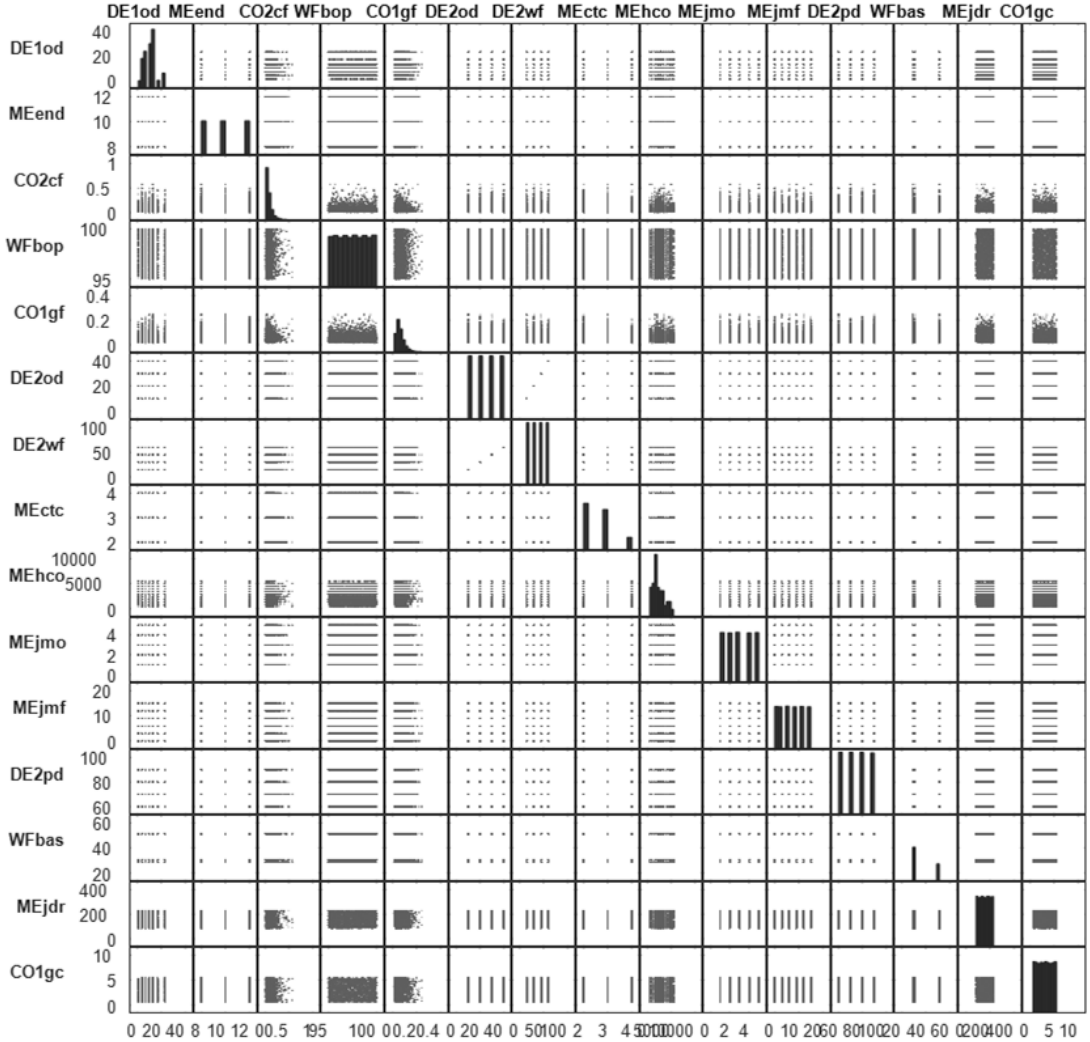


Figure 5-29: Sample plot for Case 2 Sobol' input distributions

Availability

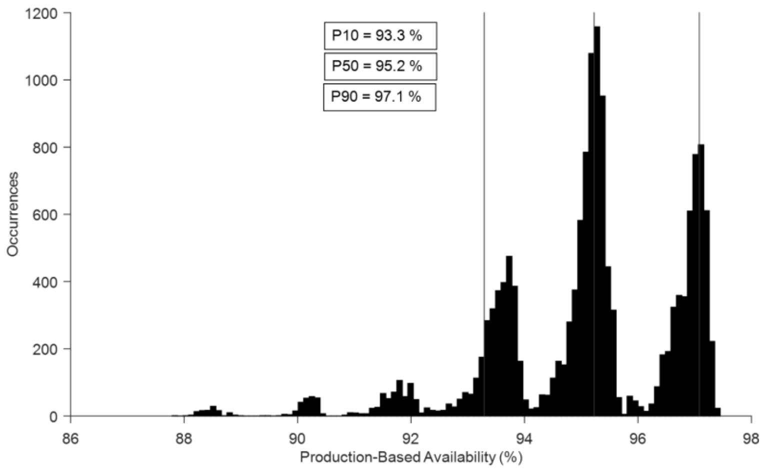


Figure 5-30: Histogram of the distribution of availability for Case 2

Figure 5-30 is a histogram of the availability results from Case 2. It is immediately obvious that an input factor with six or seven discrete values is impacting the availability as six peaks are visible. The minimum availability is 87.8% and the maximum is 97.45% with a mean value of 95.2%. These results are favourable as the wind farm is located 30 km to 50 km away from a selection of potential ports. The six distinct peak availabilities are at 88.4%, 90.2%, 91.8%, 93.7% 95.3% and 97.1%. The difference between each of the peaks ranges from 1.6% to 1.8% (Faulstich et al., 2011).

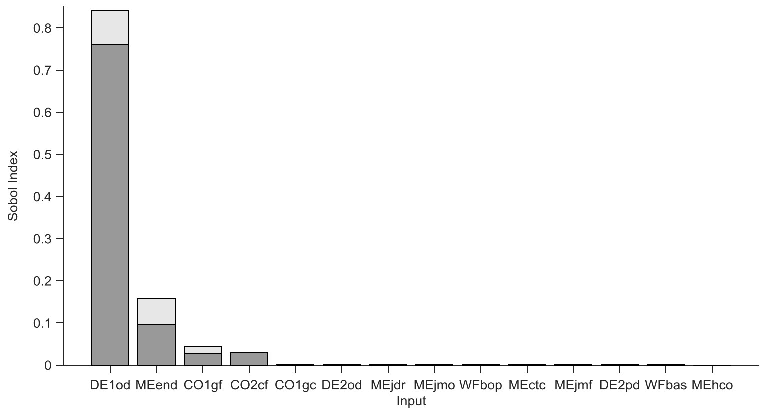


Figure 5-31: Sobol' indices for the availability of Case 2

Figure 5-31 shows the Sobol' indices for the availability of Case 2. The most important factor on the production-based availability is the operation duration of the failure Type 1, followed by the length of shift. The next factors that have registered an effect are the failure rate for major repairs of the electrical system and minor repairs of the gearbox.

Returning to the most important input factor, for the operation duration of repairs for failure Type 1, there are seven different operation durations which appears to be shown in the histogram in Figure 5-9. The operation duration has 80% of the variance in the production-based availability. The duration in real life will depend on failed component and the failure mode. If the peaks in the availability histogram are related to the decreasing operation duration, then, with all other inputs remaining fixed, with a mean fixed value of 13 hours would yield a mean annual availability of 90% or above.

Table 5-7: Sobol' indices of Annual O&M Availability for Case 2

Factor Names	S_i	S_T	$S_{T_i} - S_i$	S_T (%)
DE1od	0.7612	0.8404	0.0792	77.2%
MEend	0.0953	0.1582	0.0629	14.5%
CO1gf	0.0278	0.0445	0.0167	4.1%
CO2cf	0.0302	0.0310	0.0008	2.9%
CO1gc	0.0016	0.0024	0.0008	0.2%
DE2od	0.0000	0.0023	0.0023	0.2%
MEjdr	0.0000	0.0021	0.0021	0.2%
MEjmo	0.0000	0.0018	0.0018	0.2%
WFbop	0.0000	0.0015	0.0015	0.1%
MEctc	0.0000	0.0012	0.0012	0.1%
MEjmf	0.0000	0.0012	0.0012	0.1%
DE2pd	0.0000	0.0011	0.0011	0.1%
WFbas	0.0000	0.0006	0.0006	0.1%
MEhco	0.0000	0.0002	0.0002	0.0%

Costs

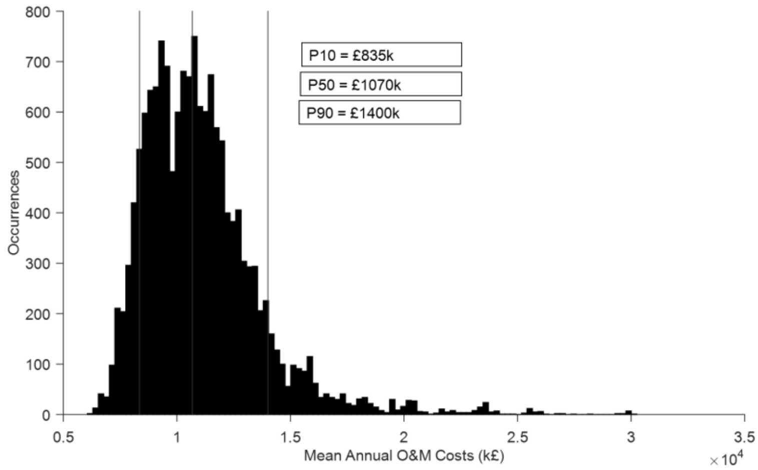


Figure 5-32: Histogram of cost results for Case 2

The range of annual costs is between £6,000,000, which is £97,000 per WTG, and £30,000,000 which is £488,000 per WTG. The mean cost is £10,000,000 per year which is £178,000 per WTG. There is distribution similar to a log-normal distribution.

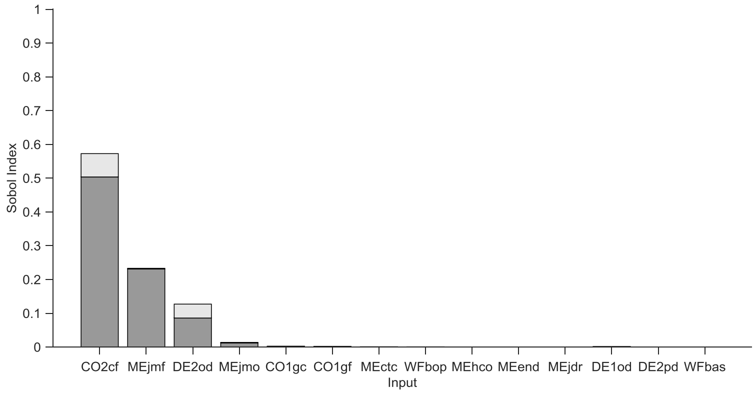


Figure 5-33: Sobol' indices of costs for Case 2

Table 5-8: Sobol' indices of Annual O&M costs for Case 2

Factor Names	S_i	S_T	$S_{T_i} - S_i$	S_T (%)
CO2cf	0.5037	0.5727	0.0690	60.0%
MEjmf	0.2314	0.2332	0.0018	24.4%
DE2od	0.0860	0.1272	0.0412	13.3%
MEjmo	0.0123	0.0138	0.0015	1.4%
CO1gc	0.0016	0.0026	0.0011	0.3%
CO1gf	0.0000	0.0021	0.0021	0.2%
MEctc	0.0000	0.0010	0.0010	0.1%
WFbop	0.0001	0.0007	0.0006	0.1%
MEhco	0.0000	0.0004	0.0004	0.0%
MEend	0.0000	0.0002	0.0002	0.0%
MEjdr	0.0000	0.0001	0.0001	0.0%
DE1od	0.0000	0.0000	0.0000	0.0%
DE2pd	0.0000	0.0000	0.0000	0.0%
WFbas	0.0000	0.0000	0.0000	0.0%

The most important factor for the costs in Case 2 is the failure rate of the electrical system, resulting in major repair operations, contributing to 60% of the total variance experienced in the GSA. The next important input factor is the number of failures allowed before the automatic mobilisation of a vessel. The third most important input factor is the operation duration of the repair for major failures. A marginal effect is contributed by the mobilisation time for HLV. The rest of the inputs are seen to be negligible.

The failure rate and the operation duration interact to affect the total costs as when multiplied results in the days that an HLV are required for (not including weather related downtime), which is multiplied by the vessel day rate.

5.6.4 Case 3

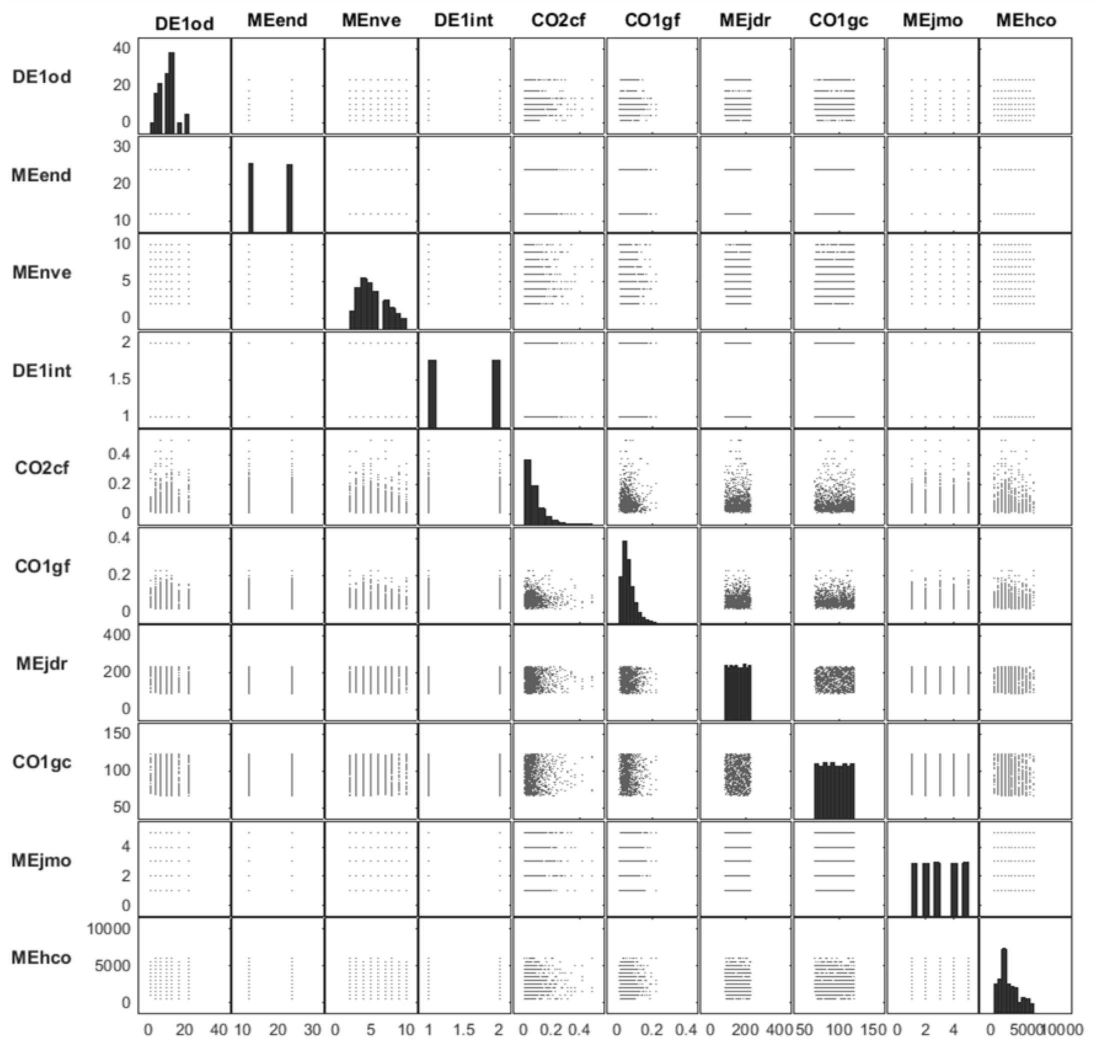


Figure 5-34: Sample plot for NB3 Sobol' input distributions

The sample plot matrix in Figure 5-34 shows the sample distribution of the ten input factors for Case 3. Six of the factors have continuous distributions, either generated from log-normal distributions or probability functions. Two factors have continuous uniform input distributions. Three of the factors have discrete input distributions, two of which are comprised of only two values. Again, using the SimLab framework 5613 samples are created and executed in the model.

Availability

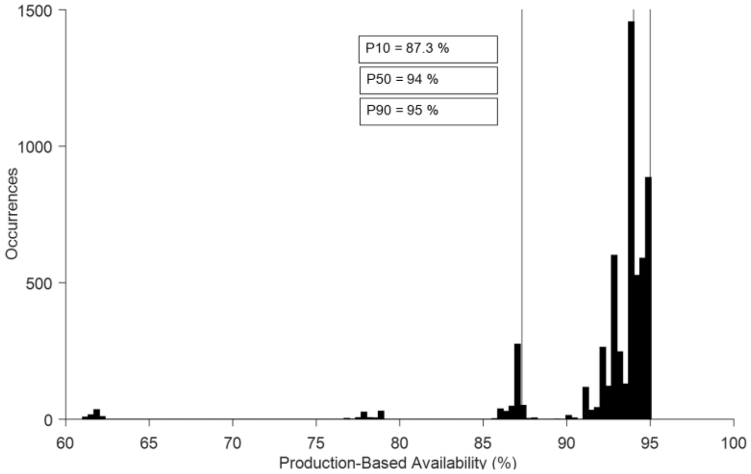


Figure 5-35: Histogram of production-based availability for NB3

The results from of the production-based availability ranges from 61% to 95.05%. There are small clusters of results around 62 %, 79 % and 87 % but over 90% of the model executions result in availabilities greater than 90 %. The peak of results occur between 93.7 % and 94 %. This is a reasonable expectation of an OWF that is located more than 50 km from the O&M port without accommodation base offshore.

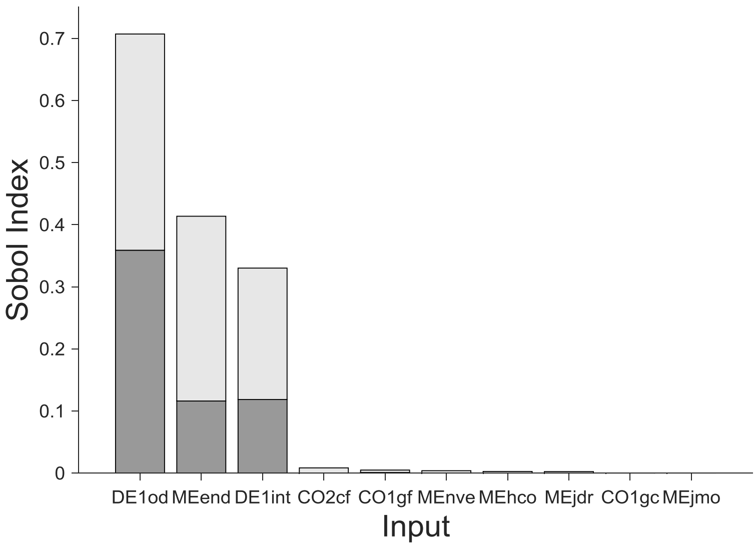


Figure 5-36: Sobol' sensitivity indices for availability for Case 3 dark grey is 1st order effects and light grey as higher order effects

Table 5-9: Sobol' sensitivity indices for availability

Factor Names	S_i	S_T	$S_{T_i} - S_i$	S_T (%)
DE1od	0.3588	0.7071	0.3482	48.0%
MEend	0.1160	0.4136	0.2976	28.1%
DE1int	0.1184	0.3301	0.2117	22.4%
CO2cf	0.0000	0.0083	0.0083	0.6%
CO1gf	0.0009	0.0048	0.0039	0.3%
MEnve	0.0000	0.0038	0.0038	0.3%
MEhco	0.0000	0.0026	0.0026	0.2%
MEjdr	0.0000	0.0023	0.0023	0.2%
CO1gc	0.0000	0.0000	0.0000	0.0%
MEjmo	0.0000	0.0000	0.0000	0.0%

The most important factors are the operation duration for repair of failure Type 1, the length of shift and the number of teams that are required for repair. In the case of an OWF further from the O&M port with more WTGs, the routine operations are dominant. In this case, the variance in the availability is, in part, affected by the interactions between three input factors. For the shift length and the number of teams, the majority of the variance is attributed to interaction with other input factors. The shift strategy is varied between 12 hours and 24 hours and the number of teams required is one and two teams. These factors are important because of the OWF's remote location from the O&M port. With travelling to and from the farm included in the shift, therefore extending the operations to 24 hour working allows for more repairs to be conducted, providing other resources are available. Similarly, reducing the amount of technicians needed for a routine repair means that the number of repairs that can be attended to simultaneously increases. The failure rates themselves are not influencing the availability.

In this set of inputs, the only factors that the operations team have control over are the number of vessels and the shift strategy, therefore they only have control over 28.3 % of the variance in availability when the WTGs are in warranty. If an operator has taken charge of the maintenance then the majority of the variance will be under their control.

This analysis has produced similar results to the LSA. The three top factors are the same but the influence of the number of vessels available has reduced. This may due to the switch to the 24 hour working strategy.

Costs

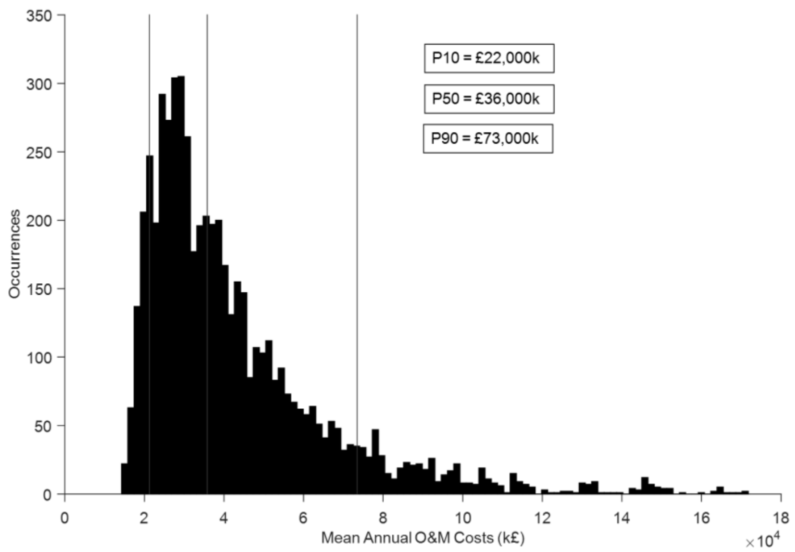


Figure 5-37: Histogram of mean annual O&M costs for Case 3 case

Figure 5-37 shows the sample results of costs from the Case 3. The annual O&M costs range from £20,000,000 to £180,000,000 which is £165,289 to £1,487,000 per WTG per year. The P50 is £241,000 per WTG per year. From the initial scenario analysis on the same case, the crew boats and helicopters scenario resulted in direct costs of £185,000 per WTG annually, therefore potentially an under estimate of the total costs that an OWF may face. The distribution appears to be similar to a log-normal, therefore indicates that the cost is heavily influenced by an input factor with the same distribution. From Figure 5-34, there are two input factors which have similar distribution to Figure 5-37: CO2cf and CO1gf, the electrical system failure rate and the gearbox failure rate.

The Sobol' indices show that the variance in the O&M cost is, indeed, overwhelmingly influenced by the failure rates of the electrical system, the component with the highest estimated mean failure rate. The reason for this strong influence is because of the large number of WTGs, 121 in this case, which results in multiple failures per year each requiring a HLV and incurring repair costs. The fixed repair costs for the electrical system, according to the NREL database of component costs, is £18,000 per failure. This does not contribute much to the total O&M costs. The daily charter rate for a HLV has minimal influence on the variance of costs so it is likely to be the fixed mobilisation costs for HLV that are causing the strong influence. The results reflect those of the LSA however the magnitude of the influence of the electrical system failure rate may have been underestimated using the Morris Method. The results of the costs from case 3 are not shown graphically as it is debatable as to whether the electrical system requires a HLV for each failure generated as most of the components can be reached internally.

5.6.5 Case Comparison

As with the LSA, by introducing the analysis in three separate cases, the variation in the key input factors is revealed. These important results would have been lost if the analysis had been conducted on truly global analysis (where no separation of cases had been done).

When comparing Case 2 to Case 3, the failure rate of the electrical system for major repairs is still the most important factor but not as overwhelming. This supports the idea that OWF with more WTGs will result in stronger influence of failure rates resulting in major repairs in the total costs.

The importance of the operation duration for routine repairs is similar to the results from Case 3, although more so for Case 3. The main effect is 50% of higher order effects for Case 3 when compared to Case 2. Actually, all of the input factors have demonstrated more main effects in Case 2. An interesting result is that cases with more WTGs have more interaction between the effects.

5.7 Conclusions

Sensitivity analysis is a well-known approach to obtain information on uncertainty of input factors in a computer model as it can quantify the effect of input variance on the output variance.

A review of SA methods and their applications to other models is performed. It is found that the main criteria for choosing a method is based on two parameters; the number of input factors and the desired information from the analysis. The more input factors in the analysis, the more computationally intensive the analysis is, the so called "curse of dimensionality". An approach to performing complex SA on models with a large number of input factors is to identify the most important ones using a LSA followed by a more complex GSA. A LSA is conducted using the Morris method on three cases of OWF. The amount of inputs is reduced from 115 to approximately 14. The factors that are significant are not the same across all cases with different numbers of turbines. Likewise, the important input factors are not the same for the costs and availability. Using the results of the LSA, three further cases are defined, two from the LSA and one from a LSA conducted in Martin, 2014.

The input distributions of 17 input factors are identified in Section 5.5. The input distributions are graded according to the quality of source of information. The primary source of data is an operational OWF. Differences between the model assumptions and real life operations are highlighted. Some input factors, such as the number of teams required to repair a component or the duration of repair operations and annual servicing are fixed throughout the project lifetime in the model, whereas in real life they are variable.

The Sobol' method for GSA is used to quantify the variability of the uncertainty in the inputs on the cost and availability. The majority of the variance in the outputs are dominated by three or less input factors. The exception to this is in the costs of Case 3, which is dominated by one input factor; the failure rate of the electrical system. This input factor is a component with a high failure rate, low repair costs but creates multiple HLV mobilisations. The conclusions of this analysis are that the uncertainty of cost and availability are contributed to by three or so constituents but which inputs they are is specific to the OWF. For this reason, a GSA needs to be conducted for each OWF individually. Also seen from the analysis, it is not just one research area that dominates uncertainty, say turbine reliability or vessel operations, but a combination.

6 Discussion of Results

As aspects of OWF O&M are variable and subject to stochastic processes or through inexperience in the field, an approach to handle uncertainty is to identify how much the variance of these aspects affect the cost and availability. A computer model has been created to calculate costs and availability. In Chapter 3, the model is introduced, the capabilities explored through scenario analysis and compared with other models. In Chapter 4, the effect of uncertainty of the input variance is quantified for a set of cases using complex SA methods. This chapter recaps the findings from Chapters 0 and 3.4.4, interprets and discusses the implications from two stand points; that of the model user and that of an OWF operator.

6.1 Case studies

Chapter 3 provides the exercises that have been conducted in order to verify ECUME's suitability for application of LSA and GSA. The results of which can also say something about the industry as a whole. Four methods of the model validation suggested by Sargent 2013 are used. The descriptions of the types can be found in Chapter 3:

- Comparison to other models
- Event Validity
- Face Validity
- Historical validation

The first year of operation of an existing wind farm is modelled as closely as possible. The results are discussed with the operators to ensure that they are representative of real costs and availability. The average annual time-based availability is found to be 0.8% compared to the measured technical availability of the first year. The model is unable to replicate the monthly availability accurately. A cost comparison is done by the operations teams and verified to be accurate. The information from the first year is used to extrapolate the results out by 20 years. The scenario is of where the operator took over the maintenance and servicing activities from the OEM after five years and major replacement tasks are introduced after year ten. Due to the relative proximity of the OWF to the O&M base and the low number of WTGs, the operating strategies are limited and did not provide a good case study for scenario analysis. It is only 9 km from the O&M port and the transfer time is approximately 30 minutes. A semi-permanent offshore base for technicians and vessels would represent a vast over-expense.

The scenario analysis of three cases of a pre-consent OWF allows other method validation techniques from the Sargent framework to be implemented, namely those that are part of the model design and run processes; animation, data relation correctness, face validity and internal validity. These cases included information specific to the study site such as the WTG capacity, number and site location. The model is at its most useful when assessing the effect of scenario changes on the operations of the OWF to support decision making. This study is chosen in addition to the operational project because few decisions on the O&M has been taken, allowing for a greater number of operational scenarios to be investigated.

An important result of the scenario analysis is the way costs and availability interact with regards to the overall profitability of the project. When the financial cost of unavailability is taken into account, the scenarios that have increased availability are more profitable. The effect of the change in sale price of electricity on the total costs (direct and indirect) can be demonstrated in the diagrams shown in Figure 6-1 to Figure 6-3. The dashed line show an approximate intercept (the lowest point between the maximum and minimum total costs) of the cases. From these graphs it can be deduced that, for Case 1, the use of motherships is the most profitable option from a fixed sale price of electricity of £65 /MWh upwards. The use of helicopters in addition to CTVs only poses a viable solution beyond £90/ MWh. Case 2 is similar to the first, save for it being slightly smaller in terms of number of WTGs and the centre of the wind farm is further from the O&M base. When comparing Figure 6-1 and Figure 6-2, it can be seen that there is a significant change in the location of the intercept to £85/ MWh. The same trend is observed where the most profitable solution is the CTVs only up to the intercept. Between approximately £70 /MWh and £115 /MWh, helicopters become the most profitable but the margin between that and CTVs alone is small. For the third case, the use of CTVs is limited to when the sale price of electricity is £35 /MWh or less.

It is difficult to make generalised, global remarks from these cases, as small changes in the fixed OWF attributes, such as WTG number and distance from the

O&M port, can change the end result. It is this simple study which results in the quest to explore multiple cases rather than seek a universal solution in the SA. Each set of sensitivity analysis results are applicable to the case under investigation.

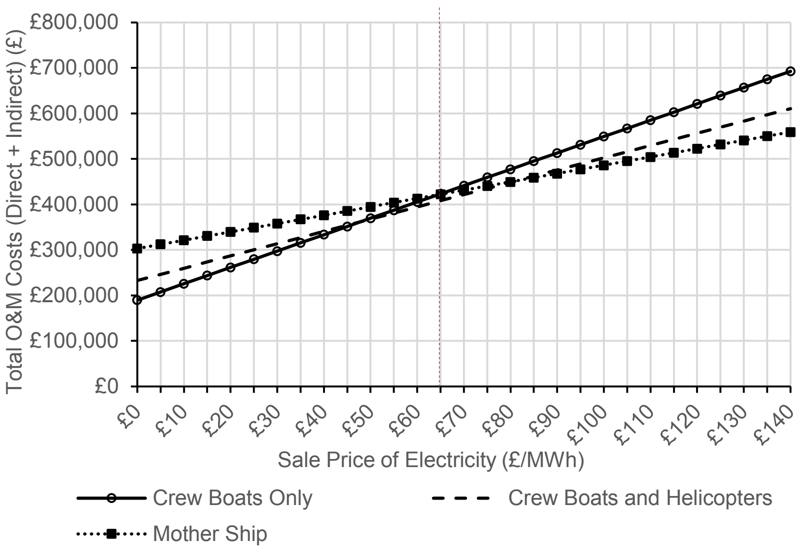


Figure 6-1: Diagram of sensitivity of total O&M costs to the fixed sale price of electricity for Case 1

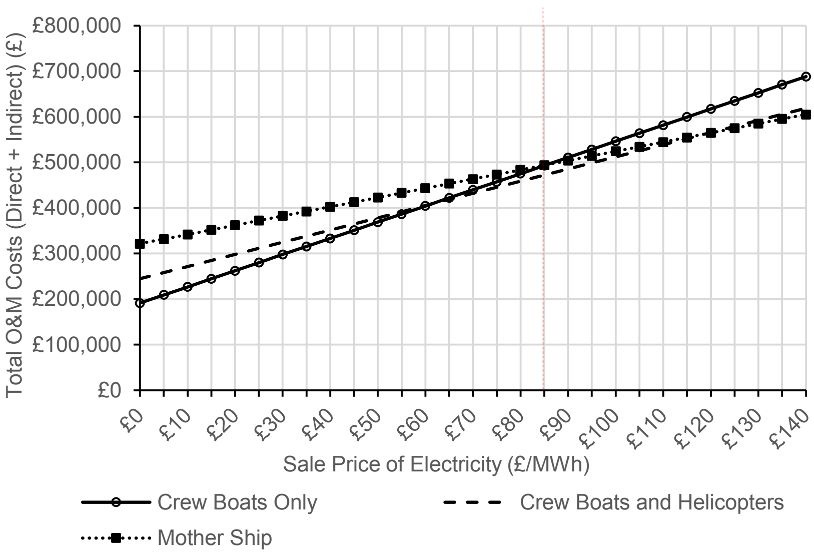


Figure 6-2: Diagram of sensitivity of total O&M costs to the fixed sale price of electricity for Case 2

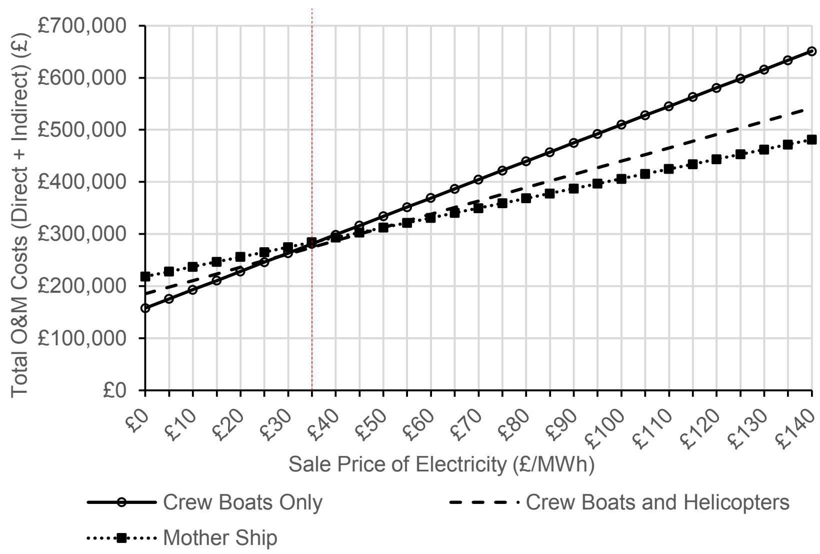


Figure 6-3: Diagram of sensitivity of total O&M costs to the fixed sale price of electricity for Case 3

The ECUME model is compared with four other similar models using a non-site-specific test case. This case is defined through discussions within the group of researchers to be representative of a Round 3 type OWF. It consists of 80 WTGs with a capacity of 3 MW. In addition to the test case, ten further cases are run to investigate the sensitivity of each model to the change in factors. The additional cases investigated changes to the number of CTVs, group failure rates and number of technicians. Some hypothetical scenarios are also explored such as isolating each repair category and exploring its effect. There are two outputs; the direct O&M costs for ten years and the annual availability.

The result from the test case are lower annual time-based availabilities than has been observed in the real industry. The average annual availability for the test case ranges between 80.8 % and 84.4 %, similar to the first years of operations at the initial UK OWFs (Busfield, 2010). What would be expected, for a OWF in it's useful life period, would be average availabilities closer to those currently observed at greater than 90% (Tavner, 2012). It is concluded that the reduced availability is due to the harsh weather data (annual average wind velocity 9.8 m/s and average significant wave height of 1.4 m) and the distance from O&M port (50 km). Only CTVs are considered to be serving the OWF to conduct routine maintenance. With a travelling speed of 20 knots, each vessel travelling to the site each shift would require 2 hours and 40 minutes out of a 12 hour shift to transport technicians. As the analysis in Section 4.3.6 and

Section 5.6 suggests, OWFs that are located at this distance from shore would benefit in terms of availability, from having offshore based technicians closer to the site. Not reported in the original journal paper (Dinwoodie et al., 2015) is the estimated costs per MWh from each model, which ranged between £16 /MWh and £30 /MWh. It is important to consider that the costs in this study are only for technicians, repairs and vessels. Insurance, BoP and fixed onshore costs are not considered. If compared against the estimates in Figure 2-2, it can be seen that ECUME produces values that are within the range of many of the studies, yet the range between the models is quite large. The results for the annual direct costs for the test case are between £181,000 and £315,000 per WTG.

This study conducts an OAT SA, with setting three input factors (number of CTVs, number of technicians, grouping of component failure rates) on two levels, as well as factor fixing, at zero, all of the repair types except one in turn. The results cannot provide detailed information on how the outputs, direct costs and time-based availability are influenced by these factors.

The subsequent cases found that the differences in the outputs between the models are attributed to the internal decision logic of the models, which are based on the current practises of different operators. Discussions between the researchers found that the models took different approaches with regards to the charter lengths of the HLVs, the number of tasks that could be conducted in parallel, how the meteorological data is processed within the simulations and how tasks are divided between the technicians. This result shows that it is not only the inputs that effect outputs but also the internal parameters of the model, as shown in Section 2.6.3. For this reason, a model cannot produce a truly universal results from SA.

6.2 Input Uncertainty and Sensitivity

A significant portion of the work undertaken in this thesis is to investigate the uncertainty surrounding the inputs into O&M for use in the LSA and GSA. For the LSA, as there are over 100 unique inputs. Uniform and discrete distributions are used after identifying the likely maximum values and minimum values expected to be encountered for the particular case. After the LSA, the number of inputs is reduced to

13 to 15 variables for each case. This allows for more focus on distribution identification.

The sources of information used in the analysis are wide-ranging. A process to find the best information available is defined and with it, a hierarchy of data quality established.

The primary objective of this work is to provide the required distributions to the GSA but another result is to provide an overview of current OWF O&M practises as it stands.

6.2.1 Annual Service Campaigns

It is found that the number of technicians deployed to a single WTG for annual servicing campaign fluctuates on a daily basis depending on demand or technician availability. In the model, the input is fixed throughout the project lifetime. An approximation of the fixed number of WTGs had to be made based on the average number of technicians deployed to a single WTG. This means that the model is not able to match the same dynamic management decisions that are used on site. This is visible in Figure 5-12, which is that the number of teams for annual servicing is flexible rather than fixed. The model could result in slightly higher costs than reality due to additional salaries, although this is not important to the results of the GSA as the model averages over the year. In the end, the results of the GSA show a minimal effect of the number of preventative maintenance teams for availability and negligible effect for costs.

The first campaign cycle of annual service from the operational wind farm is used to estimate the number of technician hours to conduct annual servicing for each WTG. It is found that the total time for each WTG is variable. The model, on the other hand requires a fixed value for the entire project lifetime. The implications for the GSA are that if the mean number of hours to conduct annual servicing in reality is lower than the fixed input value for the model, the resultant simulated availability would be lower as the downtime will be longer. From the data available it is hard to decipher why the length of time taken to conduct the service may vary but a reduction in time spent on annual servicing can be seen when ordered by start date, suggesting that a learning curve may be involved. Other possible reasons are limitation of available technicians when they are required for corrective maintenance. This would not translate to the model, however, as the teams who perform correct maintenance are separate to those who perform preventative maintenance. The results of the GSA shows a negligible effect on the availability due to changing the length of annual maintenance, therefore this inconsistency between real processes and model processes will not affect the result of the sensitivity analysis.

6.2.2 Vessels

Limited information is available about the mobilization of HLVs for repairs at OWFs. This is because it is not recorded or reported on an industry wide scale, suggesting that it is not foreseen as an important part in the downtime of OWFs. The input values used are based on this author’s experience of the preparation of a single large dynamic positioning vessel deck for installation of a pile foundation for a tidal device. More needs to be done in order to identify the distribution of possible values to validate the assumptions. The suggestion made here is that mobilisation days of HLVs could be recorded as a future input metric into the SPARTA database. The results from the GSA show that the mobilisation time does have a considerable effect on the availability of Case 1, shown in Section 5.6.2. Case 1 has a turbine population of 30 turbines and 9 of the 24 operating UK OWFs have between 25 and 30 turbines. Consequently, HLV mobilisation time is highlighted here as a key area of further research.

Work has been conducted by Dalgic et al. 2013 at the University of Strathclyde, to consider the future day rates of large vessels. Their efforts have been utilised here, although no distribution is offered. It is found that the day rate has an effect on the Case 1 costs, in Section 5.6.2. This is not the largest effect but it does interact with the operational duration for repairs and the failure rate. It is not unexpected that the costs of vessels are influencing the total costs of smaller wind farms. As about 50% of the influence comes from the interaction with other factors, this means that reduction in uncertainty using large vessel day rates is only part of the solution. It has to be considered in conjunction with failure rate reduction and operation duration reduction.

It is revealed in Section 5.5.5, that the ratio of CTVs to WTG is 0.03 for the majority of the 18 UK OWF studied. From this small population, a distribution is fitted. The number of CTVs available for Case 1 is the dominant effect on the availability and the second most dominant effect for the costs. There is little interaction with other inputs in both outputs. This is a key result in the context of identifying areas to simultaneously reduce cost and increase availability. Apart from the number of CTVs, there are no input factors which simultaneously affect both the cost and availability for a single case. As there is a lack of interaction with other inputs, it is assumed that the relation between CTVs and costs is linear, that the more CTVs there are, then the greater the O&M costs will be and that is an additive input. Likewise, it is assumed that there is an inverse linear relationship between number of CTVs and availability; that increased CTVs provides an opportunity for more teams to reach the wind farm and achieve more simultaneous repairs.

The survey of O&M vessels is limited to the UK OWFs, although it can have been extended to other European wind farms to gain a larger source of information. As the UK has 55% of the European OWFs installed capacity, it is deemed representative of Europe. As the survey is conducted manually and therefore time intensive, an improvement could be to develop a way to use the information from the marine traffic websites to conduct the surveys automatically and expand to other European markets. Another limitation is that potential seasonality in the number of CTVs is not captured as part of this survey. Automation of the survey could lead to a time interval where this information can be captured.

6.2.3 Balance of Plant Availability

Little information is found during the investigation into BoP availability for OWFs. An estimate is made based on what information is found from the industry. Recorded information in the private SPARTA database is used to validate it, to a point. The main result is that OWFs can expect to see between 2.7 to 8.5 days lost per year due to the loss of BoP functionality and their repair. Unfortunately, the results from SPARTA are not detailed enough to provide which aspects of BoP cause downtime or the actual average length of the incidents. In one of the GSA case results, BoP availability is ranked third in the Case 1 availability but contributed only 13 % to the total sensitivity.

6.2.4 Failures and Repair Operations

As there is no information in the sources in Appendix B, on the actual observed distributions of time to failures, just average failure rates, pseudo-populations of WTG failures are created based on the number of WTGs with an assumed distribution using reliability theory. By combining the all the generated data for each component into one population, the pseudo-populations are weighted according to the original database.

The WTGs in the databases are older technologies and models. The effect of possible recent developments in condition monitoring technology and advanced operational practices may not be represented. Therefore, the solutions offered as part of this discussion could have already been implemented.

From the results, the major failure have repeatedly come out as more significant compared to minor repairs. As expressed before, information regarding the proportion of major failures to the total is missing therefore a fixed split is attributed to every components' mean failure rate. However one of the results of Carroll et al. 2015 is how the severity of failure (based on cost) changed on a component basis. An improvement to the SA would be to incorporate the new information from Carroll et al. into the study.

The split of minor and major repairs of the total number of failures appears to be around 75% minor and 25% major. This is broadly supported through several independent investigations however the criteria for classification of what constitutes minor and major is different in each study. One study of large datasets of onshore WTGs uses repair time. One study into offshore WTGs uses repair costs. The vessel requirement has dictated the classification in this study but as the independent studies have produce similar results, the 75 % /25 % split seems appropriate.

It is found, after creating pseudo-populations from the aggregated data of real WTG failure rates, that there are occasionally dissimilar results between the populations. This caused the fitting of probability distributions to be difficult, as shown by the comparison of the pseudo-data and poly-normal fit in the electrical system in Figure 5-20. However, without a comprehensive dataset of multiple populations of WTG failures, this is found to be the best approach to gauge the uncertainty around failure rates on a component level. Furthermore, important for this study, it produces probability distributions of mean failure rates based on large datasets of WTGs.

It is found that the failure rate of the yaw system and the control system requiring a major repair is important for costs for Case 1, as seen in Section 5.6.2, confirming that a reduction in the frequency of major failures of the yaw system will result in reduced uncertainty and cost savings. A limitation of using the populations is that improvements to the reliability of the yaw system made by the manufacturer may already be present in this current generation of WTGs. The operators still have options for failure rate reduction through utilising CMSs. For most of the cases, failure rates affected the costs, and have negligible effect on the availability. It is not the systems with high repair costs for replacement that are important but those with the highest failure rates which lead to severe cost penalties through chartering HLVs. Another implication of this result is for those using the O&M computer models. Although, as stated before, these results are only truly applicable to the model in question. Yet, it may be useful for other model developers to see the results of a GSA on their own models. Failure rates are key to executing accurate simulations. This comes back to the importance of continued reliability analysis for offshore WTGs. The publication of real OWT data from Carroll et al. 2015, it means that the uncertainty can reduce slightly.

The fact that it is the access strategy that accounts for the high variance in costs leads to the conclusion that, if operational decisions can make potential major replacements into minor repairs, this would lead to reduction in uncertainty. Whilst how to accomplish this is outside the scope of this study, it is suggested that CMS, improved design or redundancy for electrical systems could help prevent these major replacements being required in the first place. The result of transferring major replacements into minor repairs is an obvious one. In all three cases, failure rates of components that result in replacement affect the cost. For Case 1, it is component F and D (yaw-system and control systems), or Case 2 and Case 3 it is component C, the electrical system. The replacement costs are relatively small compared to some of the other components, between £7,000 and £18,000 for each replacement. The difficulty is that limitations, such as time or budget, could mean that the operator is forced to choose which components or systems to focus on. Here, the GSA has provided clarity that a component or system with high failure rate, but not necessarily the largest repair costs is a candidate for advanced monitoring condition methods.

A shortcoming of this approach is that it cannot be taken for certain that the boundaries of each of the component categories (i.e. gearbox, yaw system, electrical system etc.) are identical for each database.

The planning delay for major repairs is another example of an input factor where not enough information is available to make an accurate distribution of possible values. Only one data point is found relating to OWF repairs. The process shown in Figure 5-6, is taken to use that value as a mean and a uniform distribution is applied.

The GSA indicates that the variance of the planning delay is not significant to the variance in cost or availability. It is believed that the range used for this study is reasonable after discussions with operators and industrial partners. The length of planning delay within these boundaries does not have a significant effect on the costs or availability when compared to the effect of other inputs. However, if new information is presented and the assumption is proved wrong then the analysis will need to be redone to ensure that the conclusion is still correct.

The small amount of information available from the operational OWF is used to establish the length of the operation for routine repairs. The range is found to be between 25 minutes and 22 hours. Such a wide range is understandable as it represents every routine repair type experience during that period of time, unlinked with component. This indicates that the type of failure and repair will impact the variance of the cost and availability. With more time and experience, the operation durations can be linked with the components or the failure modes.

It is found that the duration of the routine repair operations is the dominant factor for Case 3 production-based availability and interacts with the length of shift and the number of teams required to conduct the repair.

Like the mobilisation time for offshore operations, there is not a lot of information available for the repair time when requiring a HLV. The assumption is made that the repair time (not including any weather related downtime) is the same as installing the nacelle but doubled as the failed component is removed and a new one installed and commissioned. Only one length of time value is found in the literature

(The Crown Estate, 2014). This lack of information means that there is no adequate distribution of uncertainty to use in the GSA, only a best estimate. Again the reason for the lack of distribution information is that very little is reported in the public domain and is not in a central database. This factor shows up as having importance for the costs of Case 1. It is not the largest effect but the results indicate some interaction, most likely with the number of failures and the vessel day rate. It has a negligible effect on the availability. Although not in their direct control, this information is important for an operator so that the speed of component repair or replacement can be accounted for in the costs of OWFs located near the O&M port. It could be a consideration that is overlooked through the pre-purchase assessment of WTGs, therefore it would be prudent for an operator to include repair times as a criteria for in the assessment of different options. An avenue for offshore cost reduction can be investigations into the methods and technologies for reduction of repair times for replacement of large components.

6.2.5 Shift Length, Team Number and Operation Duration

As seen in Section 5.5.8, the estimated values used for the length of shift are based on usual working patterns for plant maintenance. It is predicted before the GSA that the length of shift would be significant for the costs and availability for the larger OWFs, located further from the O&M port as increased shift time would result in fewer transfers, more time for repairs but increased number of technicians. However the results show that the input factor has only a significant influence on the availability. The lack of effect on the cost can be explained by the fact that the factors with which the length of shift time would interact with (the total technician number and vessel costs) are eliminated at the screening stage for not having significant effects on the total costs. Therefore the variance of such extra costs does not affect the variance in the cost output. There are a few drawbacks, however, with increasing shift lengths which would not occur in the models; such as a decrease in reliability of vessels if they are being used more and the increase in risk to safety of technicians and assets during transfers if occurring at night.

It is revealed that, in reality, there is variation in the number of technician teams visiting the WTGs on a given day, whereas the model assumes that for each repair type, a fixed number of teams are required to perform the repair action. From the analysis, it is found that the number of technicians is limited between two and four. In the LSA, it is assumed that each team consisted of two members and thus the number of technicians in a WTG would be always an even number. This had to be revised after the analysis as it is shown that on many occasions, as seen in Section 5.5.2, there occasionally are three technicians in the WTG. Therefore, the number of team members is revised to one and team number varied between two and four. The number of teams for the large OWF had an effect on the availability. When more technicians are required for every repair, this is more likely to become a bottleneck for the system with regards to preventing repairs taking place, resulting in extended downtime.

The three way interaction between the operation duration, the number of teams and the end of shift length is considered more in depth here. This interactive effect on the production-based availability is connected to the number of tasks that can be accomplished simultaneously or within a fixed period, as shown in Figure 6-4.

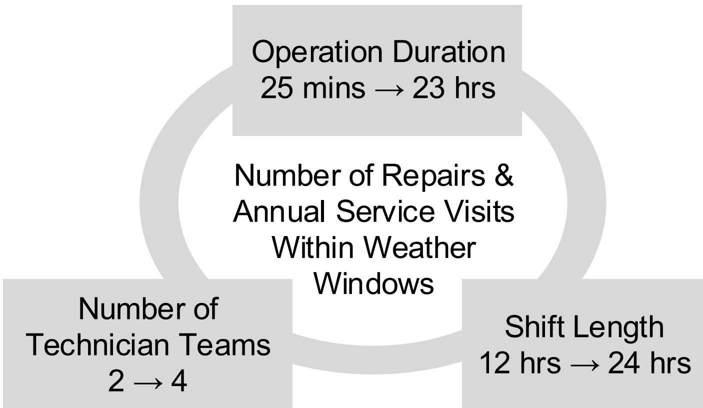


Figure 6-4: Three factor interaction between operation duration, number of teams and shift length

It is advantageous for an operator to be able to conduct multiple repairs in parallel when there are periods of good weather. As shown in the analysis for the input distributions, the results from the GSA show that these parameters are acting in a similar way within the model. The link between the operation duration and the length of shift is the minimum number of repair tasks that can occur with a given shift (if excluding travel time and weather windows). Within the inputs factors defined in the GSA, the number of possible tasks is between 0.5 and 57. This means that, for a given weather window, more WTGs can be brought back to an operational state and downtime minimised. This is particularly important in winter, when the weather windows are shorter and the potential for lost production larger due to high winds. The interaction between the number of teams and the operation duration is similar. With less teams required for each repair task, and given a fixed number of teams available, there is a greater chance for maintenance tasks to be conducted simultaneously within the weather windows and the shift length will either increase or decrease the number of tasks conducted.

As seen in the results between Case 2 and Case 3, the two top most important factors are the same but the level of interaction between those factors is different. As a percentage of the total effects, the level of interaction between the input factors for availability increases with more turbines from 2% in Case 1 to 60 % in Case 3, as more WTGs will increase the complexity. More WTGs will mean that there is more opportunity for simultaneous repair actions.

6.3 Effect of assumptions

In the investigation into the variable inputs in Section 5.5, several of the key inputs were given the least desirable grades (8-10) as there was not enough information available for the analysis in the public or private domain. Information was not available from similar industries which could be transferred across. The lowest graded impact factors were:

- Operation duration
- HLV charter rate
- Helicopter costs
- Planning delay
- Maximum number of failures before chartering HLV
- Time to mobilisation of HLV
- Cost of subcontracted workforce

These have been highlighted in the analysis and discussion. This lack of information has resulted in simplified assumptions being used, although these assumptions are justified as far as possible. Whilst every effort is made to input accurate distributions, the result of this simplification could affect the results. If overly conservative, in terms of the range of the distribution, then the factor could be highlighted as too important as the sampling number is fixed and the differential between each sample point will be too large. Similarly, if the range is too narrow, then this may result in the wrong the conclusion that the factor is not important. If the mean value of the range is too high, then the importance of the factor may be over stated. And if the mean is too low it may be missed as an important factor. In the discussion and conclusions, these factors have been highlighted as areas where, if more information becomes available and a more accurate distribution is found, then the analysis is redone to include this.

The input factors at the more desirable grades (1- 6) are based on information from the first year of a real operating OWF. The ideal source of information would be the full history of operational activity for an entire project lifetime. This would capture:

- a wider range of failure types in terms of severity and components
- the change in rate of failures over time, so mapping to a time based distribution, like the bathtub curve, could be achieved.
- the change in response of operations linked to learning and experience and development of new technology.

Even better would the collection of operational data over project lifetimes of multiple wind farms in various locations. This would capture:

- the effect of location on failure types and operations (such as wind regimes, distance from O&M base)
- the effect of different turbine size, model and number
- the effect of different operational approaches implemented by companies

Having this information would more reliable than the 1 years' worth of data from a single OWF. The data from a single year is extrapolated to 20 years linearly through assuming that it provided the average. The model simulations were then supplemented with additional data for the more severe failure types, not experienced in the 1 year of real operation, with information found in the literature. It is unlikely that this will be a true reflection of the operations at a real wind farm but serves as a starting point. As more information is captured and recorded by the industry via initiatives such as SPARTA and Offshore~WMEP, it can be used to improve the reliability of these assumptions.

6.4 Comparison with External Analysis

There have been few LSAs of OWF computer models with which to compare results, with the exception of Hagen 2013. The results from that study revealed the subgroup of important factors on the O&M costs are failure rate for manual resets, major replacement and minor repairs, HLV costs and the wave limit for a mothership. The base case is similar to the one used in this thesis except that the use of motherships is not considered. The other noticeable difference between the two LSAs is that in Hagen 2013, the failure rate is by WTG basis, not by component. There is a broader range of importance factors, but failure rates of both major replacement and minor repair feature, as well as the mobilisation and daily rates for the jack up vessel /HLV. The important factors on the availability are not reported so cannot be compared.

7 Conclusions

The offshore wind industry in the UK is focused on reaching grid parity with other conventional electricity generating technologies and a cost of energy of £100 /MWh. Whilst development and construction costs make up the largest share of the total life-cycle costs, O&M costs contributes between 14% and 30%. Therefore reduction in expenditure during the operational period is important towards reaching the aims of overall cost reduction. When considering how to manage an OWF to maximise profitability, operators and owners consider the availability of the project as well as cost. Targeted cost reduction in O&M is a multifaceted topic; requiring expertise from multiple research areas such as reliability, meteorology and naval architecture. This project brought these diverse research topics together in order to:

1. Identify the current state of the art regarding the operations of OWFs and challenges that the sector faces.

2. Identify the aspects of O&M that contribute most to the operational costs and the availability of the plant, considering the uncertainty from the inputs in a computer simulation model.

3. Using this information, decrease the uncertainty surrounding those aspects by incorporating field data from current operating OWFs.

7.1 Thesis Summary

The OWF O&M computer model is introduced in Chapter 3, with overviews of its modules and the inputs required to run it. Using a framework of validation techniques suggested by Sargent 2013, the model is verified for use in the subsequent SAs. Concurrently, in Chapter 3, the model capabilities are demonstrated. This confirms the need for a sensitivity analysis from both the operator's and industry's point of view.

To begin with, the first year of operations of an OWF are replicated in the model as close as possible. The outputs of the model are compared with the operations of the real wind farm where data is available. An estimate of the number of access days of the CTVs obtained from the model is compared to the recorded access days of the real wind farm in the same time period. The results show a mean absolute 3 day error between the monthly estimates and the observed number. Dissimilarities between modelled and observed results can be caused by a slight difference in the limitations of the vessels. The decision gate for the model on vessel launch is dependent on two parameters; significant wave height and wind speed. In reality, the parameters may also include the wave steepness and the decision gate is dependent on subjectivity of the vessel captain. Also, the decision to transfer may be made by the number of rungs that the vessel is moving past rather than the wave height. When comparing the monthly time based availability, the model is unable to account for the operational behaviours of the OWF (in this case, a complete shut-down of the WTGs during investigations of a defect) but the annual availability is close to the WTG availability. The results of the cost comparison cannot be published but operators of the OWF have confirmed that the estimated value is close. This is expected as the majority of the costs for the first year of operation, like the annual service fee, are fixed.

After the first year of operations is compared, the simulation is extrapolated out to a project lifetime of 20 years. The scenario studied is that the operator takes over responsibility for maintaining the WTG beyond year five and major replacements are required from year ten. The case shows how the model can be used to assess future scenarios but, because the operating OWF is close to the O&M port and consists of relatively few WTGs (less than 30), in comparison to future planned OWFs, there is limited options for comparing different O&M scenarios. Therefore, a future wind farm case is chosen in order to conduct a multi-scenario analysis and an SA.

The multi-scenario analysis takes a pre-consent OWF and separates it into different build phases to see if the effect on the key outputs; cost and availability. Three build cases are considered and subjected to three O&M access scenarios; via 1) CTVs; 2) CTVs and helicopters and 3) motherships and CTVs. It is found that logistical costs increased when moving from the CTVs, to incorporating helicopters and motherships as the running costs for each of the transport types increases. As the travel times decrease, the length of usable shift increases, directly leading to the increase in annual availability. When considering costs alone, the CTV access strategy seems the best option. However, if the potentially lost production is affixed with a cost greater than £35 /MWh (depending on the number of turbines), then the mothership option becomes the most profitable solution. The value of electricity that is gained through increased availability exceeds the extra cost of the vessel. This is subject, however to the sale price of electricity. In Section 6.1, a single-factor SA reveals how the most profitable solution varies between sale prices of electricity of £35 /MWh and £85 /MWh, depending on the case. Whilst the sale price of electricity proves itself to be an important aspect of access scenario choice, it does not influence either the direct cost or the availability as independent outputs.

The final stage of model validation is a comparison of computer models that estimate the costs and availability of offshore wind O&M. There are variations in the results which could be attributed to differences in the internal parameters. The model developer decides the internal parameters.

Conclusions drawn from this chapter of the thesis are that the model can be used to predict annual average costs and availability accurately. The multi-scenario analysis discussion reveals that different cases can be sensitive to different factors. The model comparison shows that the internal parameters, such as minimum charter length for HLVs and number of simultaneous tasks conducted, also have a bearing on how sensitive the model outputs are to changes in the inputs. The final outcome of this chapter is that the model can be used for SA but different cases of OWF will have to be considered. Also, it is observed that the results are model and case specific.

Chapter 3.4.4 introduces and provides a brief overview of the most commonly used SA methods to justify the choice of LSA and GSA. As the OWF O&M model incorporates over 100 inputs, even using the most basic simulation, a full GSA would be unfeasible due to computational constraints. Therefore a screening analysis is performed using the Morris method, a computationally inexpensive approach.

The cases used in the multi-scenario analysis of Section 3.4.2 is taken as a basis for the cases used in the SA. The results of Case 1 and Case 2 are found to be consistent for important factors, therefore, only the results from Case 1 are shown. The results from Case 1 and Case 3 are compared and subsequently taken forward to the GSA. The factors that affect costs are similar for Case 1 and Case 3.

For Case 1, it is WTG reliability and time to repair that can primarily affect farm availability. This is true for Case 3, but the repair strategy also is found to be important.

The LSA provides some initial results into the general effect of inputs on the outputs but without reliable quantification. The number of possibly important factors is reduced from over 100 to less than 15 for each case.

With a reduced list of factors, the input distributions can be identified. A systematic methodology for sourcing the data and for analysing the inputs is defined in order to provide clarity on the data quality. The resulting distributions are used in the GSA. The result corroborate with those found in the LSA.

One of the most important factors for availability for Case 1 is the mobilisation time for HLVs. The quality of the distribution of this input is low so this area is a target for improvement. This information can be used by operators to consider options for reduction of the mobilisation times for HLVs. Sharing of a HLV charter with neighbouring wind farms may result in a reduction in retainer charges but also could ensure that a vessel is available when necessary.

Most of the important factors interact with one or two others, leading to the conclusion that operator need to address multiple aspects for cost reduction and availability increase. For maximum reduction of uncertainty in costs, operators need to consider three aspects for major failures: reducing the failure rate, reducing the daily rate in HLV and reducing the operation duration.

7.2 Further work and improvements

As outlined in Section 5.5, a complete uncertainty analysis to define the input distribution is not possible due to lack of data or information for some of the input factors. Information is missing regarding HLVs, as this type of repair job has not been experienced by the company that is consulted as part of the project. Actions are taken to look at what existing experience there is in industry, however there is no central database where this information is collected. Many of the key findings from this study are based on the assumptions made from other industries, such as shipping and air ambulance charities. When more information specific to OWF operations becomes available, either for individual OWF operators, or through efforts across the industry, this study can be updated.

Another source of missing information is the reliability of offshore WTG components. At the beginning of the project, no complete analysis of offshore WTG reliability is available in the public domain. Therefore, the focus is on using the existing onshore reliability analysis throughout the study. In recent months, after the analysis is complete, information has come to light through one study on approximately 350 WTGs in Carroll, Mcdonald, et al., 2015. If further results are released, such as the distribution of failure events, then they can be incorporated into further GSA for more accurate results.

One of the parameters that influences the choice of method for LSA and GSA is the restriction of computational resources. The analysis is designed to be run on a standard specification laptop or desktop with eight parallel cores. Use of extended computing capabilities with 100s or 1000s of cores may have impacted on the choice of method. It may even have allowed bypassing of the screening experiment altogether and to expand the region of investigation to consider meteorological aspects and variable number of WTGs.

The chosen outputs of the SAs are the cost and availability of the model. As discussed in Section 6.1, the costs and availability could be combined to produce one factor; total direct and indirect cost. This single output could be used as an objective function for an optimisation model. An optimisation computer model uses a search pattern method within a region of investigation, made from the input factors, to identify a result or value which conforms to a given criteria. For an OWF O&M model that value would be the combined direct and indirect costs calculated by the model, dictated by the search pattern. The criteria would be to find the minimum value of combined direct and indirect costs, therefore finding the lowest costing O&M scenario which results in the highest availability.

One of the earliest outcomes of this study is that the results from the LSA and GSA are specific to the model used to conduct the analysis and the wind farm case under study. Therefore, the next logical step is to incorporate the suggested SA methods as an optional module as part of the model itself so that after each simulation of a case, the results for an SA can be produced. The SA part of the model would be optional, as the computations for the SA would take longer than the original simulation. Once the model user has built a satisfactory wind farm case, a GSA module would provide an extra level of understanding about the contribution of uncertainty of the inputs to the outputs.

The model itself is probabilistic, running Monte Carlo simulations with varying times of failure according to the failure rate inputted by the user. For the LSA and GSA, the probabilistic aspect of the model is reduced to near deterministic by executing enough simulations so that the cost values reach high convergence, then using the mean values of cost and availability. Analysis of probabilistic models is a growing area in the field of SA but a method using joint meta-models have been found in the literature. After a model has been run and a deterministic GSA conducted, the user can then produce a meta-model which can be used for GSA on the probabilistic aspects. This model can also be used to produce an optimised solution of the most important factors. This would allow the user to consider some important factors not included here, such as the stochastic failure rates and meteorological conditions on site. A model that can be used for optimisation for scenarios will aid operators to find solutions quickly.

7.3 Contributions

In terms of contribution to knowledge, the study is the first time that a GSA has been applied to an OWF O&M model and the results published in the public domain. The work has advanced the field of OWF O&M through contributing to reference and case work. This allows other model developers to compare their decisions against it. The other contribution to knowledge is demonstration of how GSA methods can be used to identify the effect of uncertainty in the interaction of factors and the contribution of variance in cost and production-based availability.

One of the most significant findings is that, with large amounts of WTGs (of the order of 100s in a wind farm), the uncertainty of costs stems from major failures. Employing mechanisms to convert potential failures resulting in major replacement into less severe repairs that do not require a HLV, will decrease the uncertainty in the costs. Secondary to this would be, for major replacement activities, to find ways to get HLVs to site quickly, once a failure has occurred and have it ready to perform the operation in the least time possible. For more routine operations, having the teams in place to conduct the required tasks simultaneously to utilise favourable weather windows, would also contribute.

For other OWF O&M model developers, this work extends the efforts of Hagen 2013 from simple OAT SA, through to GSA and considering the interaction between factors. The thesis itself demonstrated the process and provides ways to assess the input factor distributions using standard methodologies, to use in their own investigations.

This analysis demonstrated that GSA can be used to study individual cases as long as that model can replicate the resultant availability and costs on an annual basis. In the study in Section 3.4.1 ECUME is only accurate for results based on annual averages, therefore the GSA is more applicable when looking at project lifetime simulations of multiple years.

7.4 Concluding Remark

Operators of offshore wind farms need to simultaneously decrease costs and increase energy yield to achieve a levelised cost of energy of £100/MWh and grid parity with other conventional sources of electricity generation. However, aspects of the O&M remain uncertain, either through stochastic processes or through inexperience in the field.

The work presented here demonstrates how, using a computer model, uncertainty in input factors can be defined and the effect of the variance on the cost and availability is quantified.

The work presented here shows that, out of an original list of over 100 inputs affecting the cost and availability of OWFs, the variance of approximately three input factors contributes the most to the variance in either the cost and production-based availability. The results are model and case specific but do show that the list of important factors changes with the number of turbines and distance to shore. This information can be used by operators to develop their own strategies for maximising cost reduction and availability improvements, which in turn, would reduce the overall cost of energy.

References

4C Offshore Limited. (2014a). 4C Offshore Vessel Database. Retrieved October 14, 2014, from http://www.4coffshore.com/windfarms/vessels.aspx

4C Offshore Limited. (2014b). Offshore Wind Turbines Database. *4C Offshore Website*. Retrieved December 14, 2014, from http://www.4coffshore.com/windfarms/turbines.aspx

4C Offshore Limited. (2015). 4C Offshore Offshore Wind Farm Database. Retrieved August 16, 2015, from http://www.4coffshore.com/windfarms/

Abdmouleh, Z., Alammari, R. A. M., & Gastli, A. (2015). Review of Policies Encouraging Renewable Energy Integration. *Renewable and Sustainable Energy Reviews*, *45*, 249–262. doi:10.1016/j.rser.2015.01.035

ABPmer. (2008). *Teesside Offshore Wind Farm : Metocean Study*.

ABPmer. (2015). Atlas of UK Marine Renewable Energy Resources. Retrieved July 10, 2015, from renewables-atlas.info

Ampelmann. (2015). Ampelmann A Type Infographic. Retrieved January 5, 2016, from http://www.ampelmann.nl/assets/uploads/2015/08/Ampelmann-A-Type-infographic.pdf

Anaya-lara, O., Campos-Gaona, D., Moreno-Goytia, E., & Adam, G. (2014). *Offshore Wind Energy Generation: Control, Protection and Integration to Electrical Systems* (1st ed.). Chichester: Wiley.

Andrawus, J. (2008). *Maintenance Optimisation for Wind Turbines*. The Robert Gordon University.

Arabian-Hoseynabadi, H., Oraee, H., & Tavner, P. (2010). Failure Modes and Effects Analysis (FMEA) for Wind Turbines. *International Journal of Electrical Power & Energy Systems*, *32*(7), 817–824. doi:10.1016/j.ijepes.2010.01.019

Areva. (2010). Areva M5000 Technical Specification. Retrieved April 15, 2015, from http://india.areva.com/home/liblocal/docs/India Offer/Renewable/Wind/AREVA M5000 Technical Data.pdf

Auder, B., De Crecy, A., Iooss, B., & Marquès, M. (2012). Screening and Metamodeling of Computer Experiments with Functional Outputs. Application to Thermal–hydraulic Computations. *Reliability Engineering & System Safety*, *107*, 122–131. doi:10.1016/j.ress.2011.10.017

Bedford, T., Bayley, C., & Revie, M. (2013). Screening, Sensitivity, and Uncertainty for the CREAM Method of Human Reliability Analysis. *Reliability Engineering*

& System Safety, *115*, 100–110. doi:10.1016/j.ress.2013.02.011

Bedford, T., & Cooke, R. (2009). *Probabilistic Risk Analysis: Foundations and Methods* (6th ed.). Cambridge University Press. doi:10.1198/016214502760301264

Bharadwaj, U., Speck, J., & Ablitt, C. (2007). A Practical Approach to Risk Based Assessment and Maintenance Optimisation of Offshore Wind Farms. In *ASME 2007 26th International Conference on Offshore Mechanics and Arctic Engineering*. San Diego.

Bilgili, M., Yasar, A., & Simsek, E. (2011). Offshore Wind Power Development in Europe and its Comparison with Onshore Counterpart. *Renewable and Sustainable Energy Reviews*, *15*(2), 905–915. doi:10.1016/j.rser.2010.11.006

Birolini, A. (1997). *Quality and Reliability of Technical Systems* (2nd ed.). Springer. doi:10.1007/978-3-642-97983-5

BMU, & PTJ. (2012). FINO 1 Meteorological Dataset 2004 - 2012. Retrieved December 1, 2012, from http://fino.bsh.de

Bolton, S. (2014). Operation and Maintenance. In K. Thomsen (Ed.), *A Comprehensive Guide to Successful Offshore Wind Farm Installation* (2nd Editio., pp. 243–283). Elsevier Inc.

British Standards Institution. Glossary of Terms Used in Terotechnology. , Pub. L. No. BS 3811:1993 (1993).

Burton, T., Jenkins, N., Sharpe, D., & Bossanyi, E. (2011). *Wind Energy Handbook* (2nd Editio.). Wiley.

Busfield, A. (2010). Estimating the Availability of a Concept Offshore Wind Farm. *Helm Wind Project Report*.

BVG Associates. (2010). *A Guide to an Offshore Wind Farm*.

Byon, E., Perez, E., Ding, Y., & Ntaimo, L. (2010). Simulation of Wind Farm Operations and Maintenance using Discrete Event System Specification. *Transactions of the Society for Modelling and Simulation International*, *87*(12), 1093–1117. doi:10.1177/0037549711376841

Cacuci, D. G. (2003). *Sensitivity and Uncertainty Analysis: Volume I*. Chapman & Hall / CRC.

Campbell, K., McKay, M. D., & Williams, B. J. (2006). Sensitivity Analysis when Model Outputs are Functions. *Reliability Engineering & System Safety*, *91*(10-11), 1468–1472. doi:10.1016/j.ress.2005.11.049

Campolongo, F., Cariboni, J., & Saltelli, A. (2007). An Effective Screening Design for Sensitivity Analysis of Large Models. *Environmental Modelling & Software*, *22*(10), 1509–1518. doi:10.1016/j.envsoft.2006.10.004

Campolongo, F., & Saltelli, A. (1997). Sensitivity Analysis of an Environmental Model: an Application of different Analysis Methods. *Reliability Engineering & System Safety*, *57*(1), 49–69. doi:10.1016/S0951-8320(97)00021-5

Campolongo, F., Saltelli, A., & Cariboni, J. (2011). From Screening to Quantitative Sensitivity Analysis. A Unified Approach. *Computer Physics Communications*, *182*(4), 978–988. doi:10.1016/j.cpc.2010.12.039

Carlsson, F., Eriksson, E., & Dahlberg, M. (2010). *Damage Preventing Measures for Wind Turbines Phase 1- Reliability Data*.

Carroll, J., May, A., Mcdonald, A., & McMillan, D. (2015). Availability Improvements from Condition Monitoring Systems and Performance Based Maintenance Contracts. In *European Wind Energy Association Offshore Proceedings* (Vol. 1). Copenhagen.

Carroll, J., Mcdonald, A., & McMillan, D. (2015). Failure Rate, Repair Time and Unscheduled O&M Cost Analysis of Offshore Wind Turbines. *Wind Energy*. doi:10.1002/we.1887

Centre for Environment Fisheries and Aquaculture Science. (2015). CEFAS WaveNet Map. Retrieved July 24, 2015, from http://cefasmapping.defra.gov.uk/map

Chan, K., Tarantola, S., & Saltelli, A. (2000). Variance-Based Methods. In A. Saltelli, K. Chan, & E. M. Scott (Eds.), *Sensitivity Analysis* (pp. 167–197). John Wiley & Sons Ltd.

Charity Commission. (2015). Charities Commission Charity Search. Retrieved August 17, 2015, from http://apps.charitycommission.gov.uk/Showcharity/RegisterOfCharities/SearchMatchList.aspx?RegisteredCharityNumber=0&SubsidiaryNumber=0

Cicek, K., & Celik, M. (2013). Application of failure modes and effects analysis to main engine crankcase explosion failure on-board ship. *Safety Science*, *51*(1), 6–10. doi:10.1016/j.ssci.2012.06.003

Cosenza, A., Mannina, G., Vanrolleghem, P. a., & Neumann, M. B. (2013). Global Sensitivity Analysis in Wastewater Applications: A Comprehensive Comparison of Different Methods. *Environmental Modelling & Software*, *49*, 40–52. doi:10.1016/j.envsoft.2013.07.009

Cotter, S. (1979). A Screening Design for Factorial Experiments with Interactions. *Biometrika*, *66*(2), 317–320.

Council Directive 2009/28/EC. (2009). On the Promotion of the Use of Energy from Renewable Sources. *OJ L 140/16*.

Crundwell, F. (2008). Risk in Engineering Projects. In *Finance for Engineers: Evaluation and Funding of Capital Projects*. Springer.

Cukier, R., Levine, H., & Shuler, K. (1978). Nonlinear Sensitivity Analysis of Multiparameter Model Systems. *Journal of Computational Physics*, *26*, 1–42. doi:10.1016/0021-9991(78)90097-9

Dalgic, Y., Lazakis, I., Dinwoodie, I., McMillan, D., & Revie, M. (2015). Advanced Logistics Planning for Offshore Wind Farm Operation and Maintenance Activities. *Ocean Engineering*, *101*, 211–226. doi:10.1016/j.oceaneng.2015.04.040

Dalgic, Y., Lazakis, I., & Turan, O. (2013). Vessel Charter Rate Estimation for Offshore Wind O&M Activities. In *International Congress of the International Maritime Association of the Mediterranean*. Coruna.

Dalgic, Y., Lazakis, I., & Turan, O. (2015). Investigation of Optimum Crew Transfer Vessel Fleet for Offshore Wind Farm. *Wind Engineering*, *39*(1), 31–52. doi:10.1260/0309-524X.39.1.31

Dalgic, Y., Lazakis, I., Turan, O., & Judah, S. (2015). Investigation of Optimum Jack-up Vessel Chartering Strategy for Offshore Wind Farm O&M Activities. *Ocean Engineering*, *95*, 106–115. doi:10.1016/j.oceaneng.2014.12.011

Das, M. K., Panja, S. C., Chowdhury, S., Chowdhury, S. P., & Elombo, a. I. (2011). Expert-based FMEA of wind turbine system. *2011 IEEE International Conference on Industrial Engineering and Engineering Management*, 1582–1585. doi:10.1109/IEEM.2011.6118183

de Rocquigny, E., Devictor, N., & Tarantola, S. (2008). *Uncertainty in Industrial Practice*. Wiley.

Department of Defence. (1980). MIL-STD-1629A: Procedures for Performing A Failure Mode, Effects and Criticality Analysis.

Department of Defence. (1991). *MIL-HDBK-217K: Reliability Prediction of Electronic Equipment*. Washington DC.

Department of Energy & Climate Change. (2011). *UK Renewable Energy Roadmap*.

Department of Energy & Climate Change. (2012). *UK Electricity Generation Costs Update*. *Mott MacDonald*.

Department of Energy & Climate Change. (2013). Contract for Difference.

Department of Energy & Climate Change. (2014). Contract for Difference: Allocation Process High Level Summary.

Department of Energy & Climate Change. (2015). Contracts for Difference (CFD) Allocation Round One Outcome.

Dinwoodie, I. A., & McMillan, D. (2014). Operational strategies for offshore wind turbines to mitigate failure rate uncertainty on operational costs and revenue. *IET Renewable Power Generation*, *8*(4), 359–366. doi:10.1049/iet-rpg.2013.0232

Dinwoodie, I., Mcmillan, D., Revie, M., Lazakis, I., & Dalgic, Y. (2013). Development of a Combined Operational and Strategic Decision Support Model for Offshore Wind. *Energy Procedia*, *35*, 157–166. doi:10.1016/j.egypro.2013.07.169

Dinwoodie, I., Van Endrerud, O., Hofmann, M., Martin, R., & Sperstad, I. (2015). Reference Cases for Verification of Operation and Maintenance Simulation Models for Offshore Wind Farms. *Wind Engineering*, *39*(1), 1–14. doi:10.1260/0309-524X.39.1.1

DNV. (2007). *Recommended Practice: Statistical Representation of Soil Data*.

Douard, F., Domecq, C., & Lair, W. (2012). A Probabilistic Approach to Introduce Risk Measurement Indicators to an Offshore Wind Project Evaluation – Improvement to an Existing Tool. *Energy Procedia*, (24), 255–262. doi:doi:10.1016/j.egypro.2012.06.107

Drwiega, A. (2013). Helicopter Operations to Offshore Wind Farms; London Conference Update. *Rotor and Wing*. Retrieved August 17, 2015, from http://www.aviationtoday.com/rw/commercial/offshore/Helicopter-Operations-to-Offshore-Wind-Farms-London-Conference-Update_79581.html#.VdGULPlVgSU

Dudgeon Wind Farm. (2013). Dudgeon Wind Farm Website. Retrieved April 14, 2014, from http://dudgeonoffshorewind.co.uk/index.php

Dykes, K., Ning, A., Graf, P., Scott, G., Damiani, R., Hand, M., … Veers, P. (2012). Sensitivity Analysis of Offshore Wind Cost of Energy. In *Offshore Windpower*. Virginia Beach.

Eiselt, H., & Sandblom, C. (2010). *Operations Research: A Model-Based Approach*. Springer.

European Wind Energy Association. (2013). *The European Offshore Wind Industry - Key Trends and Statistics 1st Half 2013*.

European Wind Energy Association. (2015a). *The European Offshore Wind Industry*

- *Key Trends and Statistics 1st Half 2015*.

European Wind Energy Association. (2015b). The European Offshore Wind Industry - Key Trends and Statistics 2014.

Faulstich, S., Hahn, B., & Tavner, P. (2011). Wind Turbine Downtime and its Importance for Offshore Deployment. *Wind Energy*, *14*(3), 327–337. doi:10.1002/we

Gertsev, V., & Gertseva, V. (2004). Classification of mathematical models in ecology. *Ecological Modelling*, *178*(3-4), 329–334. doi:10.1016/j.ecolmodel.2004.03.009

Graves, A., Harman, K., Wilkinson, M., & Walker, R. (2008). Understanding Availability Trends of Operating Wind Farms. In *AWEA Windpower Conference*. Houston.

Hagen, B. A. (2013). *Sensitivity Analysis of O & M Costs for Offshore Wind Farms*. Norwegian University of Science and Technology.

Halvorsen-Weare, E. E., Gundegjerde, C., Halvorsen, I. B., Hvattum, L. M., & Nonås, L. M. (2013). Vessel Fleet Analysis for Maintenance Operations at Offshore Wind Farms. *Energy Procedia*, *35*, 167–176. doi:10.1016/j.egypro.2013.07.170

Hameed, Z., Vatn, J., & Heggset, J. (2011). Challenges in the Reliability and Maintainability Data Collection for Offshore Wind Turbines. *Renewable Energy*, *36*(8), 2154–2165. doi:10.1016/j.renene.2011.01.008

Hamilton, A., & Quail, F. (2011). Detailed State of the Art Review for the Different On-Line / In-Line Oil Analysis Techniques in Context of Wind Turbine Gearboxes. In *ASME Turbo Expo*. Vancouver.

Hau, E. (2006). *Wind Turbines* (2nd ed.). Berlin Heidelberg: Springer.

Heptonstall, P., Gross, R., Greenacre, P., & Cockerill, T. (2012). The Cost of Offshore Wind: Understanding the Past and Projecting the Future. *Energy Policy*, *41*, 815–821. doi:10.1016/j.enpol.2011.11.050

Higgins, P., & Foley, A. (2014). The Evolution of Offshore Wind Power in the United Kingdom. *Renewable and Sustainable Energy Reviews*, *37*, 599–612. doi:10.1016/j.rser.2014.05.058

Highlands and Islands Enterprise. (2010). *Offshore Wind Operations and Maintenance A National Renewables Infrastructure Plan Stage 2 Information Paper*.

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. doi:10.1260/0309-524X.35.1.1

Hofmann, M., Heggset, J., & Nonås, L. M. (2010). A Concept for Cost and Benefit Analysis of Offshore Wind Farms with Focus on Operation and Maintenance. In *24th International Congress on Condition Monitoring and Diagnostics Engineering Management*.

Hofmann, M., & Sperstad, I. B. (2013a). Analysis of Senstivities in Maintenance Strategies for Offshore Wind Farms Using a Simulation Model. In *EWEA Offshore*. Frankfurt.

Hofmann, M., & Sperstad, I. B. (2013b). NOWIcob – A Tool for Reducing the Maintenance Costs of Offshore Wind Farms. *Energy Procedia*, *35*(1876), 177–186. doi:10.1016/j.egypro.2013.07.171

Hora, S. C. (1996). Aleatory and Epistemic Uncertainty in Probability Elicitation with an Example from Hazardous Waste Management. *Reliability Engineering and System Safety*, *54*(2-3), 217–223. doi:10.1016/S0951-8320(96)00077-4

Hsu, S. (1988). *Coastal Meteorology*. London: Academic Press.

International Electrotechnical Commission. WIND TURBINES - Part 26-1: Time Based Availability for Wind Turbines. , Pub. L. No. IEC 61400-26-1 (2010).

Islam, M. R., Guo, Y., & Zhu, J. (2014). A Review of Offshore Wind Turbine Nacelle: Technical Challenges, and Research and Developmental Trends. *Renewable and Sustainable Energy Reviews*, *33*, 161–176. doi:10.1016/j.rser.2014.01.085

Joint Research Centre IPSC. (2008). SimLab 2.2. Retrieved April 15, 2015, from http://ipsc.jrc.ec.europa.eu/?id=756

Jonkman, J., & Musial, W. (2010). *Offshore Code Comparison Collaboration (OC3) for IEA Task 23 Offshore Wind Technology and Deployment*.

Kahrobaee, S., & Asgarpoor, S. (2011). Risk-based Failure Mode and Effect Analysis for wind turbines (RB-FMEA). *2011 North American Power Symposium*, 1–7. doi:10.1109/NAPS.2011.6025116

Kaltschmitt, M., Streicher, W., & Wiese, A. (2007). *Renewable Energy Technology, Economics and Environment*. Springer.

Karimirad, M., Meissonnier, Q., Gao, Z., & Moan, T. (2011). Hydroelastic Code-to-Code Comparison for a Tension Leg Spar-Type Floating Wind Turbine. *Marine Structures*, *24*(4), 412–435. doi:10.1016/j.marstruc.2011.05.006

Karyotakis, A. (2011). *On the Optimisation of Operation and Maintenance Strategies for Offshore Wind Farms*. University College London.

King, D. M., & Perera, B. J. C. (2013). Morris Method of Sensitivity Analysis Applied to Assess the Importance of Input Variables on Urban Water Supply Yield - A

Case Study. *Journal of Hydrology*, *477*, 17–32. doi:10.1016/j.jhydrol.2012.10.017

Kleijnen, J. P. (2008). Screening Designs. In *Design and Analysis of Simulation Experiments* (pp. 157–172). Springer.

Koutoulakos, E. (2008). *Wind Turbine Reliability Characteristics and Offshore Availability Assessment*. TU Delft.

Lamboni, M., Makowski, D., Lehuger, S., Gabrielle, B., & Monod, H. (2009). Multivariate Global Sensitivity Analysis for Dynamic Crop Models. *Field Crops Research*, *113*(3), 312–320. doi:10.1016/j.fcr.2009.06.007

Lamboni, M., Monod, H., & Makowski, D. (2011). Multivariate Sensitivity Analysis to Measure Global Contribution of Input Factors in Dynamic Models. *Reliability Engineering & System Safety*, *96*(4), 450–459. doi:10.1016/j.ress.2010.12.002

Lopez, J. (2010). Iberdrola Engineering´s SW Optimisation tool for Electrical Infrastructures and O&M Strategies on OWFs. *Wind Energy Update O&M Summit*. Madrid.

Luengo, M., & Kolios, A. (2015). Failure Mode Identification and End of Life Scenarios of Offshore Wind Turbines: A Review. *Energies*, *8*(8), 8339–8354. doi:10.3390/en8088339

Madariaga, A., De Alegría, I. M., Martín, J. L., Eguía, P., & Ceballos, S. (2012). Current Facts About Offshore Wind Farms. *Renewable and Sustainable Energy Reviews*, *16*(5), 3105–3116. doi:10.1016/j.rser.2012.02.022

Maples, B., Saur, G., & Hand, M. (2013). Installation, Operation, and Maintenance Strategies to Reduce the Cost of Offshore Wind Energy. *NREL/TP-5000-57403*.

Marine Traffic Ltd. (2014). Marine Traffic Live Vessel Tracking Website. Retrieved May 3, 2014, from https://www.marinetraffic.com/

Marrel, A., & Iooss, B. (2012). Global Sensitivity Analysis of Stochastic Computer Models with Joint Metamodels. *Statistics and Computing*, *22*(3), 833–847.

Martin, R., Lazakis, I., & Barbouchi, S. (2014). Analysis of Input Factors To Operations And Maintenance of Two Offshore Wind Farm Case Studies ; A Screening Process . In *Renewable Power Generation Conference (RPG 2014)* (pp. 4–9).

Martin-Tretton, M., Reha, M., Drunsic, M., & Keim, M. (2012). Data Collection for Current U.S. Wind Energy Projects : Component Costs, Financing, Operations, and Maintenance. *NREL/SR-5000-52707*.

MATLAB. (2015). Poissrnd Function Documentation. Retrieved October 27, 2015, from http://uk.mathworks.com/help/stats/poissrnd.html

Morandeau, M., Walker, R., Argall, R., & Nicholls-Lee, R. (2013). Optimisation of Marine Energy Installation Operations. *International Journal of Marine Energy*, (3-4), 14–26.

Morris, M. D. (1991). Factorial Plans for Preliminary Sampling Computational Experiments. *Technometrics*, *33*(2), 161–174. doi:10.1080/00401706.1991.10484804

Musial, W., & Ram, B. (2010). Large-Scale Offshore Wind Power in the United States: Assessment of Opportunities and Barriers. *NREL/TP-500-40745*.

National Statistics. (2015). *Digest of United Kingdom Energy Statistics 2015*. London.

Obdam, T., Rademakers, L., Braam, H., & Eecen, P. (2007). Estimating Costs of Operation & Maintenance for Offshore Wind Farms. In *European Offshore Wind Energy Conference*. Berlin.

ORE Catapult. (2015a). *Cost Reduction Monitoring Framework - Summary Report to the Offshore Wind Programme Board*.

ORE Catapult. (2015b). Our Projects: SPARTA. Retrieved January 21, 2015, from https://ore.catapult.org.uk/our-projects/-/asset_publisher/fXyYgbhgACxk/content/sparta

OREDA Participants. (2002). *Offshore Reliability Data Handbook*. Trondheim: SINTEF Industrial Management.

Pardalos, P., Rebennack, S., Pereira, M., Pappu, V., & Iliadis, N. (2013). *Handbook of Wind Power Systems*. Springer. doi:10.1007/978-3-642-41080-2

Pillai, A. C., Chick, J., Johanning, L., Khorasanchi, M., & de Laleu, V. (2015). Offshore Wind Farm Electrical Cable Layout Optimization. *Engineering Optimization*, *47*(12), 1689 – 1708. doi:10.1080/0305215X.2014.992892

PTC-Relex, & Durham University. (2007). *Whole System Reliability Model*.

Pujol, A. G., Iooss, B., Janon, A., Veiga, D., Fruth, J., Gilquin, L., … Touati, T. (2015). Senstivity Analysis Package Documentation.

Quaglietta, E. (2013). Supporting the Design of Railway Systems by Means of a Sobol' Variance-Based Sensitivity Analysis. *Transportation Research Part C: Emerging Technologies*, *34*, 38–54. doi:10.1016/j.trc.2013.05.007

Rademakers, L., & Braam, H. (2003). *O&M Aspects of the 500MW Offshore Wind Farm at NL7* (Vol. 7).

Rademakers, L., Braam, H., Obdam, T., & Van de Pieterman, R. (2009). *Operation* *and Maintenance Cost Estimator (OMCE): Final Report*.

Rademakers, L., Braam, H., Zaaijer, M., & Van Bussel, G. J. W. (2003). Assessment and Optimisation of Operation and Maintenance of Offshore Wind Turbines. In *European Wind Energy Conference*. Madrid.

Rausand, M., & Hoyland, A. (2004). *System Reliability Theory* (2nd ed.). Hoboken: Wiley-Interscience.

RDS_PP. (2015). RDS-PP. Retrieved January 21, 2015, from http://www.rds-pp.com/index.html

Redfern, R., & Phillips, J. L. (2009). Assessing the Impact of Serial Defects on the Performance of Offshore Wind Projects. In *EWEA Offshore*. Stockholm.

RenewableUK. (2012). *Offshore Wind Cost Reduction Task Force Report*.

Ribrant, J. (2006). *Reliability Performance and Maintenance - A Survey of Failures in Wind Power Systems*. Kungliga Tekniska Hogskolan University.

Saltelli, A., Andres, T., & Homma, T. (1995). Sensitivity Analysis of Model Output. Performance of the Iterated Fractional Factorial Design Method. *Computational Statistics & Data Analysis*, *20*(4), 387–407. doi:10.1016/0167-9473(95)92843-M

Saltelli, A., Annoni, P., Azzini, I., Campolongo, F., Ratto, M., & Tarantola, S. (2010). Variance Based Sensitivity Analysis of Model Output. Design and Estimator for the Total Sensitivity Index. *Computer Physics Communications*, *181*(2), 259–270. doi:10.1016/j.cpc.2009.09.018

Saltelli, A., Chan, K., & Scott, E. (2008). *Sensitivity Analysis* (1st ed.). Chichester: Wiley.

Saltelli, A., Tarantola, S., Campolongo, F., & Ratto, M. (2004). *Sensitivity Analysis in Practice: A Guide to Assessing Scientific Models*. Wiley.

Sargent, R. (2013). Verification and Validation of Simulation Models. *Journal of Simulation*, *7*, 12–24. doi:10.1057/jos.2012.20

Scrira Offshore Energy. (2012). Sheringham Shoal Fact Sheet. Retrieved April 15, 2015, from http://www.scira.co.uk/downloads/SSWOF OM Fact Sheet AW web 3.12.pdf

Siemens Wind Power Ltd. (2011). Siemens Wind Turbine SWT-3.6-107 Technical Specifications. Retrieved April 15, 2015, from http://www.energy.siemens.com/hq/pool/hq/power-generation/renewables/wind-power/wind turbines/E50001-W310-A103-V6-4A00_WS_SWT_3_6_107_US.pdf

Sinha, Y., & Steel, J. a. (2015). A progressive study into offshore wind farm maintenance optimisation using risk based failure analysis. *Renewable and Sustainable Energy Reviews*, *42*, 735–742. doi:10.1016/j.rser.2014.10.087

Smith, A., & Hinchcliffe, G. (2003). *RCM: Gateway to World Class Maintenance*. Butterworth Heinemann.

Sobol', I. (1990). On Sensitivity Estimation for Nonlinear Mathematical Models. *Matematicheskoe Modelirovanie*, *2*(1), 112–118.

Sobol', I. (2001). Global Sensitivity Indices for Nonlinear Mathematical Models and Their Monte Carlo Estimates. *Mathematics and Computers in Simulation*, *55*(1-3), 271–280. doi:10.1016/S0378-4754(00)00270-6

Spinato, F. (2008). *The Reliability Wind of Turbines*. Durham University.

Stevens, J., & Graves, A. (2009). Availability Trends in the US Wind Power Market. In *AWEA Asset Management Conference*. San Diego.

Stiesdal, H., & Madsen, P. (2005). Design for Reliability. In *Offshore Wind 2005*. Copenhagen.

Tavner, P. (2011). *Recommendations from the ReliaWind Consortium for the Standardisation for the Wind Industry of Wind Turbine Reliability Taxonomy, Terminology and Data Collection*.

Tavner, P. (2012). *Offshore Wind Turbines: Reliability; Availability and Maintenance* (1st ed.). The IET.

Tavner, P., Greenwood, D. M., Whittle, M. W. G., Gindele, R., Faulstich, S., & Hahn, B. (2012). Study of Weather and Location Effects on Wind Turbine. *Wind Energy*, (May 2012), 175–187. doi:10.1002/we

Tavner, P., & Xiang, J. (2007). Reliability Analysis for Wind Turbines. *Wind Energy*, (July 2006), 1–18. doi:10.1002/we

Tegen, S., Hand, M., Maples, B., Lantz, E., Schwabe, P., & Smith, A. (2012). 2010 Cost of Wind Energy Review. *NREL/TP-5000-52920*.

The Crown Estate. (2014). *Jack-up Vessel Optimisation*.

Thies, P. R., Flinn, J., & Smith, G. H. (2009). Is it a Showstopper? Reliability Assessment and Criticality Analysis for Wave Energy Converters. In *European Wave and Tidal Energy Conference*. Uppsala, Sweden.

Tian, W. (2013). A Review of Sensitivity Analysis Methods in Building Energy Analysis. *Renewable and Sustainable Energy Reviews*, *20*, 411–419. doi:10.1016/j.rser.2012.12.014

Troche, L., & Malone, L. C. (2000). Finding Important Independent Variables Through Screening Designs: A Comparison of Methods. In *Proceedings of the 2000 Winter Simulation Conference*.

Uptime International AS. (2010). Uptime. Retrieved January 5, 2016, from http://www.uptime.no/

Van Bussel, G. J. W., & Bierbooms, W. (2003). Analysis of Different Means of Transport in the Operation and Maintenance Strategy for the Reference DOWEC Offshore Wind Farm. In *Offshore Wind and Other Marine Renewable Energies in Mediterranean and European Seas*. Naples, Italy.

Van Bussel, G. J. W., Boussion, C., & Hofemann, C. (2013). A Possible Relation Between Wind Conditions, Advanced Control and Early Gearbox Failures in Offshore Wind Turbines. *Procedia CIRP*, *11*, 301–304. doi:10.1016/j.procir.2013.08.001

Van Bussel, G. J. W., & Henderson, A. R. (2003). State of the Art and Technology Trends for Offshore Wind Energy : Operation and Maintenance Issues. *CA-OWEE*.

Van Bussel, G. J. W., & Schöntag, C. (1997). Operation and Maintenance Aspects of Large Offshore Windfarms. In *European Wind Energy Conference*. Dublin: European Wind Energy Association.

Van Bussel, G. J. W., & Zaaijer, M. (2003). *Estimation of Turbine Reliability figures within the DOWEC project*.

Van Bussel, G. J. W., & Zaaijer, M. B. (2001). Reliability , Availability and Maintenance aspects of large-scale offshore wind farms , a concepts study. In *MAREC 2001 Marine Renewable Energies Conference* (Vol. 113, pp. 119–126).

Van de Pieterman, R., Braam, H., Obdam, T., Rademakers, L., & van de Zee, T. (2011). *Optimisation of Maintenance Strategies for Offshore Wind Farms*.

Van Endrerud, O.-E., Liyanage, J., & Keseric, N. (2014). Marine Logistics Decision Support for Operation adn Maintenance of Offshore Wind Parks with a Multi Method Simulation Model. In A. Tolk, S. Dialllo, O. Ryzhov, L. Yilmaz, S. Buckley, & J. Miller (Eds.), *Winter Simulation Conference*. Savanah.

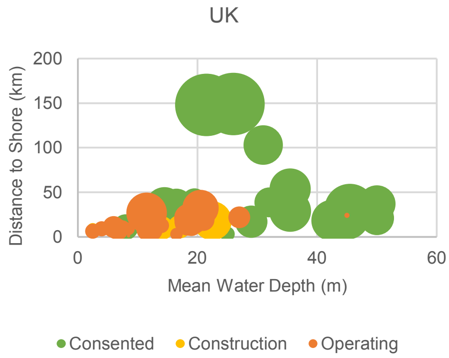
Vestas Wind Systems. (2011). Vestas V164 7.0 MW Technical Specification. Retrieved April 15, 2015, from http://pdf.directindustry.com/pdf/vestas/vestas-v164-70-mw-offshore/20680-244371.html

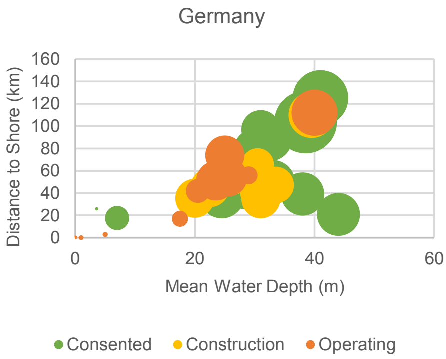
Wilkinson, M., Hendriks, B., Spinato, F., Gomez, E., Bulacio, H., Tavner, P., … Roca, J. (2010). Methodology and Results of the Reliawind Reliability Field Study. In *European Wind Energy Conference (EWEC 2010)*. Warsaw.

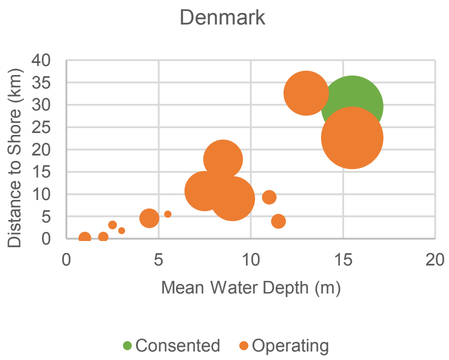
Yu, X., Martin, R., Barbouchi, S., Ingfield, D., Lazakis, I., & Seraoui, R. (2013). Determining the Applicability of Onshore Wind FMECAs to Offshore Wind Applications. In *EWEA Offshore*. Frankfurt.

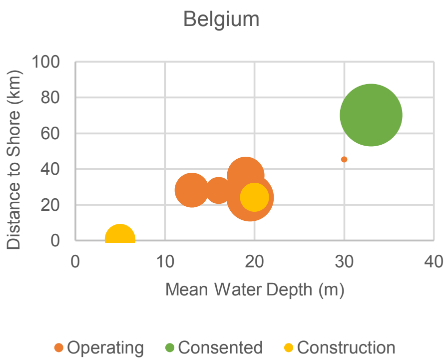
Zhang, X.-Y., Trame, M., Lesko, L., & Schmidt, S. (2015). Sobol Sensitivity Analysis: A Tool to Guide the Development and Evaluation of Systems Pharmacology Models. *CPT: Pharmacometrics & Systems Pharmacology*, *4*(2), 69–79. doi:10.1002/psp4.6

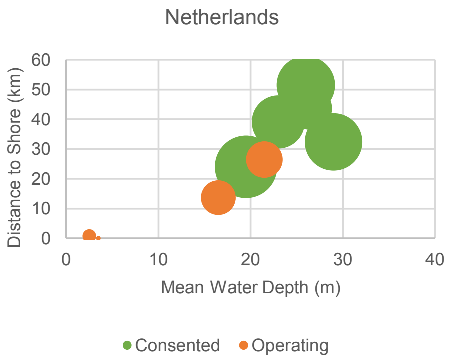
Appendix A – Water depth, distance from shore and total capacity of European projects

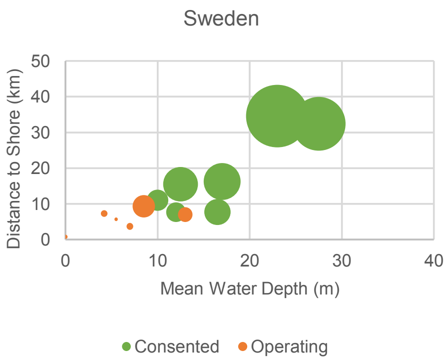












Appendix B – OWT component failure and stop data

Table B-1 Failure and WTG stop data per component from onshore and offshore WTG databases and operational reports

Database	Turbines	Years	Turbines	Hub	Blades /Pitch	Generator	Electrical System
Drift… & Felanalys	n/a	2000-2004, 2005	~650	0	0.052	0.021	0.067
VTT	n/a	2000-2004	~70	0.01	0.2	0.08	0.11
WindEnergie	n/a	2004-2005	~800	0.01	0.22	0.05	0.49
Danish Energy Agency	n/a	1999 - 2001		0	0.04	0.05	0.12
Betriever Databasis/ IWET	n/a	1999 - 2001			0.09	0.1	0.24
WMEP 1	0-1500	1998 - 2000	1496	0.04	0.195	0.386	0.528
WMEP 2	560-1500	1998 - 2000	69	0.11	0.499	0.11	0.938
LWK Schleswig-Holstien 1	0-1500	1999-2000	543		0.132	0.134	0.321
LWK Schleswig-Holstien 2	500-1500	1999-2001	288		0.161	0.167	0.337
EPRI California	40-600	1986 - 1987	290	0.14	0.357	0.374	1.491
WMEP 3	>1000	2008	1500	0.26	0.51	0.26	<1
WMEP 4	500-1000	2008		0.31	0.26	0.15	<1
WMEP 5	<500	2008		0.15	0.07	0.08	0.45
DOWEC Estimations *	n/a	n/a			0.07	0.13	0.27
Egmond aan Zee Wind Farm**	n/a	2007-2009	36		2	9	9
Anonymous ***	2000 - 4000	n/a	~350	0.24	1.596	1	0.435

Database / Report	Control System	Drive Train	Sensors	Gears	Mechanical Brakes	Hydraulics	Yaw Systems	Structure
Drift… & Felanalys	0.05	0.004	0.054	0.045	0.005	0.061	0.026	0.006
VTT	0.1	0	0.12	0.15	0.04	0.36	0.1	0.09
WindEnergie	0.26	0.05	0.16	0.12	0.1	0.21	0.13	0.07
Danish Energy Agency	0.01	0.004			0.03	0.04	0.06	0.004
Betriever Databasis/ IWET			0.05		0.03	0.08	0.09	
WMEP 1		0.056			0.138	0.226	0.163	0.084
WMEP 2		0.124			0.335	0.608	0.33	0.244
LWK Schleswig-Holstien 1	0.229		0.062		0.067	0.125	0.105	
LWK Schleswig-Holstien 2	0.241		0.067		0.066	0.107	0.084	
EPRI California		0.205	2.681		0.452		1.245	
WMEP 3	<1	0.8	0.75		0.11	0.59	0.25	0.22
WMEP 4	0.82	0.6	0.34		0.2	0.33	0.23	0.23
WMEP 5	0.6	0.5	0.22		0.18	0.2	0.2	0.08
DOWEC Estimations *	0.21				0.01		0.2	
Egmond aan Zee Wind Farm**	84				2		48	2
Anonymous ***	0.428		0.346				0.189	0.185

Database / Report	Air Brake	Gearbox	Wind Vane / Anemometer	Inverter	Instrumentation	Entire Unit	Source
Drift… & Felanalys						0.011	Ribrant 2006
VTT							Ribrant 2006
WindEnergie							Ribrant 2006
Danish Energy Agency	0.02	0.05				0.06	Van Bussel et al. 2003
Betriever Databasis/ IWET	0.03	0.08	0.03				Van Bussel et al. 2003
WMEP 1	0.041	0.102		0.08	0.198		Van Bussel et al. 2003
WMEP 2	0.048	0.277		0.1	0.498		Van Bussel et al. 2003
LWK Schleswig-Holstien 1	0.034	0.133	0.043	0.002			Van Bussel et al. 2003
LWK Schleswig-Holstien 2	0.026	0.152	0.044				Van Bussel et al. 2003
EPRI California	0.195	0.264					Van Bussel et al. 2003
WMEP 3		0.26					Carlsson et al, 2010
WMEP 4		0.24					Carlsson et al, 2010
WMEP 5		0.04					Carlsson et al, 2010
DOWEC Estimations *		0.25		0.2			Van Bussel et al. 2003
Egmond aan Zee Wind Farm**		20		9			Tavner, 2012
Anonymous ***		0.633					Carroll et al 2015

*based on onshore data and expert knowledge
**number of stops/turbine/year
***not use in failure rate analysis

Appendix C – Classification of models reviewed

Table C1 - Classification of Models Reviewed

Model Name	Reference	Description	SA Method Used	k	n	Stochastic/ Deterministic	Continuous/ Discrete	Analytical/ Numerical
Production forecasting with uncertainty quantification PUNQ	Marrel & Iooss 2012	An oil reserve model derived from real data.	Sobol’ indices with a metamodel for stochastic models	8	1000	Stochastic		
Integrated membrane bioreactor (MBR)	Cosenza et al. 2013	Simulates biological nutrient removal process	Comparison between Extended-FAST, SRC and Morris method	79	eFAST:395k SRC: 800 Morris: 800	Deterministic	Continuous	Numerical
GMSK	Campolongo & Saltelli 1997	Models oceanic production of Dimethylsulphide (DMS) for the purposes of climate modelling	Comparison between Sobol’, SRC and Morris Method	35	Morris: 360 Sobol': 3600 SRC: 3400	Deterministic		Analytical
AZODYN	Lamboni et al. 2011	Wheat crop development model	Comparison between Sobol-Saltelli, eFAST and FFD	13	Sobol’: 6555 eFAST: 6552 FFD: 6561	Deterministic	Continuous	Numerical

Appendix D – List of identified important factors from local sensitivity analysis

Table D -1Case 1

	Factor Code	Factor Description	Min	Max	μ^*	σ
Availability	DE1od	Operation duration of repair for failure Type 1	3 hrs	14 hrs	1.649	1.658
	MEend	Work end time	17:00	20:00	1.139	1.033
	CO2cf	Failure rate of electrical system for failure Type 2	0.005	0.02	2.722	0.8794
	WFbop	Average BoP availability	90%	100%	4.378	0.4109
Cost	CO2cf	Failure rate of electrical system for failure Type 2	0.005	0.02	5200	1960
	CO1gf	Failure rate of gearbox for failure Type 1	0.19	0.65	3840	1210
	MEjdr	Day rate of HLV	£50k	£125k	1290	908.6
	CO1gc	Repair cost for gearbox for failure Type 1	£10k	£19k	2310	711.7
	DE2wf	Cost of subcontracted workforce to conduct failure Type 2 repair	£20k	£100k	947.7	607.5
	DE20d	Operation hours to conduct failure Type 2 repair	1 hr	20 hrs	1010	584.2
	MEctc	Number of technicians per corrective maintenance team	2	3	1660	258.5
	MEhco	Annual fixed cost of helicopter	£2,000k	£6,000k	3070	190.4
	MEjmo	Time to mobilize HLV	5 hrs	24 hrs	473.3	401.3
	MEjmf	Maximum number of failures before mobilization of HLV	1	5	471	398.6
	DE2pd	Planning delay to conduct failure Type 2 repair	18 hrs	47 hrs	334.9	301.2
	WFbas	Distance to O&M base from the OWF centre	30 km	50 km	880	154.4

Table D-2: Case 3

	Factor Code	Factor Description	Min	Max	μ^*	σ
Availability	DE1od	Operation duration of repair for failure Type 1	3 hrs	14 hrs	17.08	16.12
	MEend	Work end time	17:00	20:00	9.308	13.23
	MEnve	Number of type CTV	4	6	4.328	6.981
	DE1int	Number of teams required to repair failure Type 1	2	3	5.107	5.241
Cost	CO2cf	Failure rate of electrical system for failure Type 2	0.005	0.02	9290	3660
	DE1od	Operation duration of repair for failure Type 1	3 hrs	14 hrs	1950	3040
	CO1gf	Failure rate of gearbox for failure Type 1	0.19	0.65	7320	2400
	MEjdr	Day rate of HLV	£50k	£125k	2320	1590
	CO1gc	Repair cost for gearbox for failure Type 1	£10k	£19k	4310	1230
	MEend	Work end time	17:00	20:00	825	1220
	MEjmo	Time to mobilize HLV	5 hrs	24 hrs	1780	948.1
	MEhco	Annual fixed cost of helicopter	£2,000k	£6,000k	3130	357.7

Appendix E – SPARTA project

Introduction

In the literature review in Section 2.5.1, the current state of the art of reliability data for WTGs is given. It is found that, in the public domain, there has not been a cooperative effort to collect WTG reliability data specifically for offshore WTGs and provided it to operators in the same way that there has been for onshore WTGs, despite the obvious demand. Assessments have been made on the impact of the offshore climate on the performance of machinery (Thies et al., 2009; Yu et al., 2013) but this impact has yet to be validated with observations from operating offshore projects.

The most popular approach of reliability analysis is to rely on the results of failure rate analysis using the data collected from populations of onshore WTGs from campaigns that began in the late 1990 and early 2000s. However, there is a significant absence of the same dedicated monitoring campaigns for offshore wind in order to have comparable quality data sets. The purpose of which would be to minimize the risk of incorrect assumptions being made of the effect on failure rates by oceanic climates or, alternatively, validation of those assumptions.

There are aspects of the onshore databases which have since proved to be hurdles for the commencement of an offshore equivalent. One of which is the method of data collection and the question of data ownership and commercial sensitivity. For the onshore WMEP database in Germany, data was collected from the project Owner /Operators (O/Os) through direct link to the SCADA data and maintenance logs. This has proved difficult with many offshore O/Os. Another issue is standardisation of the data collected as O/Os have their own systems of data collection and management. One of the outcomes of the Reliawind project was to generate a standard form for data collection, with a clear definition of system structures for reporting (Tavner, 2011). The uptake of this reporting has been minimal.

There are currently two multi-operators projects of WTG reliability data collection existing in the European wind energy industry. The offshore~WMEP is a descendant of one of the onshore WTG failure rate databases instigated by the German government and administered by the Fraunhofer Institute. It follows the same structure of the existing WMEP database, where all data is passed to the Fraunhofer Institute. The strength of this approach is that the data is processed in the same way, independent of which operator it has originated from. The commercial hurdles of data transfer, rather than technical challenges, means that uptake from O/Os has been minimal in the first few years of operation.

A different approach is to allow O/Os to analyse their data independently then submit them to a shared database. This may reduce the level of the data handling compared to a singular body calculating all the data in the same way, but it allows for easier access for operator as the majority of their data remains in their possession. This is the approach of the System Performance Availability Reliability Trend Analysis project (SPARTA).

Structure

The SPARTA project is spear-headed by The Crown Estate, the legal entity that issue licenses for use of the seabed in UK waters. The administering body for SPARTA is the Offshore Renewable Energy Catapult (ORE Catapult), which is a specialist Technology Innovation Centre launched through InnovateUK. Technical assistance and expertise is provided by a third party contractors such as DNV GL Renewables and a software design and web company. Finally, there are the offshore wind project O/Os.

The project commenced in the summer of 2013. Between summer 2013 and spring 2014, the Crown Estate, ORE Catapult, 3rd party consultancies and the OWF project O/Os collaborated on the input metrics. The object was to provide useful information to the owner O/Os on the performance and reliability of their wind farms. From April 2014, the project entered a pilot phase, where the database operational but changes could be made based on the feedback from the O/Os. From April 2014, the project left the pilot phase and went into the operational phase. In the first year and a half, the project was supported by the Crown Estate. From the operations handover in April 2015, the majority of cost are to be covered by contributions from the O/Os.

A priority of the project is maintaining the commercial interested of the O/Os, consequently all data inputted into the system remains anonymous. Any output that only has values contributed from only two O/Os will not be visible.

For commercial sensitivity reasons, the list of contributing O/Os is not available to be published however the majority of UK OWFs are currently represented in the database.

Inputs and Outputs

There are 69 separate input values that can be entered into the SPARTA system. All of the values are optional, however, the SPARTA user agreement stipulates a minimum percentage in order to maintain a useful system. When an operator begins to contribute to the project, for each wind farm a base set of inputs are required. These values are fixed through the project lifetime, such as the number of WTGs, the capacity of the wind farm, etc. There are occasions when these values will change, for example when a wind farm is extended.

The monthly variable input values are divided into three categories; performance, maintenance and operational strategies. In the performance category, the energy generated in MWh is recorded from an offshore and onshore location. The generation hours; availability for the WTGs and entire project; and the data availability is required. Also requested are the losses suffered due to curtailment and the number of remote resets. In the maintenance category, the number of repairs is recorded for different subsystems for both repairs requiring a HLV and those not. There are 30 subsystem categories or repairs allocated via the RDP-SS system of plant machinery designations. The operational strategies categories provide information on how the site is maintained such as the number of CTVs and helicopters, if they are owned or contracted by the O/O and if an offshore structure used for accommodation. Details of the metrological conditions are also inputted such as the number of weathers days, the mean wave height and the mean wind speed. These values are decided upon through a series of workshops prior the pilot stage and involved representatives from the ORE Catapult, the O/Os and 3rd party consultancies.

The outputs are provided on monthly basis to the O/Os are in the form of benchmarking graphs, tornado diagrams and heat maps. The WTG and project availability are shown on candlestick graphs. Each candlestick graph shows the maximum and minimum values inputted that month and the ± 1 standard deviation from the industry mean, which is also shown. Each of the O/O are provided with an individual account to a secure website where their own wind farms are shown on the candlestick graph. A tornado graphs illustrate the deviation of the wind farm value for a number of outputs from the industry mean. Heat maps show a qualitative representation of the difference in the number of repairs from the industry mean. The values behind the graphs are available in a CSV file.

Some output graphs are generated directly from the input values, such as availability, generation and non-access days. Others are calculated from inputs, such as a failure rate per WTG for different components which is the sum of all repairs divided by the number of WTGs. This failure rate is issued on monthly basis. A capacity factor for each wind farm is calculated by amount of energy generated divided by the total hours multiplied by the capacity.

These outputs are used by the O/Os to benchmark the performance of wind farms. The capacity factor benchmark is useful to see how the amount of power generation compares with other OWFs whilst respecting the installed capacity. Although this will not help to identify the cause of a reduction in generation, it can be used in collaboration with other graphs to identify clues, such as the number failures, the mean wind speed or the amount of access days.

The data can be used by an O/O to identify improvements for increased performance of the wind farm. As an example, if there is a significantly lower capacity factor showing for a wind farm, the mean wind speed could be compared with other OWFs in the same region. If mean wind speed or failure rate is not significantly differently, then the operator can look at the O&M strategy, such as mean number of vessels used or number of technician transfers. This information can provide a starting point for further investigation.

It is hoped that by providing this information to the O/Os, the performance of the industry will increase and bring down the levelised cost of energy. Additionally, the collection of performance and reliability data will build over time to a suitable size from which reliability analysis can be performed.

The input metrics and output graphs are devised through a workshop process between the administrators, consultancies and O/O representatives. It is a challenge to coordinate the inputs so that they are achievable for all O/Os to gather and report. The outcome from the workshop approach was that the O/Os are provided with the list of inputs required and guidance on how to calculate them. Due to the differences in data management structures of each O/O, it is not always possible for every O/O to conform to the guidance. For this reason, the calculation of each of the inputs needs to be established separately.

For most of the operators, the contribution has been developed around the data used by the performance analysis or asset management teams. The following is an example from one of the participating O/Os. The source of data for the inputs in the performance categories is from the inbuilt reporting system supplied by the OEM SCADA. These reports are provided as monthly summation of availability, generation hours, SCADA availability. The availability for the WTGs only is calculated as:

$$A_{turbine} = \frac{periodhours - (standstillhours - (gridfaulthours + windfaulthours + otherhours))}{periodhours} \quad [32]$$

The availability for the project including WTGs, balance of plant and grid to the onshore substation is calculated as:

$$A_{project} = \frac{periodhours - (standstillhours - windfaulthours)}{periodhours} \quad [33]$$

Where *periodhours* is the total hours in the month, *standstillhours* is the total hours when the WTGs are not generating, *windfaulthours* is the total hours when the wind speed was too high and the WTG cut-out, *gridfaulthours* is the total hours where WTG standstill was caused by grid related outages, *otherhours* is any other standstill hours not due to the reasons thus specified or from maintenance activities.

Other approaches are to use the 10 minute logs from SCADA and calculate the availability directly. This circumnavigates any potential errors in the monthly report calculation.

For the inputs in the maintenance category, the data is taken from the maintenance logs of the WTGs supplied by the OEM. For other, non-WTGs related maintenance such as to the supporting structure of the WTG, the count is maintained through frequent contact with the operations teams.

For the inputs in the operation strategy category, the information is taken from operational logs of the O&M port by counting the number of WTG transfers and the number of vessels used during one period month.

Assessment

The database now has over a year's worth of information from the majority of the UK OWFs, although, during the pilot phase, there are changes to some of the input specification to make the approaches for input calculation more homogenised.

To assess the effectiveness of this project a Strength, Weaknesses, Opportunities and Threats (SWOT) analysis was conducted:

Table E-1: SWOT analysis of SPARTA Project

Strength	Weakness
The ability for easy access for commercial O/Os as the risk of sharing commercial data is low. The continued uptake of the database by O/Os means that the outputs are more valuable as they show an accurate reflection of the industry. The methodology for calculating inputs is becoming standardized by some of the O/Os, meaning that it is possible to compare values, outside of the SPARTA system, whilst, at the same time using previously existing data sources and methodologies.	Not yet enough WTG population to dissect the data geographically in a meaningful way. No quality checks for data inputs other than the length of input, so O/Os could accidently input erroneous data.
Opportunity	**Threat**
Working with other project delivery bodies across Europe to expand the database outside of the UK Allowing access for researchers to anonymised data in order to conduct independent failure analysis and further the understanding of failure rates and O&M strategies in the public domain. Improving sophistication of the inputs, such as allowing production-based availability to, build confidence and usefulness.	The system could be deliberately sabotaged by erroneous data by a contributing O/O. The O/Os decide not to allow academic researchers access for reliability analysis, thus sacrificing an opportunity.

Conclusions

After the first year of operation, the SPARTA project has developed enough confidence from the UK offshore wind industry, to the point that the majority of O/Os are contributing financially as well as consistently providing data on a monthly basis. Definition and improvement of the inputs needs to continue to become more sophisticated. For example, currently, availability is provided on a time basis only but efforts are underway to devise a methodology for production-based availability and producing a standard methodology for calculating lost-production. If the project extends to beyond the UK, then the population of WTGs will grow, allowing for analysis which can be dissected in different manners. Currently this is limited due to the relatively small number of participating OWF and the requirement for three or more OWF for each query.

The SPARTA project is the first time an OWF performance and reliability database that has been established with all O/Os contributing from one country. The necessary work to get it to this point has been through sustained collaboration of the administrative bodies with representatives of the asset management and performance analysis teams from the OWF operators. The outlook for the project is for it to continue successfully as almost purely industry driven and supported. It will be possible to track the changes in the offshore wind industry with the ageing of offshore WTGs and the introduction of new models in the same way that the early onshore WTG reliability databases have been able to.

This appendix shows how SPARTA is an important step towards collaborative efforts to collect data of offshore WTGs. Whilst the data has not be robust enough to be used extensively in the uncertainty analysis of Section 5.5, it has been used to support some of the assumptions made.

Appendix F – Input factors for global sensitivity analysis

Table F -1: Case 1

Code	Description	Unit	Distribution	Value
PRntm	Number of teams for preventative maintenance		Discrete	1 to 3
PRopd	Operation duration of preventative maintenance	hrs	LogNormal	$\mu = 3.92$ $\sigma = 0.33$
MEjmf	Max number of failures for mobilisation of HLV		Discrete	0 to 25
MEjmo	Time to mobilise HLV	days	Discrete	1 to 5
WFbop	Average BoP availability	%	Uniform	95 - 100
DE20d	Operation hours to conduct failure Type 2 repair	hrs	Discrete	10 to 40
MEjdr	Day rate of HLV	k£	Discrete	85 to 230
CO2ff	Failure rate of yaw system for failure Type 2	λ	LogNormal	$\mu = -3.95$ $\sigma = 1.15$
CO2df	Failure rate of control system failure Type 2	λ	LogNormal	$\mu = -4.65$ $\sigma = 1.43$
CO1gf	Failure rate of gearbox for failure Type 1	λ	LogNormal	$\mu = -2.84$ $\sigma = 0.52$
CO1cf	Failure rate of electrical system for failure Type 1	λ	LogNormal	$\mu = -1.83$ $\sigma = 0.82$
DE2pd	Planning delay to conduct failure Type 2 repair	days	Discrete	60 to 90
DE2wf	Cost of subcontracted workforce to conduct failure Type 2 repair	k£	Uniform	15 to 60
MEnve	Number of CTVs		LogNormal × Wfnum	$\mu = -3.13$ $\sigma = 0.5$

Table F-2: Case 2

Code	Description	Unit	Distribution	Value
DE1od	Operation duration of repair for failure Type 1	hrs	Discrete	1 to 23
MEend	Work end time	from time 0	Discrete	8 to 12
CO2cf	Failure rate of electrical system for failure Type 2	λ	LogNormal	μ = 2.84 σ = 0.832
WFbop	Average BoP availability	%	Uniform	95 to 100
CO1gf	Failure rate of gearbox for failure Type 1	λ	LogNormal	μ = -2.84 σ = 0.52
MEjdr	Day rate of jack up vessel	k£	Discrete	85 to 230
CO1gc	Repair cost for gearbox for failure Type 1	k£	Uniform	630 to 5670
DE2wf	Cost of subcontracted workforce to conduct failure Type 2 repair	k£	Discrete	15 to 60
DE20d	Operation hours to conduct failure Type 2 repair	hrs	Discrete	10 to 40
MEctc	Number of technicians per corrective maintenance team		Discrete	2 to 4
MEhco	Annual fixed cost of helicopter	k£	Discrete	500 to 5500
MEjmo	Time to mobilise HLV	days	Discrete	1 to 5
MEjmf	Maximum number of failures before mobilisation of HLV		Discrete	0 to 15
DE2pd	Planning delay to conduct failure Type 2 repair	days	Discrete	60 to 90
WFbas	Distance to O&M base from the wind farm centre	km	Discrete	29.1 to 51.9

Table F-3: Case 3

Code	Description	Unit	Distribution	Value
DE1od	Operation duration of repair for failure Type 1	hrs	Discrete	1 to 23
MEend	Work end time	from time 0	Discrete	12 to 24
MEnve	Number of type CTV vessels		LogNormal × Wfnum	μ = -3.13 σ = 0.5
DE1int	Number of teams required to repair failure Type 1		Discrete	1 to 2
CO2cf	Failure rate of electrical system for failure Type 2	λ	LogNormal	μ= -2.83 σ = 0.83
CO1gf	Failure rate of gearbox for failure Type 1	λ	LogNormal	μ= -2.84 σ = 0.52
MEjdr	Day rate of HLV	k£	Discrete	85 to 230
CO1gc	Repair cost for gearbox for failure Type 1	k£	Uniform	66.7 to 123
MEjmo	Time to mobilise HLV	days	Discrete	1 to 5
MEhco	Annual fixed cost of helicopter	k£	Discrete	500 to 5500

Appendix G – Conference paper

Martin R, Lazakis I, Barbouchi S. Analysis of Input Factors To Operations And Maintenance of Two Offshore Wind Farm Case Studies ; A Screening Process . Renewable Power Generation Conference (RPG 2014), 2014.