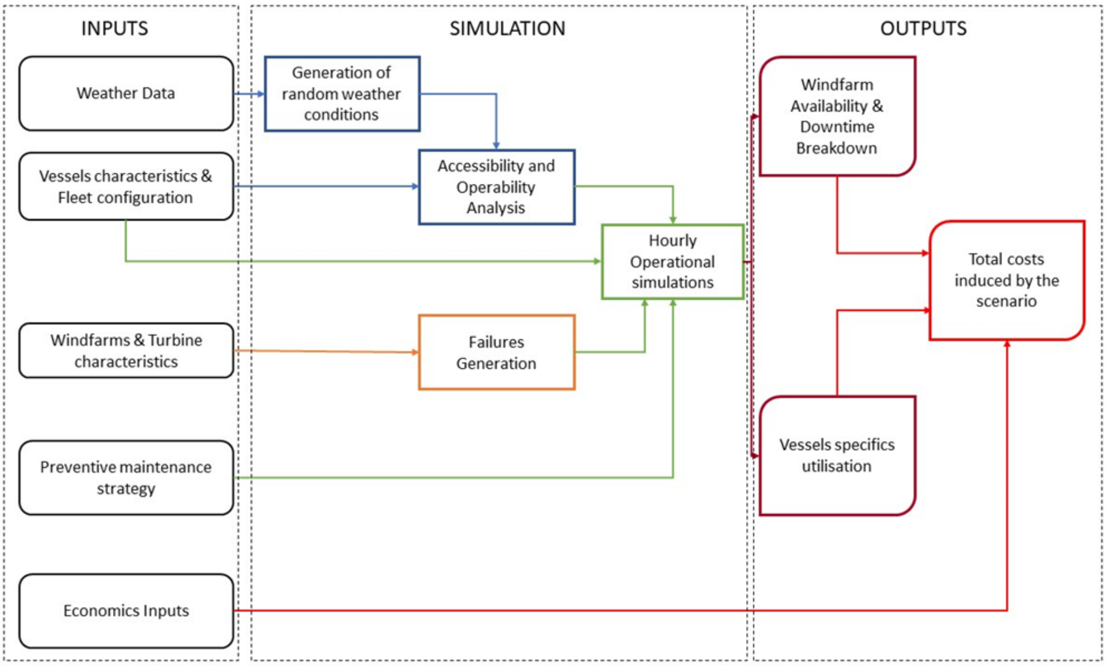
KTH Industrial Engineering and Management

Logistics strategy optimization for offshore windfarms with power purchase agreement

Aubin Pottier



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Abstract

Offshore wind is on the road to become commercially viable and competitive means for large-scale electricity production. This new industry is expected to occupy a major role in the energy transition. Operational costs and especially logistics cost for offshore maintenance are major factors and already today represent important levers to reduce the electricity production costs.

In this study, a methodology to design and optimize an offshore windfarm's logistics strategy is developed. This methodology is based on a software able to simulate a large number of logistics strategies and their interactions with weather conditions. The main outputs of the simulation are the monthly availability of the turbines and the logistics costs.

The case study illustrates that the critical windfarm's size for which a logistics strategy based on a vessel remaining at sea for weeks (offshore-based) becomes more beneficial than a strategy based on vessels going back to the port every day (onshore-based strategy), is close to 170 turbines for conditions typical to geographical areas similar to the North Sea. The simulation results, combined with scientific literature review, identify the distance to shore, number of turbines and transfer capacity of vessels as key parameter of logistics strategy design.

SAMMANFATTNING

Vindkraft ute till havs är på väg att bli kommersiellt gångbart och konkurrenskraftigt medel för storskalig elproduktion. Denna nya industri förväntas inta en viktig roll i energiomställningen. Driftskostnader och särskilt logistikkostnader för reparationer och underhåll till havs är tunga faktorer och utgör redan idag viktiga spakar för att minska elproduktionskostnaderna.

Denna studie utvecklar en metod för att designa och optimera logistikstrategi för underhåll av havsbaserad vindkraft. Metoden bygger på en programvara som kan simulera ett stort antal strategier och deras interaktion med väderförhållandena. De viktigaste resultaten av simuleringen är vindturbinernas månatliga tillgänglighet och logistikkostnader.

Studien vilar på en fallstudie som illustrerar att den kritiska vindkraftsparkens storlek är närmare 170 turbiner då en logistikstrategi baserad på ett fartyg som stannar kvar i havet i flera veckor (offshore-baserat) blir mer fördelaktig än en strategi baserad på fartyg som går tillbaka till hamn varje dag (landbaserad strategi), för förhållanden som är typiska för geografiska områden som liknar Nordsjön. Simuleringsresultaten, kombinerat med vetenskaplig litteraturöversikt, identifierar avståndet till land, antalet turbiner och fartygens överföringskapacitet som nyckelparameter för logistikstrategidesign.

Contents

List of Figures

List of Tables

Abbreviations

CAPEX: Capital Expenditures

CTV: Crew Transfer Vessel

HLO: Helicopter Landing Officer

HS: Significant wave height

JUB: Jack Up Barge

LCOE: Levelized Cost of Energy

MCR: Main Component Replacement

MTBF: Mean Time Between Failures

MTTF: Mean Time to Failure

MTTR: Mean Time to Repair

NARMA: Nonlinear Auto-Regressive Moving Average model

O&M: Operations and Maintenance

OCC: Operations Control Command

OSV: Offshore Supply Vessel

SCADA: Supervisory Control and Data Acquisition

SOV: Service Operation Vessels

OPEX: Operating Expenditures

PPA: Power Purchase Agreement

U.C: Unit Costs

WTG: Wind Turbine Generator

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1 INTRODUCTION

1.1 Background

1.1.1 Offshore wind technology status

By the end of 2019, there was a total installed capacity of offshore wind turbines of 29.1 GW, out of which 6.9 GW were installed during 2019 (Global Wind Energy Council). Europe was first to develop a large scale effort in offshore wind deployment and therefore it is currently the leading geographical area in terms of installed capacity. Thus, in 2020 there are 25GW installed in Europe, constituted of 5402 turbine units distributed across 12 countries, mainly in the North Sea region (Wind Europe, 2021).

Nowadays, China is the country with the most significant annual growth in installed offshore wind capacity with 2.14 GW commissioned in 2019; while South Asia is expected to become the leading geographical area in terms of installed capacity by 2030 (Global Wind Energy Council).

The offshore industry is evolving very quickly with a lot of innovations, especially regarding the size of wind turbines. The average nameplate capacity of wind turbine units in 2020 was 8 MW whereas it was 3 MW in 2015. This sharp increase in unit capacity and other technical developments lead to an important decrease in Levelized Cost of Energy (LCOE) from offshore wind. In Europe, all the auctions in 2019 lead to prices between 40 and 50 €/MWh (Wind Europe, 2021). Thus, the offshore wind energy is a very dynamic sector, already experiencing serious decrease in associated costs and offering economic competitiveness in its own right.

Offshore wind energy has an estimated carbon emission intensity over its lifetime between 5 and 20 kg CO_2eq/MWh (Wang, et al., 2011) (Reimers, et al., 2014). Therefore, offshore wind can be considered as a very low carbon intensive electricity production source. This is linked to the typically higher availability of wind resources out at sea and thus higher productivity of offshore wind turbines, as opposed to land-based wind turbines.

However, offshore wind turbines are subjected to a harsher environment and experience logistical challenges with regards to installation, power transmission and all sorts of aftermarket maintenance procedures. Specifically the maintenance demands might cover a substantial part of the LCOE and require continuous optimization.

Offshore wind turbines can be divided in two main types of technology:

- Fixed foundations: The turbine is set up on a foundation that reaches the seabed and is firmly attached to it. Depending on water depth and bottom material, the fixed foundation can be a monopole rammed into the seabed, a tripod carrying a lattice structure, or a gravity-based counterweight lying on the seafloor.

- Floating foundations: The turbine is mounted on a massive floater of various structures, which represents a foundation that is not firmly attached to the seabed but only anchored in place and connected by cables to one or more anchoring points.

As of year 2021, only fixed foundation concepts are commercially available and well established. Fixed foundations are technically less challenging than floating foundations, but are limited to water depths roughly down to or less than 100 m depth.

Floaters present important stability challenges, especially in open sea environment were wind and wave loads could be critical. Overcoming these challenges could open up the possibility for massive utilization of deep-water far-offshore locations, leading to an enormous growth rate of offshore wind energy in the near future.

Therefore, floating foundations could significantly increase the potential for further development of offshore wind and again underline the ever greater importance of maintenance optimization as the distances to the site would be longer and the local weather conditions in the open ocean might be constantly challenging. Several pilot projects of floating wind turbines are already installed and undergoing rigorous testing. According to various sources the technology is expected to become commercially available around 2030.

1.1.2 Market Analysis

The offshore market sector is highly concentrated with regards to wind turbine generator (WTG) manufacturers. Only 3 companies are today producing WTGs for offshore applications: namely Siemens Gamesa Renewable Energy (SGRE), Vestas Wind Systems and GE Renewable Energy.

With 3674 WTG units at 16.9 GW cumulative capacity, SGRE accounts for 68% of European installed offshore capacity. Vestas follows with 1290 installed WTG units at 5.7 GW cumulative, accounting for 23.9% of European installed capacity – among them some of the first large-scale groundbreaking offshore projects that have clocked nearly 20 years of operation. GE has installed 74 WTG units at 0.4 GW cumulative capacity (Wind Europe, 2021).

On the other hand, the market for offshore wind project developers, owners and operators is more competitive. The most active companies are Orsted, RWE Renewables and Vattenfall. They respectively own 17%, 10% and 6% of the total European installed capacity. (Wind Europe, 2021)

Therefore, the turbine manufacturers have a strong position when negotiating with developers. Thus, WTG prices are not a strong lever to gain competitive advantage for developers. This contributes to the growing importance of Operation and Maintenance (O&M) strategy in order to win auctions and decrease costs.

In 2020, six corporate Power Purchase Agreement (PPA) contracts were signed in Europe for offshore wind projects, only one auction was attributed to the Netherlands with a zero subsidy bid. Developers tend to focus on projects with PPA as they avoid being subjected to fluctuating market's risks. This motivates the present study herein to consider exclusively projects with PPA contracts.

Furthermore, the European Union sets its goal of reaching 300GW offshore wind capacity by 2050. Adding Norway and the UK, the potential market expands to 400GW or more by 2050. To meet these aggressive ambitions, it is very likely that auctions with subsidy will be deployed largely. On the other hand, it could also be expected that they trigger continuous technological development with a steady decrease of costs, also leading to the establishment of a massive industrial base for maintenance procedures to sustain the enormous installed capacity in operating condition.

The auctions are usually government-driven. National governments perform pre-feasibility studies and then identify an area deemed suitable for an offshore windfarm of a particular capacity. Usually, the government would offer some type of subsidy. There are several ways to organize the subsidies, all of which are resulting in some sort of price guarantees for the project operator.

Project development companies are therefore invited to present an offer to construct a windfarm on the designated location. This offer includes a PPA price. This is usually the main criterion of choice. The company who bid at the lowest level will be awarded the tender and will build and operate the windfarm. Yet, other criteria such as environment management or local consent have started to gain importance in tender allowance.

1.2 Objectives

1.2.1 Operation and Maintenance definition

Once a windfarm has been built, a series of activities have to be completed throughout the entire lifetime to ensure reliable electricity production. These activities can be divided in two categories: Operation and Maintenance.

Operation refers to the general management of the asset. It includes both technical actions, such as remote condition monitoring and output control, environmental monitoring, etc., as well as economical activities such as electricity sales, insurances and other support from back office and general administration. Operations represent a significantly lower cost than maintenance.

Maintenance activity is the actual repair of the physical components of the asset. It encompasses technical and administrative actions that are needed to preserve or restore the ability of the physical equipment to function. Due to the human resources and material costs involved in maintenance activities, these are usually significantly more costly than the operation's activities.

Maintenance for offshore wind farms is often divided in three main categories: minor corrective maintenance, preventive maintenance and Main Component Replacement (MCR).

Minor corrective maintenance refers to all the actions that are to be taken in order to fix issues arising unpredictably and concerning components that can be fixed by windfarm's O&M team. Those failures could either be solved remotely or require an intervention on site. Technicians may be able to fix those failures with a simple visit or may need several interventions to first establish a diagnosis and then fix the failure. Minor corrective failures account typically for the greatest share of failures in all sorts of industrial machinery, including wind turbines.

Preventive maintenance refers to planned actions that are undertaken to reduce the probability of unpredictable failures and to assure a correct aging of the WTG. This includes regular inspections as well as preventive replacement of some parts and common disposables such as lights, lube oil, sensors, etc. These actions are usually performed during yearly campaigns when regular visits to the site are taking place. Preventive maintenance campaigns are usually undertaken during periods of low productivity for the windfarm combined with good weather – typically in the summer season – in order to minimize the time spent and the induced loss in power generation when the turbines are forcefully shut down for inspection.

Main Component Replacement (MCR) refers to the replacement of large and major components, which in the case of WTGs typically requires a big effort and could be very challenging – such as the replacement of turbine blades, blade bearing, nacelle bearing, electrical generator, transformer, control system components, electronic cabinets, other large auxiliary components, etc.. In the case of offshore WTGs these interventions require the use of a Jack Up Barge (JUB) and other specially adapted vessels able to deliver the new component and perform the replacement task.

Jack Up Barges are flat-decked vessels that feature large cranes and support legs of a considerable length enabling an anchoring of the barge and a rising of the deck for assuring stability. Such vessels are also used during the construction phase for mounting the turbines. Due to its very high cost, a JUB is typically not included in the windfarm's permanent vessel fleet. Moreover, their operation requires specialized personnel. This leads to arduous contracting procedures and long mobilization time whenever a major MCR activity is necessary.

Therefore, when a failure occurs unpredictably, the induced downtime on the productive asset is usually very large. However, some MCR can be predicted or expected in advance, allowing to better plan MCR campaigns and thus reducing both downtime and costs of intervention.

The various maintenance categories contain failures and actions that can lead to very different downtimes and types of interventions. Nonetheless, all these failures create the same need: namely to organize and lead a maintenance team, possessing the necessary knowhow and material base, that should be able to fix planned or unpredicted failures either remotely or by accessing the wind turbine site in a very short timeframe.

1.2.2 Logistics strategy of a windfarm

Operation and Maintenance of an offshore windfarms requires to set up an organization that is able to manage the three types of maintenance activities listed in the previous section. The common O&M scheme is organized in the following way:

An Operation Control Centre (OCC) monitors all the information and alarms sent by the inbuilt Supervisory Control and Data Acquisition System (SCADA). All the alarms and corrective actions that can be undertaken remotely are handled by the OCC. When issues requiring a site intervention are detected, the information is sent to the O&M base team.

The O&M base team refers to permanently employed or hired technicians and other staff that contribute to assuring the reliability of the production asset. Aside from the repair technicians who perform the maintenance intervention, personnel in charge of support functions such as logistics planners, managers, marine crews, etc., are also part of the O&M base team. The O&M base is located in a suitable harbor and is equipped with the necessary vessel fleet in order to access regularly to the offshore windfarm location.

The technicians can access to the offshore WTGs mainly through three different logistics means:

- <u>Crew Transfer Vessel</u> (CTV) are regular ships of a size between 15 and 30 meter long. These vessels can only perform transfers from harbor to the WTG and typically are not equipped for complex maintenance operations but only serve for transport and are adapted to allow for docking at the WTG;
- <u>Helicopter Landing Officer</u> (HLO) comprises helicopters and gear that can quickly transfer technicians directly to a given WTG or to a dedicated platform at the windfarm location by air. The load capacity is limited and typically only human resources are transferred with minimum materials and hardware;
- <u>Service Operation Vessel</u> (SOV) are large vessels (above 50m long) that are equipped to stay offshore for long time and remain anchored at the windfarm location, manned in shifts of typically two-week periods, residing on site and always ready to intervene.

All types of logistics solutions should be able to perform transfers in various weather condition and naturally are associated with a different cost structure. The specific costs are not only linked to the means of transportation to the offshore site, but also to the type and scale of the necessary maintenance activity.

Preventive maintenance can be performed by the in-house O&M team or by an externally hired team or by both together. Additional vessels can therefore be called to intervene on the windfarm site for the time of preventive maintenance campaign.

MCR always requires the intervention of larger vessels, specifically equipped for the task. These vessels are rarely part of the windfarm's permanent vessel fleet. MCR activities can be managed through different contract schemes, which do not have a strong impact on the initial logistics choice of the project.

Designing the O&M logistics strategy consists of selecting the number and type of vessels and technicians to attend permanently and seasonally to the windfarm in order to perform corrective and preventive maintenance as well as MCR. In addition to the classic difficulty of planning a maintenance scheme, the considerations for offshore windfarms should take into account the constraints of working at sea and the challenges of traveling to the site related to weather conditions and transportation time. Harsh weather conditions, especially wind and waves, can prevent the technicians from accessing to the WTG or from carrying out certain types of operations inside or outside the WTG.

1.2.3 Need for an optimization of logistics strategy

Annual operational expenditure costs accounts for 13 to 57% of the levelized cost of energy for offshore wind (Poulsen, et al., 2017). Logistics alone accounts on average for 17% of annual operational expenditure costs, and therefore for 2 to 10% of the levelized costs of energy. (Poulsen, et al., 2017). This high share of levelized cost of energy means that logistics solutions should be designed and estimated carefully during the tender process. Moreover, the considerable cost share also shows that logistics solutions are in demand of continuous optimization. Thus, logistics can be an effective lever for cost reductions.

CTV are the least expensive logistics means, yet they are also subjected to the strongest weather constraints and longest dispatch times. HLO are more expensive than CTV but can transfer technicians the fastest and with weaker weather constraints than CTV or SOV. However, HLO are submitted to a visibility constraint which can be a very strong limiting factor during winter season in locations such as Northern Europe for instance, due to the short days and frequent fogs.

SOV are considerably more expensive than CTV and HLO, as they are constantly dispatched at the site. They are submitted to weather constraints less important than CTV and more important than HLO. Their main advantage compared to CTV and HLO is that they offer the possibility to work by shift and are able to intervene immediately. SOVs can be considered as the means for continuous operation as they remain anchored at the windfarm for long periods of time.

Therefore, CTV and HLO are part of an onshore-based strategy whereas SOV is the definition of an offshore-based strategy.

CTV, HLO and SOV have also different requirements regarding harbors. Also, the optimum distance between the wind farm site offshore and the closest suitable harbor can be different for each of these logistics means. Some sites can be located close to a harbor receiving CTV but very far from the closest harbor able to receive an SOV.

However, as SOV spend most of their time offshore, the availability they can deliver is less affected by the distance between the windfarm and the harbor than it is for CTV. Hence, the logistics optimization procedure should be specified and investigated in detail for each particular wind farm size, location and geographical area of nearest shoreline.

A design of a logistics strategy is therefore not self-evident for most of the sites.

Moreover, the wind and wave conditions change randomly and as the failures also occur randomly, there is no simple way to derive the expected availability provided by a particular logistics solution. For instance, a statistics analysis can provide the information that with the chosen vessel the accessibility is of 20%. Yet, this could mean that every day out of 5 the WTGs are not accessible or that every whole week out of five weeks the WTGs are not accessible. In the first case the failures can be fixed on a regular basis whereas in the second case the turbines might regularly experience week-long downtimes with consequently serious loss of energy production, while the maintenance team should be sized in order to face peaks of activity following the week without accessibility. Thus, although these two situations share the same accessibility in terms of statistical probability, they lead to very different availability of energy production and require different solutions for optimal logistics strategy.

Therefore, in order to both assess and reduce the costs of logistics solutions, careful simulations must be performed involving power generator performance specifications, maintenance strategies and fleet configuration with specific cost structure, local weather conditions and other limiting factors, etc. Only simulations could deliver the expected availability for each logistics strategy, allowing to compare the cost of the logistics solution and the profit realized by the sale of production. This enables the windfarm operator to find the best balance between an expensive logistics solution leading to higher availability and a less expensive logistics solution trade-off with a lower availability.

The development of a tool for designing an optimum logistics strategy is the objective of this study.

Additionally, the investigation is limited to windfarms operating under power purchase agreements, which translates into all the MWh produced having the same value throughout the entire lifetime of the windfarm under consideration. Therefore, the considerations herein exclude any possible electricity market variations or market influence on the power output by the windfarm, or any market influence on the maintenance requirements of the windfarm.

Further aspects that are generally involved in windfarm O&M management would not be considered in this study either, due to their widely fluctuating nature, irregularity and dependency on local conditions that prevents their proper integration into universally applicable optimization tools. These are, for instance, the storage of spare parts or delivery arrangements for such, warranty contracts with the turbine manufacturer, onshore workshop space, rents or various service taxes charged by the harbor, etc.

1.3 Methodology

The structure of the proposed optimization process with the necessary input and output parameters is summarized and presented graphically in Fig.1. A discussion on critical inputs together with simplifications and assumptions follows in the sections below.

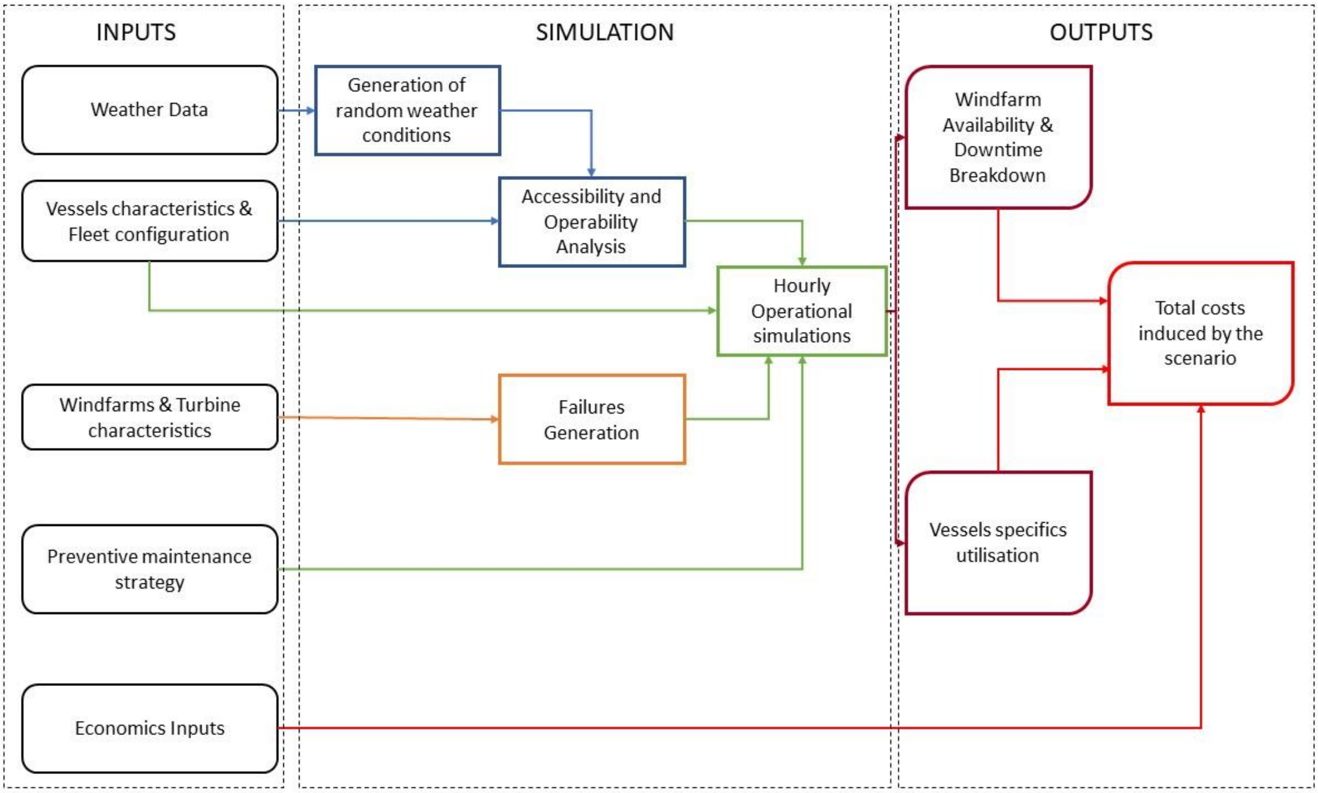

Figure 1: Methodology

1.3.1 Weather Data

An important piece of meteorological data is needed in order to properly conduct the simulations. Hourly values for both significant wave height and wind speed statistical distribution at the offshore site spanning over at least 15 years are required. As the purpose of the analysis is to assess the technical availability of the WTG and not its actual energy production, no detailed derivations are conducted in order to obtain specific wind speed values at hub height. The wind speed values generally observed at the given location are enough to use for the analysis.

Furthermore, there is no need to consider wake effect at this stage. Neither any obstructions nor productivity losses due to aerodynamic interaction among the turbines inside the windfarm would influence the main maintenance strategy, unless such interactions lead to increased probability for technical failures. As this might be the case in some windfarms, such parameters could be added at a later stage when adapting or calibrating the optimization tool.

The available weather data in the form of time series is fed to a neural network in order to simulate the desired weather variables. The neural network's output results in time series of two parameters. These are different for each iteration of the simulation.

The role of the weather-related parameters is to assess whether the offshore site is physically accessible or not for each simulated hour. This allows to fully model the stochastic combination of random failures and random weather conditions, identifying the periods of extended downtime when a given need of maintenance would not be possible to be addressed before the weather conditions allow the maintenance team to gain access to the WTG.

Therefore, it is crucial to calibrate well the weather model so that on average the simulated operability is equal to the one observed. Even minor imperfections or irregularities in weather data might cause significant deviations of output results for the optimization analysis, leading to wrong conclusions and inflicting considerably higher costs.

The monthly capacity factor for the windfarm, used in the energy production estimation for other parts of the analysis, is also derived from the observed wind conditions at the site.

1.3.2 Vessels' characteristics and Fleet configuration

1.3.2.1 Weather Constraints on vessel operation

Four main weather elements could potentially prevent the access to an offshore WTG, namely: tides, daylight or visibility factors, strong winds and high waves.

Tides:

Sites that are close to the shore could be unreachable by floating vessels during periods of low tides or at times of strong tide currents. For such locations the tide history is therefore necessary to be considered and transformed into hourly time-series identifying hour-based constraints and raising accessibility or inaccessibility flag as an output.

A positive aspect of tides is that they offer very high predictability. Long-term observations and precise measurements are usually available and are not challenging to process and integrate in mathematical analysis. The only critical condition is the proper prediction of extreme tidal events (such as very high or very low tides), such conditions might occur at various time periods for the different locations, such as from once per each season to once in many years.

HLO is typically not affected by tides.

Visibility:

Floating vessels are generally not hindered by daylight-related factors. All vessels are equipped with lights that enable them to perform transfer during night hours. However, during periods of daytime low visibility (for instance dense mist, snowstorm, etc.) or challenging docking procedure at night, vessels would remain at harbor due to safety reasons even if they are technically fit to sail.

As a result, precise weather data including correct forecasts become crucial for identifying the probable hours when a maintenance team would be hindered from accessing the WTG due to visibility constraints, even if the prevailing weather conditions generally allow a transfer.

Furthermore, according to international regulations HLO are allowed to perform transfer only during daylight hours. The sunrise and sunset hours are therefore calculated over one standard year and transformed into an hour-based constraint, integrated in the simulation tool.

Wind:

High wind speeds can make the anchoring and docking process, the gangway between the vessel and the WTG, or the working environment inside the WTG unsafe due to movements and vibrations induced on the turbine. Besides, high wind speeds can prevent technicians from using cranes or applying precision when unloading or mounting large tools and spare parts from the service vessel to the WTG.

Therefore, it is typically considered that above a certain predefined wind speed the WTG is rendered inaccessible regardless of the other weather parameters. The specific wind speed factor as well as the height above the average sea level where the wind speed reading is taken, might vary for the various locations according to prevailing weather or marine conditions, geographic position, type of WTG, type of docking arrangements, etc.

The limiting wind speed for safe maintenance access is usually far lower than the typical maximum wind speed of WTG operation. In this study, the wind speed constraint is integrated as a variable input parameter in the optimization tool, thus the limiting wind speed can be defined or varied by the user according to local conditions.

Waves:

Waves affect the ability of CTV and SOV to safely dock at and transfer technicians to the WTG. High waves prevent CTV to stabilize themselves against boat landing so that technicians can climb on a ladder or walk along a gangway to access the WTG. When the waves are too strong, the contact between the boat landing and the vessel is not permanent as the vessel's position is largely fluctuating in all possible degrees of freedom. Damage could also be inflicted both on the vessel and on the landing platform of the WTG if the fluctuations are too high.

Typically, a CTV is equipped only with simple gear for docking and landing and is more prone to putting the technicians at risk of slipping or falling. The SOVs on the other hand usually rely on more advanced solutions such as a weatherproof and stabilized transition piece between the vessel and the landing platform, which allows the transfer to be performed safely at higher waves and stronger winds than for a CTV.

The important wave characteristics affecting the vessels' ability to perform safe transfer are the wave height (both average and extreme), oscillation period and direction of the waves. All these need to be known and taken under consideration for the analysis.

As the actual height of each single wave varies constantly even in a seemingly stable wave pattern, the significant wave height (often denoted as "HS"), which is the average height of the top tier of waves, is used to characterize this constraint. The HS is naturally the value that meteorologists and marine scientists would typically observe and record, and is a target of weather forecasting.

Different approaches could be applied for estimating the extreme wave height as a function of the HS value, depending on the specific geographic area and climate pattern. Extreme waves might occur randomly and could be deemed most dangerous, therefore the maximum wave height is used when defining the governing factor for evaluating the constraints. As a rule of thumb, the highest wave that can be expected is most often assumed to correspond to twice the typical HS for the given location and a given season (Bureau of Meteorology).

The influence of wave oscillation period on the transfer capacity is not straightforward. As the wave frequency increases, the maximum allowed HS value at which a vessel can perform safe transfer would initially decrease and then start to increase.

Very high oscillation frequency makes the wave pattern more predictable and decreases the extreme amplitudes, thus making it easier for the vessel to handle the transfer. Furthermore, CTV and SOV are affected differently by the wave oscillation period; also vessels of different sizes and different hull shape would react differently to varying oscillation periods (Wu, 2014).

Wave direction could be very critical for floating vessels' stability, especially for vessels of relatively small size. When waves are orientated orthogonally to the boat, the capacity for safe transfer is considerably reduced (Wu, 2014). Thus, the boat landing gear or the transition piece should be positioned so that the vessel is mostly facing the prevailing wind and avoids orthogonal waves. Alternatively, the landing platform could be designed to be accessible from all directions so that the vessel would be able to choose from which position to approach the WTG, according to the governing wave pattern at the given moment.

For the sake of simplicity and reliability of the modeling process, wave constraint on vessel transfer is reduced to a predefined HS limit. The value denotes the maximum-average HS at which vessels can perform safe transfer of technician crews to and from the WTG, which is used as a key input parameter in the simulation tool. Uncertainty and variability of this parameter is important as vessels may perform significantly differently from one site to the other due to change in wave period and wave direction distribution.

HLO are also restricted in terms of HS. For safety reasons, HLO should always fly above a sea that would allow for enough time to activate floaters if the HLO was to crash in the sea, which is adversely affected by the roughness of the sea surface. However, the maximum allowed HS for HLO operation is very high and therefore HS is not a strong constraint for HLO in comparison with visibility and wind speed constraints.

The critical constraints to vessel transfer operation and the extent to which they are integrated in the simulation model are summarized in Table 1.

Table 1: Summary of environmental constraints for vessel access

	CTV	**SOV**	**HLO**
Tides	Yes	Yes	No
Visibility	No (very low)	No (very low)	Yes
Wind speed	Yes	Yes	Yes
Wave height	Yes (1.5-2m HS)	Yes (2.5-3.5m HS)	Yes (weak effect)
Wave period	Yes (via HS value)	Yes (via HS value)	No
Wave direction	Yes (via HS value)	Yes (via HS value)	No
Speed (nm/h)	~20	~10	80+

1.3.2.2 Fuel Consumption and Fuel Costs

Fuel consumption derivations are based on a distribution of service vessels' activities into two main categories, such as:

- Transit:
  The vessel travels at high speed from the O&M base to the offshore location or from one WTG to another WTG inside the windfarm, resulting in high fuel consumption per hour of operation.
  In modern offshore windfarms with large unit-size turbines the distance between two nearest turbines is over 1 km. Therefore, it is not necessary to reduce the speed significantly when navigating through the windfarm, yet a frequent start-stop procedure when transiting inside the windfarm with the purpose of calling at many different WTGs for repetitive maintenance activities could lead to increased fuel consumption levels.
  Docking and crew transfer between the vessel and the WTG are also considered as transit activities as the vessel's engines are operating at high power.
  Specific fuel consumption per hour of operation and per unit load is particularly high for HLO transit solutions, however HLO offers the fastest way of transit and would generally operate for shorter durations than marine vessels.

- On site:
  The vessel is calmly waiting nearby the WTG while technicians are performing maintenance work on the WTG. The vessel's main engines are idling or running at very low output, or are switched off entirely if another (secondary) engine is available onboard for providing the necessary power in such occasions.
  The fuel consumption per hour of operation in this case is low, yet it is not zero and should still be taken into account especially if long waiting hours on site are involved in the maintenance activities.
  Long on-site residence time is a major parameter for SOV category vessels that remain anchored at the windfarm site for long periods of time.

Two different fuel consumption rates are therefore assigned to each activity category and multiplied by the number of hours spent in each activity.

Additional expenses related to fuel storage onshore or fuel delivery and tanking procedures might also need to be included in the overall fuel cost derivations. However, these are dependent on local arrangements, difficult to specify and are not taken into account for the optimization analysis in this study.

1.3.3 Windfarm and Turbine Characteristics

1.3.3.1 Energy production modeling

Undoubtedly, the type and size of wind turbines involved in the analysis need to be known, as well as their technical characteristics to be properly defined for estimating the energy yield and thereafter the loss of energy production during forced downtime.

The modelling software used in this study enables a very large number of simulations. Thus, it is possible to integrate in the model a continuous estimation process for deriving capacity factor values in order to estimate an average hourly energy yield per month by each WTG, even though the offshore windfarm under analysis might not yet be commissioned and put into operation. This is obtained by interpolating the wind velocity input values and the power curve of the WTG under study, in a similar way as the project developer would be preliminary assessing the expected energy yield within a standard year.

Alternatively, real field data from existing wind turbines in the same geographical area could be inserted in the simulation model, applying typical capacity factor values already observed for the area and directly estimating the expected energy yield for a given stretch of time.

Thus, the model captures the seasonality of energy production while remaining sufficiently simple.

1.3.3.2 Failure rates and maintenance indicators

A WTG under operation is considered to have two possible states, depicted in Fig.2:

- Working: The turbine is operating properly and the power output corresponds to the estimated per-hour or other time-average level or energy production.
- Failed: The energy production is stopped and the turbine is out of operation for a technical reason (technical failure). The forced downtime continues until the required repair action has been completed.

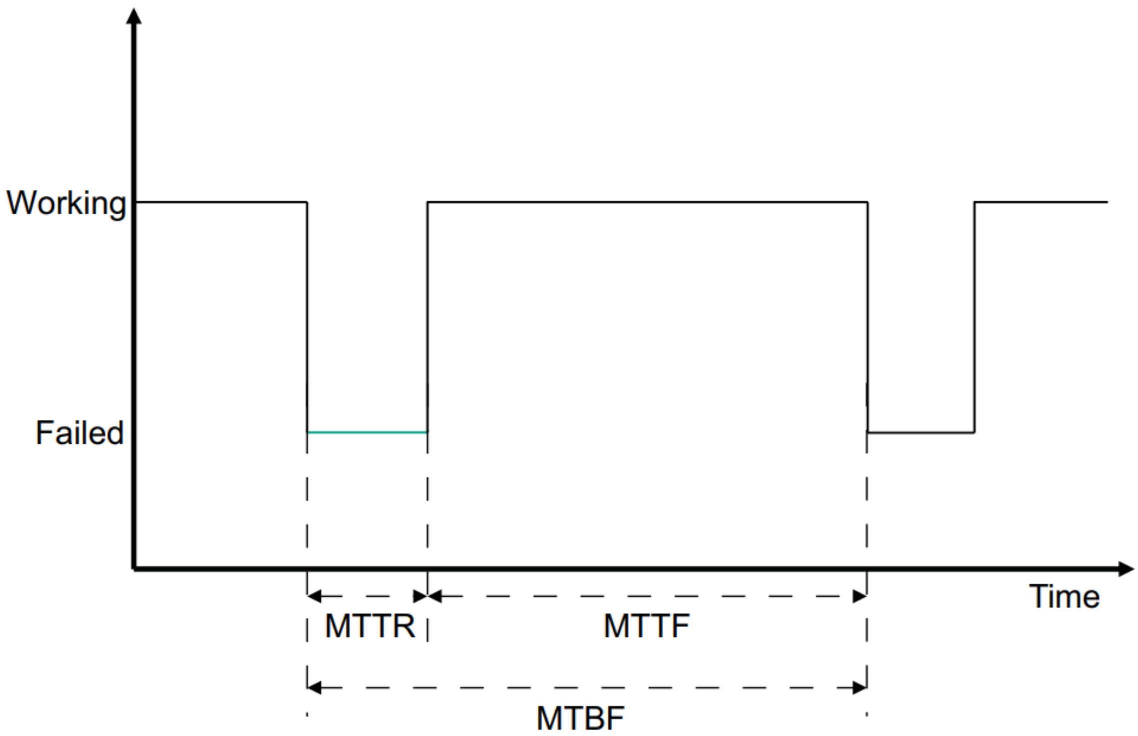

Figure 2: Definition of maintenance time indicators (Münsterberg, 2017)

Three key indicators are usually used to quantify the reliability of a machine and to specify the severity of necessary maintenance tasks for bringing the machine back to fully operational state. These are:

- Mean Time Between Failures (MTBF): The statistical average time lapse between two failure occurrences, related to the whole system or to a single assembly or component.
  The MTBF is a universal summed parameter that indicates the frequency of necessary corrective actions, but does not specify the actual state of operation during this time – the machine could either be quickly repaired and put back into operation or it could be taking long time to repair and then failing again soon after been put into working state.

- Mean Time To Failure (MTTF): Representing the average time after a repair action has been completed until a following failure occurs, denoting particularly a time lapse when the machine is properly functioning, i.e. in working state.
  Longer MTTF indicates higher technical availability and therefore higher productivity of the machine; this is particularly important when the machine is sited at a remote location.

- Mean Time To Repair (MTTR): Defines specifically the average time that it takes for a repair action to be completed and the machine to be put back into working state. It is a function of many factors, including human factors, but is usually taken as an average value for the particular type of machine and location.
  MTTR corresponds to the downtime during which the machine is out of operation and production is lost. The longer the MTTR, the more severe the loss of productivity.

For offshore wind turbines, MTTR should be negligible as opposed to MTTF, otherwise the maintenance costs would increase tremendously and render the project unfeasible. When the MTTR is decreased to infinitesimal values, then the MTBF is composed mostly of the MTTF so that MTBF and MTTF could be assumed equal.

Maintenance indicators are usually estimated in hours. MTTF values are modelled with a parametric stochastic law following for most components a Weibull probability density function. This could also be understood as the probability for a failure to occur after a time *t*.

Weibull distribution is defined by a scale factor λ and a shape factor β. The density function is :

$$d(t) = e^{-\left(\frac{t}{\lambda}\right)^{\beta}}$$

The popularity of Weibull's function in reliability modeling is due to its flexibility and adaptability to various applications through the shape factor. In the case of machine maintenance evaluation, this provides the ability to describe aging failure modes ($\beta>1$) as well as infant mortality ($\beta<1$) (Lonchampt, et al., 2019).

These considerations are particularly applicable to wind turbines and to offshore technology in general, as wind turbines are usually not extensively tested and verified for the entire length of their expected lifetime before they are deployed in commercial operation. As a result, many wind turbines have experienced classic failures of infant mortality type, such as major component failures after relatively short time of operation already at the beginning of their lifetime, demanding costly replacements.

Early failures might be based on design flaws, under-dimensioned components, faulty materials, etc. If such failures persist, the project developer might ultimately call for a revision of the entire turbine design or for a massive preventive replacement of these components in all turbine units, in order to avoid a long chain of imminent failure events.

On the other hand, the high degree of wear and tear typical for wind turbines and especially so in offshore locations also pave the road to multiple and frequent failures towards the end of the expected lifetime. The higher probability for a failure to occur at advancing age is typical for all types of machinery including wind turbines. While the severity of those failures is usually low and the necessary repair effort relatively small, many of these failures could largely be avoided by regular inspections and preventive maintenance procedures.

The failure probability function considerations are summarized in Fig.3.

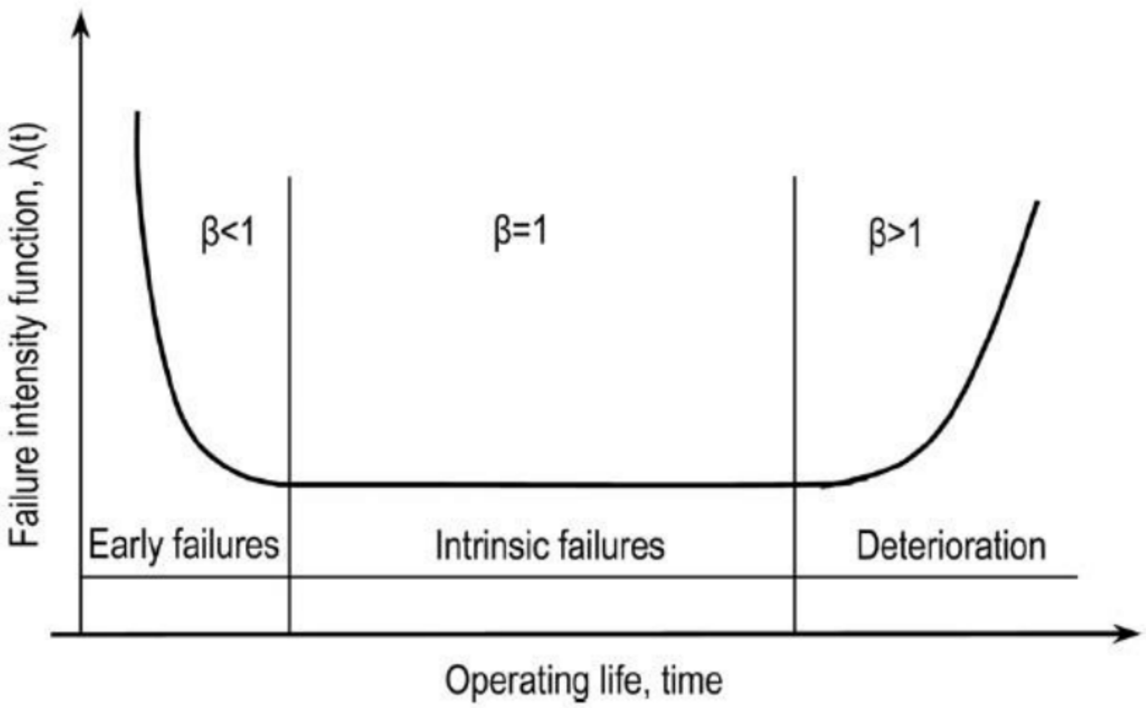

Figure 3: The bathtub curve (Spinato, et al., 2008)

For the purpose of simulation analysis in this study, after a failed component has been repaired or replaced it is considered to be as good as new. Its failure probability would be modeled as if the component were just starting its operational life.

1.3.3.3 Failure consequences

All failures are considered to fully stop the energy production and the WTG enters into a downtime state until the repair action is completed.

Corrective failures are separated into four different categories with different repair times associated with those, with reference to (Maples, et al., 2013). For every failure category, the OCC analyses the alarm signal sent in by the SCADA system and then triggers a first diagnosis action to be planned and executed by the O&M base. Depending on the complexity of the failure, different preparation times are assumed per the different failure categories.

Once the maintenance team is prepared for the intervention, it can start its travel toward the WTG. Additional preparation time is usually considered when using a HLO solution depending on local conditions. Once the vessel or HLO has arrived at the WTG, one team is transferred to the WTG and begins the repair task. If the team has the time to complete the repair, the WTG is put into production mode (working state) after the team is transferred back on the vessel. In this case, the time necessary for traveling back to the base is not included in the turbine downtime.

If due to a constraint the first team has to leave the WTG without having completed the repair, the turbine energy production will remain down (failure state) until a new team arrives at the WTG and covers the remaining number of hours until the repair is completed. This includes the time to travel back to the base for the first team and the new travel and transfer to the WTG for the second maintenance team, provided that there are no active constraints. Therefore, the repair tasks are considered as fully split, but some constraints would have a cumulative effect resulting in multiple extensions of the downtime.

The different corrective maintenance categories with associated preparation and repair times are summarized in Table 2.

Table 2: Failures and intervention classes

	Description	Preparation time (h)	Time to repair (h)	Resources mobilized
Remote reset	Alarms that can be managed remotely	0	0.5	OCC
Minor Failure	Repair/replacement of consumables	1	2	OCC + vessel + technicians
Small Failure	Repair of small components	2	4	OCC + vessel + technicians
Medium Failure	Repair of larger parts, requiring a thorough diagnosis	4	16	OCC + vessel + technicians
MCR	Replacement of a major component	72 to 720 (3 to 30 days)	1 day	JUB + external technicians

For instance, if the travel time between the O&M base and the WTG is assumed to be 1 hour, a repair scenario would be described as follows:

- 08:00 A small failure occurs on WTG A. The operation of WTG A is stopped. The OCC receives the alarm and communicates it to the O&M base.
- 10:00 With further information from the OCC, a technicians team needs 2 hours to prepare for intervention and is now ready to leave the O&M base.
- 11:00 The technicians team arrives on WTG A and begins the repair task.
- 14:00 Due to changing weather conditions, the team is forced to abandon the WTG and travels back to the O&M base having performed 3 hours out of the 4 hours required for completion of the repair task.
- D+1 08:00: The weather conditions on the next day are now allowing access to the WTG. A new team is sent on WTG A.
- D+1 09:00: The team arrives on WTG A.
- D+1 10:00: The team has completed the repair. The technicians are transferred back on the vessel. The turbine is put into full production mode, meaning that the WTG enters working state of operation 26 hours after the failure was detected.

The number of permanent teams required to perform a repair task is considered to be constant. Major intervention such as MCR is assumed to be performed by a specialized team that arrives together with a specialized vessel such as a JUB, consequently requiring much longer time for preparation and planning, for acquiring the spare part and for the repair task.

1.3.4 Financial Assumptions

Logistics Cost Distribution

CTV are usually not owned by the windfarm operators. A charterer company owns the vessel and operates it. The charterer commits to an availability of the boat and sometime also to a transfer performance. The fuel costs are usually borne by the windfarm operator.

The CTV costs are therefore composed of a fixed annual fee and of a variable fuel cost depending on the specific fuel consumption as a function of vessel's engine type, size, operational pattern, fuel market price, etc.

The fuel price is assumed to be constant throughout the entire lifetime of the project. As the fuel costs represent usually around 10% of the total costs induced by a vessel and because fuel prices for commercial users are not expected to vary largely in the near future, using an average and constant value for the fuel price is a reasonable assumption.

SOV follows the exact same scheme as CTV. However, in some cases the SOV could be owned and operated by the windfarm project developer, or hired for a very long time period of many years and permanently anchored at the windfarm site. Nevertheless, the financial analysis considerations for an SOV are in all ways similar to a CTV.

HLO are also owned and operated by an external company. The HLO costs are usually divided into two categories:

- Annual fixed costs;
- Variable costs which are given as a fee per flying hour. Variable costs include the fuel consumption.

Technicians costs

For the simulation process, a model team of trained maintenance technicians is assumed to be always available during regular working hours. However, in reality, personnel are sometime on leave or sick or have compulsory days off for resting. Therefore, in order to calculate the number of technicians that will be effectively hired by the project, the number of technicians used in the logistics simulations is multiplied by a coefficient called technician factor.

The technician factor depends on the country regulation and working scheme. For offshore projects it is common to consider that 2.5 staff members are needed in order to have always one person on duty.

Costs incurred by the maintenance team include the wages and additional remunerations, the specific equipment that is necessary to be provided and the demand for training courses every year. All these costs are summed and represented as a fixed average annual cost per technician.

As far as the goal is to compare and optimize logistics strategies in the present time, an average technician's cost could be deducted and used as an input parameter. Annual increase in wages or widening of the training courses with time is assumed negligible or unimportant for the analysis, even though such variables deserve to be taken into account if an extended analysis is performed for a very long duration such as the entire lifetime of the windfarm.

PPA

Depending on the project, an estimated PPA is used to derive revenues and thus the cost of loss in production due to unavailability. PPA estimation is critical as it is essential for the proper comparison of strategies. However, due to the fact that CAPEX represents an important part of the project's costs, it is possible to know in advance the order of magnitude of the PPA at which the company will be bidding.

For current offshore projects under development, a bidding range of between 50 to 100 $/MWh is commonly assumed.

1.3.5 Outputs and objective function

All the assumptions as stated herein enable the modeling software to simulate hour by hour the windfarm's status. For each turbine, failures occur randomly, then depending on the weather conditions and on the level of resource available, the model associates actions to solve the failure. For every hour, each turbine is therefore either in full operation (working state) or fully stopped (failure state). Thus, the availability of the windfarm as an aggregation of a given number of turbines can be derived hourly and then averaged monthly and yearly. A large number of iterations are performed in order to fully capture the stochastic character of the weather constraint and of the failure occurrences.

Therefore, the time-based availability is the main output of the model. The main virtue of this data is that it can be easily used by operator teams assessing the expected capacity factor of the windfarm with complex wind modelling and power curves modeling. The time-based availability can also be estimated via average monthly capacity factor. Then, the energy-based availability is obtained by the product of the monthly time-based availability and the monthly capacity factor.

Once the state of operation and the possible power output have been identified, the downtime and consequently the lost energy production during the number of hours needed for the maintenance activity can be derived.

All input and output values and resources are modelled on an hourly basis in the simulation process. For every hour, each intervention resource is either mobilized or not mobilized. This allows to derive the cost of fuel consumption and of mobilization of additional external resources.

Capacity auction represents an important part of offshore wind globally and especially in Europe. In order to be able to bid at the best price, offshore windfarm developers have to be able to reduce their costs and estimate accurately their return on investment. The most common approach is to derive the levelized cost of energy (LCOE) (Johnston, et al., 2020).

LCOE captures the total lifecycle costs of the asset and compares it to the total amount of net energy produced and delivered; in the case of offshore wind the output product is only electricity. LCOE can be derived as follows (International Renewable Energy Agency, 2015) :

$$LCOE = \frac{\sum_{t=0}^{y} \frac{CAPEX_t + OPEX_t}{(1+r)^t}}{\sum_{t=0}^{y} \frac{E_t}{(1+r)^t}}$$

Where :

- $CAPEX_t$: Capital expenditures in the year t
- $OPEX_t$: Operating expenditures in the year t
- E_t : The electricity generation in the year t
- r : Discount rate
- y : Lifespan of the project in years

Minimizing the LCOE should allow the bidders to offer the lowest PPA price per kWh electricity produced and delivered by the windfarm.

In the context of this study the choice of the logistics scenario is assumed to affect only the OPEX. No changes in CAPEX are expected.

In some cases, the simplifying assumptions may not be valid. For instance, if a windfarm is to be built not too far away from another (already existing) windfarm, synergies can appear in the O&M process and the two windfarms could share their O&M bases. The operator could face a situation where there is a choice between building a new O&M base in the closest harbor or using the existing O&M base that is likely to be further away. The first option lowers the CAPEX for the new asset (as it saves some investment) but increases the OPEX and lowers the total electricity production due to longer routes and longer downtimes every time when maintenance crews need to access the new windfarm.

The second option leads to the opposite effects. Thus, a global assessment of the LCOE has to be taken into account to determine the best strategy. However, those cases are currently unusual and therefore not considered in this study.

The assumptions allow for the following relation :

$$\min(\mathrm{LCOE}) = \frac{\sum_{t=0}^{y} \frac{CAPEX_t}{(1+r)^t}}{\sum_{t=0}^{y} \frac{E_t}{(1+r)^t}} + \min \frac{\sum_{t=0}^{y} \frac{OPEX_t}{(1+r)^t}}{\sum_{t=0}^{y} \frac{E_t}{(1+r)^t}}$$

The logistics strategy in this study is made of two components: the vessels and the personnel. Other parameters such as the costs of spare parts or storage area are neglected or are included as fixed invariable annual fees. Therefore, the OPEX can be divided in three main categories:

$$OPEX_t = \ Logistics\ mean_{\ t} + Personnel\ costs_t + Fixed\ costs_{\ t}$$

The optimization problem to solve therefore becomes:

$$\min \frac{\sum_{t=0}^{y} \frac{Logistics\ mean_{\ t} + Personnel\ costs_t}{(1+r)^t}}{\sum_{t=0}^{y} \frac{E_t}{(1+r)^t}}$$

However, solving this optimization problem would not perfectly reflect the reality. Companies' objective is to maximize their profit. Due to the competition involved and the large share of CAPEX in the LCOE, competitors tend to overestimate the PPA level. Moreover, as the logistics strategy is decided after the auction has been won and the project is secured, the governing PPA price is already known.

The optimization problem that companies are facing in reality is therefore the following:

$$\max\ \lambda \times \sum_{t=0}^{y} \frac{E_t}{(1+r)^t} - \sum_{t=0}^{y} \frac{Logistics\ mean_{\ t} + Personnel\ costs_t}{(1+r)^t}$$

Where λ is the PPA price per units of electricity produced.

Let us introduce the Lost Production term so that:

$$\text{Lost production}_t = \lambda \times (8760 \times CF \times Capacity - E_t)$$

Where:

- CF is the annual capacity factor of the entire windfarm based on full technical availability. CF is assumed to be constant throughout the year.
- Capacity is the total installed (rated) capacity of the windfarm.
- E_t is the actual (real) energy production in a given year.

The optimization problem can be reworked as :

$$\max \lambda \times \sum_{t=0}^{y} \frac{\left(8760 \times CF \times Capacity - \frac{\text{Lost production}}{\lambda}\right)_t}{(1+r)^t} - \sum_{t=0}^{y} \frac{Logistics\ mean_{\ t} + Personnel\ costs_t}{(1+r)^t}$$

This is equivalent to solving the following optimization process:

$$\min \sum_{t=0}^{y} \frac{Logistics\ mean_{\ t} + Personnel\ costs_t + Lost\ Production_t}{(1+r)^t}$$

This is the optimization problem that a project developer company would need to solve once it has been awarded the right to build a windfarm. This objective function will therefore be used to hierarchize the different logistics strategies for several cases of offshore windfarms.

2 LITERATURE REVIEW

2.1 Wind turbines' maintenance requirements

The first WTG models designed for offshore applications were initially installed onshore and subjected to prolonged testing and verification. The study of failure rates in onshore WTGs, where more data is available, provides therefore interesting insights for the expected offshore failure rates and distribution. In onshore windfarms, the majority of the downtime is caused by a small number of severe failures, mainly MCR; whereas the majority of occurring failures overall are relatively unchallenging and induce little downtime. (Faulstich, et al., 2009)

Separation in different failure category provides a good estimation of the necessary average repair effort and is largely used in the scientific community. However, failures and associated downtimes might vary significantly from one recorded event to the other, and from one literature source to another, as the examples below illustrate; see Tables 3 through 5.

Liu and co-authors (Liu, et al., 2013) propose a representative rate of 0.5 failures per WTG per year with a total downtime of 24h per year. They identify that a properly functioning SCADA system is the strongest lever for reliability since a high number of recorded failure events are due to false alarms or are small enough to be solved remotely, causing nearly zero downtime.

More recent articles propose a more detailed breakdown of failures and higher failure rates in modern large WTGs.

Table 3: Failure rates hypothesis, according to Caroll et al., 2016 and Dinwoodie et al., 2015

Table I. O&M modelling inputs from reference.[21]

	Manual reset	Minor repair	Medium repair	Major repair	Major replacement	Annual service
Repair time	3 h	7.5 h	22 h	26 h	52 h	60 h
Required technicians	2	2	3	4	5	3
Vessel type	CTV	CTV	CTV	FSV	HLV	CTV
Failure rate	7.5	3	0.275	0.04	0.08	1
Repair cost	0	£1000	£18,500	£73,500	£334,500	£18,500

Table II. O&M modelling inputs from this paper and reference[21] compared.

	Minor repair		Major repair		Major replacement	
	This paper	Ref.[21]	This paper	Ref.[21]	This paper	Ref.[21]
λ (/turbine/year)	6.81	3.00	1.17	0.31	0.29	0.08
Repair time (days)	6.67	7.50	17.64	24.00	116.19	52.00
Req. technicians	2.61	2.00	3.44	3.50	9.14	5.00
Repair cost	£140	£1000	£1726	£46,000	£40,906	£334,500

(Caroll, et al., 2016) and (Dinwoodie, et al., 2015)

Table 4: Failure hypothesis according to Dalgic et al. 2015

Table A-6
Wind farm/turbine inputs.

No	Name	Value				Unit
1	Number of turbines	150				turbine
2	Generation capacity	3.6				MW
3	Distance	20				nmile
4	Hub height	77.5				m
5	Power curve	3.6 MW turbine power curve				N/A
6	Cut in speed	4				m/s
7	Cut out speed	25				m/s
8	Failure mode	Manual reset	Minor	Medium	Major	N/A
9	Required repair time	1	4	12	24	h
10	Required number of technicians	1	3	6	8	person
11	Transportation type	CTV/helicopter	CTV/helicopter	OAV	Jack-up vessel	N/A
12	Repair window	Cumulative	Cumulative	Cumulative	Single	h
13	Failure impact	100	100	100	100	%
14	Failure distribution	5/turbine/year	2/turbine/year	0.3/turbine/year	0.1/turbine/year	N/A
15	Required preventive maintenance	50				h
16	Preventive maintenance technicians	3				person
17	Preventive maintenance start month	January–April–July–October (referring to Table 9)				N/A
18	O&M technician allocation order	(referring to Table 9) Corrective maintenance or preventive maintenance Preventive maintenance after corrective maintenance Preventive maintenance only after corrective maintenance				N/A

(Dalgic, et al., 2015)

A possible way to predict a WTG failure rate is also to proceed with a subassemblies detailed approach as presented by (Koukoura, et al., 2021).

Table 5: Failure hypothesis according to Koukoura et al., 2021

Annual failure rates and repair times baseline scenario.

System	Failure rates [Per year/Turbine]			Repair times [h]		
	Minor	Major	Replacement	Minor	Major	Replacement
Gearbox	0.644	0.157	0.028	8	22	231
Generator	0.049	0.018	0.008	7	24	81
Electrical system	0.37	0.043	0.002	5	14	18
Pitch system	0.397	0.02	0.008	9	19	25
Yaw system	0.259	0.036	0.012	5	20	49
Blades	0.2	0.045	0.04	9	21	288
Main shaft	0.231	0.026	0.009	5	18	48

(Koukoura, et al., 2021)

In order to compare all these modeling hypotheses, the data are rearranged in Table 6:

Table 6: Comparison of different failure modeling hypotheses in the scientific literature

	Koukoura et al., 2021	Caroll et al., 2016	Dinwoodie et al., 2015	Dalgic et al., 2015
Total failures per WTG/year	2.60	8.27	3.39	7.4
Total downtime (h/WTG/year)	42	100	34	19
Downtime excl. MCR (h/WTG/year)	22	66	30	17

The variability of expected failure rates and downtime for offshore wind turbines seems important to properly account for. Due to constant evolution of the technologies and the absence of large recent public database, there is no consensus on this subject at the moment.

In the past, increasing size and complex design lead to a decrease in availability. There is therefore an uncertainty about the reliability of the future offshore WTG. The average unit capacity of the installed WTG increased from 4 MW in 2015 to 8 MW in 2019 and turbine manufacturers announced that further growth in nominal power will be reached in the next 10 years. This rapid evolution leads to uncertainties in failure rates for future WTGs. (Faulstich, et al., 2009)

2.2 Vessel-to-WTG access conditions

Two different concepts exist to transfer technicians from a marine vessel to an offshore WTG:

- Boat landing with ladder climb (Fig. 4):
  Typically used by CTVs and other small vessels without specialized equipment other than a fender at the bow deck. To perform a transfer, the CTV pushes onto two metal pipes and achieves relative stability and proximity for the crew to leap across from the deck to the WTG. The metal pipes constitute the boat landing, they are purposely designed and positioned around a ladder on the Transition Piece of the WTG.

  Once the vessel is stabilized and there is a constant contact between the fender and the boat landing without the risk of slipping or falling, the technicians climb the ladder and enter the turbine tower. If there are tools and equipment to be transported from the vessel to the WTG, the process is carried out with the help of a davit crane placed on the deck of the transition piece, after the technician crew has been safely transferred.

Figure 4: View of a CTV fender pushing onto a WTG boat landing to perform a transfer (Wu, 2014)

- Gangway transfer (Fig. 5):
  Typically used by OSVs and other specially-equipped vessels. The OSV approaches the WTG and stabilizes itself several meters away from the turbine tower. Then a gangway equipped with automatic motion compensation is deployed directly towards the platform of the transition piece. The technicians then walk along the gangway and enter directly onto the WTG's platform.

  If there are tools and equipment to be transported from the vessel to the WTG, the process is carried out with the help of a crane based on the SOV, able to reach across and unload the goods on the WTG's platform.

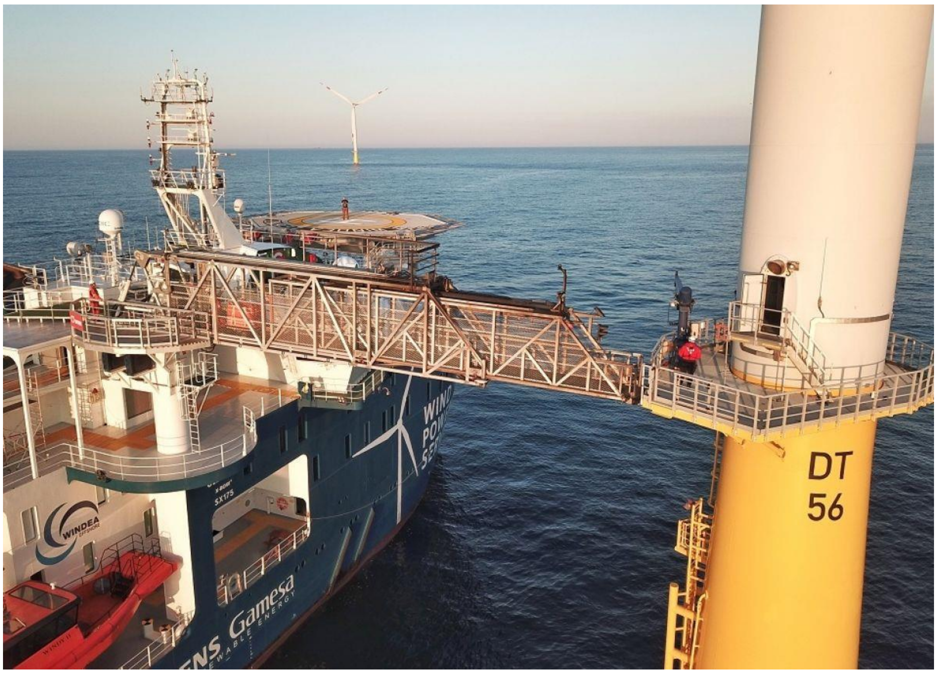

Figure 5: SOV transfer to a WTG through a gangway (Maritime Journal)

During these transfers, waves can induce motion to the vessels that prevent them to stabilize themselves. Usually, vessel's constructors only indicate a maximum HS at which the vessel can perform a safe transfer. In reality, this HS limit can vary significantly with the wave period and wave relative direction to the boat landing as demonstrated by (Wu, 2014).

Table 7 and Table 8 further below present the limiting wave HS values for the two existing concepts derived by a numerical analysis by (Wu, 2014).

Table 7: Limiting HS value (in meters) for a CTV transfer to a WTG boat landing for different wave oscillation period and wave orientation parameters

Limiting significant wave heights (m).

Heading β (°)	Wave peak period T_p (s)							
	3	5	7	9	11	13	15	17
0	2.09	0.82	0.92	1.07	1.20	1.28	1.34	1.38
45	1.54	0.96	1.10	1.24	1.33	1.39	1.42	1.43
90	4.44	2.16	1.80	1.67	1.60	1.56	1.53	1.51
135	1.81	1.04	1.17	1.29	1.37	1.41	1.43	1.45
180	2.40	0.88	0.98	1.12	1.23	1.31	1.36	1.39
225	1.81	1.04	1.17	1.29	1.37	1.41	1.43	1.45
270	4.44	2.16	1.80	1.67	1.60	1.56	1.53	1.51
315	1.54	0.96	1.10	1.24	1.33	1.39	1.42	1.43

Table 8: Limiting HS value (in meters) for an OSV transfer to a WTG with a heave compensated gangway for different wave oscillation periods and wave orientations parameters

Limiting H_s (m) when gangway reaches out longitudinally.

Heading β (°)	Wave peak period T_p (s)							
	3	5	7	9	11	13	15	17
0	68.4	8.87	5.41	4.51	4.38	4.44	4.52	4.60
45	26.8	5.03	2.60	2.54	3.05	3.56	4.11	4.43
90	6.50	3.39	2.50	2.29	2.67	3.02	3.38	3.74
135	50.5	7.24	2.86	2.67	3.21	3.68	4.21	4.38
180	75.0	11.7	6.51	4.89	4.54	4.52	4.57	4.63
225	50.5	7.24	2.86	2.67	3.21	3.68	4.21	4.75
270	6.50	3.39	2.50	2.29	2.67	3.02	3.38	3.74
315	26.8	5.03	2.60	2.54	3.05	3.56	4.11	4.67

Table 9, Continued:

Limiting H_s (m) when gangway reaches out laterally.

Heading β (°)	Wave peak period T_p (s)							
	3	5	7	9	11	13	15	17
0	68.4	8.87	5.41	4.51	4.38	4.44	4.52	4.60
45	45.3	8.50	4.38	4.27	4.07	4.19	4.32	4.43
90	11.0	5.72	4.22	3.86	4.06	4.08	4.24	4.38
135	55.6	7.82	4.37	4.12	3.99	4.12	4.26	4.38
180	72.2	11.7	6.51	4.89	4.54	4.52	4.57	4.63
225	67.8	10.7	4.82	4.50	5.26	5.17	5.12	5.09
270	11.0	5.72	4.22	3.86	4.51	4.63	4.59	4.53
315	45.3	8.38	4.13	4.28	4.89	4.96	4.99	5.00

Wu's quantification of the influence on the HS capacity on both CTV and SOV allows to refine the access limit conditions. For instance, the mean wave oscillation period in the North Sea's southern areas is approximatively 5 seconds, whereas in the North Sea's norther territories it reaches 7 seconds. (Galanis, et al., 2012)

Therefore, the CTV understudy in (Wu, 2014) would have a maximum HS of 2.16 m in the south and of 1.80 m in the north, for a North Sea offshore location. Assessing the wave oscillation period is therefore necessary and requires an as precise as possible quantification, even when comparing sites that are located in the same geographic region. (Wu, 2014)

2.3 OSPREY modeling tool description

OSPREY is a software tool developed in-house by EDF R&D to predict windfarm's availability and assist with the design of maintenance logistics strategy. The software models WTG's failures, actions undertaken to restore its operating state and local weather conditions. This section details how the software works and how models are built.

2.3.1 Weather time series simulations

The weather model was developed by EDF R&D, the methodology has been described by (Lonchampt, et al., 2019) and is presented below.

The weather element, here wind speed and wave height are modelled as time series with a time step of one hour. The values are thus continuous and correlations between variables can be taken into account. For instance, the wave height is correlated to the wind speed.

These time series are then used to determine whether vessels can access to WTG or not. Thus, the weather time series play an essential role in assessing the availability of a windfarm.

Therefore, it is critical that the times series generated are statistically consistent with the existing data. In order to do so, a Nonlinear Auto-Regressive Moving Average model (NARMA) is used. This model is used once seasonal components have been removed from the data, the data is then called "detrended" (Chen, et al., 1989).

The model for a time series X_t can be written as :

$$X_t = N\big(m\big(X_{t-1}; \dots; X_{t-p}\big); \sigma(X_{t-1}; \dots; X_{t-p})\big)$$

Where:

- X_t is the realization of a Gaussian process
- m(X) is the mean of the Gaussian process followed by X_t.
- σ(X) is the standard deviation of the Gaussian process followed by X_t
- p being an integer representing the autocorrelation time span of the variable.

The difficulty in this model is therefore to determine the functions $m: X \mapsto m(X)$ and $\sigma: X \mapsto \sigma(X)$. These two functions are modelled with an artificial network such as the one presented below in Fig. 6.

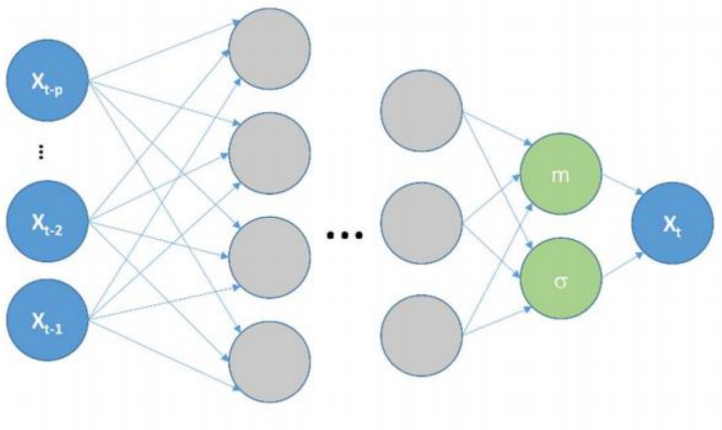

Figure 6: Artificial Neural Network used to generate weather time series (Lonchampt, et al., 2019)

In order to train this neural network, an objective function (L) is assigned to it and then minimized. The log-likelihood is used as an objective function.

$$L = -\frac{ln(2\pi)}{2} - ln(\sigma) - \frac{(X_t - m)^2}{2 \cdot \sigma^2}$$

The neurons of the same layer all take k inputs. They all give an output O calculated as follows:

$$O = \frac{1}{1 + e^{\Sigma_k w_k \cdot I_k - b}}$$

Where :

- w_k are the weights of the neurons (real numbers)
- I_k are the inputs, given by the neurons of the precedent layer
- b is the bias of the neurons (b)

The weights and bias are modified randomly, if the modification reduces the objective function it is kept valid, otherwise it is ignored. Once the defined number of iterations has been performed, the process stops. This is called a standard stochastics gradient descent.

It is assumed that the wind influences the wave height but that the wave height has no influence on the local wind conditions. Thus, the wind values are modelled before the wave parameters; and then introduced as input in the wave modelling, as illustrated in Fig. 7.

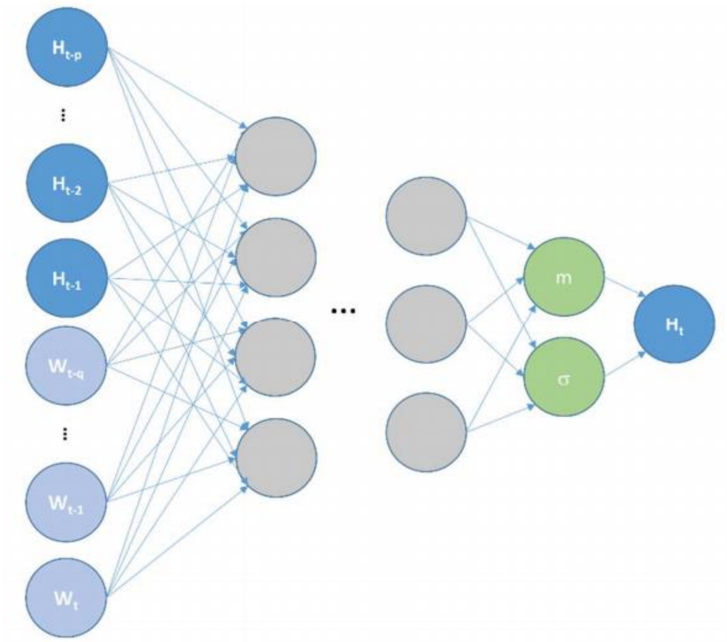

Figure 7: Artificial Neural Network for wave height (H) correlated with wind speed (W) (Lonchampt, et al., 2019)

2.3.2 Tasks and constraints

The software tool functions with 4 different types of object:

- Failure
- Task
- Resource
- Environment elements

Failures are objects that entail certain tasks stochastically, following a probability law specified by the user. For common minor WTG failures, exponential laws are used whereas for MCR failures, bath-curve probability distribution is used.

Tasks are objects that mobilize resources for a certain number of hours and impact the WTG energy production. The user can choose whether the task stops the production from its activation to its completion or whether it has no impact on the production, such as a CTV transfer for instance. The user can also choose whether the task is splittable or not.

Tasks can be gathered into alternatives. This allows the software to choose from a list of tasks, one to complete depending on the resource available. This is a good representation of how the real windfarm operates. When some turbines require an intervention, the technician crews can access it by CTV or helicopter, only one or several CTV can be used. The option is chosen intending to maximize the production.

However, time penalty can be applied in the option ranking process in order to be more realistic. For instance, if two failures have occurred during the night, only one CTV will be mobilized in the next morning in order to transfer two technician teams and not two CTV carrying one team each.

Resources are objects that represent vessels and technicians teams. They are mobilized during tasks. Their number is fixed by the user. The software then calculates at every hour the number of resources available and of resources mobilized. The number of working hours for each resource is derived this way.

Environment element are time series that have a value for each hour. The user fixes limit values that entail that some resources are not available outside of the limit. For instance, wave height and wind speed are environment element objects that influence CTV performance, above a certain wave height CTV transfer is not available anymore. Time is an environment element object that influence the technicians, outside working hours, the technicians are not available and therefore cannot be mobilized in any task.

OSPREY therefore allows for a large flexibility in modelling failures, operations and maintenance tasks to be performed. It dispatches some resources on some tasks induced by stochastic failures and under randomly simulated weather constraints. This increases the reliability of the outputs. However, one of the main limitations is that the software makes choices with perfect knowledge of the weather conditions. In reality, during days when the weather is close to the operating limits, technicians tend to be conservative and avoid going at sea or immediately return back to shore as soon as the weather starts to change.

2.3.3 Scope of Results

Simulation results are obtained on a monthly basis and for each iteration launched. Therefore, assessing a windfarm over 30 years lifetime with 200 iterations would produce results for 72000 modelled operation-months of the windfarm.

The primary type of delivered result is the windfarm's availability. Both time-based and energy-based availability are obtained monthly which allows for checking seasonality and refine the strategy if large differences between winter season and summer season are observed. Since the availability is obtained for each iteration, probabilistic distribution of the availability can be used. Therefore, depending on the level of confidence required, the user can choose to use P50 or P90 values or any other level of confidence.

Furthermore, for each monthly result, the number of time each task is activated, stopped and completed is obtained. Similarly, the number of times a failure occurs and the spent hours by each mobilized resource is also given as an output. This allows to derive with high precision the expected cost and to check efficiently whether the strategy modelled can be implemented or not.

Finally, the model provides the causes of downtime hours. Downtime can be caused by running a repair task, by delaying the task due to no resources available to conduct the repair, or when the weather conditions are temporarily preventing the repair task. The model gives as an output the specific breakdown of downtime hours for each repair task. Thus, a complete understanding of the elements limiting the availability can be observed. This is very useful for optimizing the logistics strategy and identifying the elements that have the greatest impact.

2.3.4 Other modelling solutions

StrathOW-OM:

StrathOW-OM is a software developed by the University of Strathclyde and commercial partner organizations. The software adopts a methodology very similar to OSPREY's.

The stochastic weather time series are derived from observation data using Multivariate Auto-Regressive (MAR) model. According to Dalgic and co-authors, the key characteristics of mean and variance as well as annual distribution, access window duration periods and temporal correlation are preserved as well as the relationship between wind and wave conditions. Besides, as in heavy seas waves cause additional resistance on the vessel hull, the model captures the effect of waves on the vessels' speed. (Dalgic, et al., 2015)

Each wind turbine is modelled as a series of subsystems, for which a probability of 'moving from an operating state to a failed or reduced operating state' is envisaged. In the operational simulations, all the information from previous blocks is collected and O&M activities are simulated on daily basis. After identifying a failure, the O&M technicians are allocated to the wind turbine, if the current weather conditions are within the turbine access limits as defined in the model inputs. If these conditions are not met, the O&M technicians stay at the O&M port and the turbine remains out of service. (Dalgic, et al., 2015)

Shoreline:

Shoreline is a commercial software product used in the industry by several large offshore operator companies. Its methodology is very similar to what has been previously exposed.

Other models exist too. They all tend to follow a Monte-Carlo approach and tend to lead to the same optimal logistics strategy. However, they can deliver different results of availability and sensitivity to key inputs. (Bakken Sperstad, et al., 2017)

Multiple previous studies made with O&M simulation tools tend to agree on the fact that SOV strategy becomes interesting for sites larger than 90-100 turbines and at least 100 km off the nearest suitable harbor. (Münsterberg, 2017) (Saraswati, et al., 2017)

3 CASE STUDY

3.1 Context of optimization

3.1.1 Site general characteristics

Due to confidentiality issues, the exact site location and precise assumptions used for this study cannot be revealed. Besides, results for costs will be given in a "unit-cost" valorization approach, relative to a baseline scenario, that has been chosen arbitrarily in order to not disclose any insight on the financial parameters used by the company as it could provide a competitive advantage to other windfarm developers.

Nonetheless, the presentation of this case study illustrates precisely the described methodology, the implementation of the simulation analysis and the important conclusions that can be drawn on the basis of attained results.

The offshore site under consideration is located approximatively 35 km from the potential O&M base harbor able to welcome CTV and 165 km from the closest harbor accessible to SOV. HLO are assumed to be able to transport technicians from the O&M base to the WTG.

Furthermore, due to a site specific constraint as observed in many existing offshore locations, it is also assumed that the navigating speed for vessels within the windfarm boundaries is limited from beginning of November to the end of April. This constraint leads to a 25% increase in travel time between the O&M base and a WTG and to a 70% increase in travel time between any two WTGs inside the windfarm.

The project is designed to be part of a PPA scheme lasing 25 years with electricity selling tariff of about 0.06 UC/MWh.

Four different windfarm sizes as per the total number of turbines within one location but regardless of the specific rated capacity of each turbine unit, are investigated in the simulation process, namely:

- 60 WTG,
- 90 WTG,
- 110 WTG,
- 170 WTG.

Each simulated case corresponds to one of the four windfarm sizes. All of these cases represent relatively large-scale windfarms, the largest of which could reach beyond 1GW total installed capacity if the most modern turbines of 8-to-12 MW rated capacity are employed.

For each case, a variation of the number of technician teams allows to determine the optimal number of technicians for a particular combination of vessels. All scenarios presented in each different section below are summarizing the optimum results. When a vessel combination is not presented, it means that it was largely underperforming as compared to the outlined combinations.

A scenario is named after the number and type of vessels used, the number of corrective technicians mobilized per year (CT) and the number of mobilized technicians for preventive campaigns (PT).

For each option, the number of technicians is varied until the optimum is found. A large number of simulation iterations is therefore performed. Then only the best performing strategies are taken into account and further analyzed.

The resulting charts enable to observe clear threshold effects. When the number of technicians is not high enough, the energy productions losses due to lower availability become very important. Increasing the number of technicians increases as well the costs but decreases the production losses, that is increases the possible annual energy production. However, beyond a certain number of technicians, increasing further the number of technicians does not lead to a significant decrease in production losses anymore while adding enormously to the costs.

Figure 8 and the following figures further below summarize the simulation results and zoom into the specified cases with discussion and explanation on the optimization analysis.

3.1.2 Preventive maintenance strategy

Preventive maintenance is assumed to be completed during regularly planned summer campaigns with additional resources. CTV are thus either permanent or seasonal, while a seasonal vessel hired for preventive maintenance is always taken into account. As such, preventive maintenance is not directly included in the optimization task but still adds to the costs, yet its effectiveness is decisive for the necessity of unplanned corrective maintenance.

Both extra personnel and extra vessels can be mobilized for preventive campaigns. It is assumed that the costs of the extra vessels and resources as well as the wages of the seasonal technicians are equal to the permanent ones.

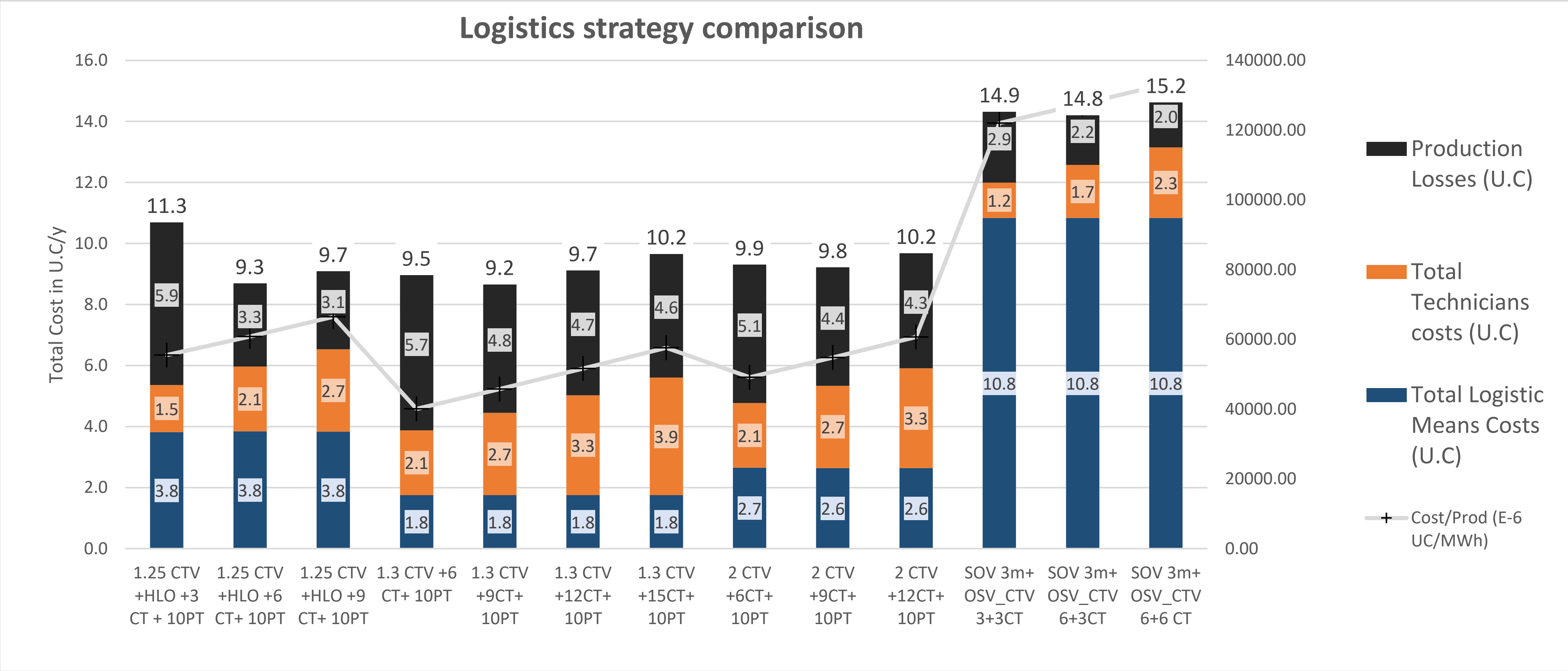

Figure 8: Method of comparison for offshore logistics strategy analysis in this study

3.2 Simulation results and sensitivity analysis

3.2.1 60 WTG case

For the 60WTG case, an onshore strategy is clearly optimum. Only one CTV is required to assure the maintenance of the windfarm. Nowadays, this case is a good representation of a mainstream offshore windfarm of a not particularly challenging size. New developments are expected to be much larger in number of turbines.

Adding a second permanent CTV leads to higher logistics cost without providing a significant increase in production. Therefore, a two CTV strategy is largely underperforming and is not represented in the figures below. This indicates that the availability is limited more by the weather conditions rather than the level of resources.

Adding an HLO, provides a small increase in wind energy production. However, it is not enough to offset to cost of the HLO which is very high. The optimal HLO strategy leads to equal performance to the optimal CTV strategy if the HLO costs could be reduced by 20%.

It can be noted that the optimal HLO strategy mobilized 3 technicians less than the optimal CTV strategy. This is explained as the HLO is under less restrictions than the CTV, it allows for more days of work and therefore less work per day and therefore the number of technicians always on duty is reduced.

Therefore, this case allows for a clear identification of the optimal logistics and is a benchmark for the baseline CTV-only strategy.

The best representing chart for this case is exposed in Fig.9. The results are simplified to only show the two optima of the two best performing strategies as explained above, out of an array of options with varying sub-parameters.

For the other cases further below, the optimization results will be charted in a similar way.

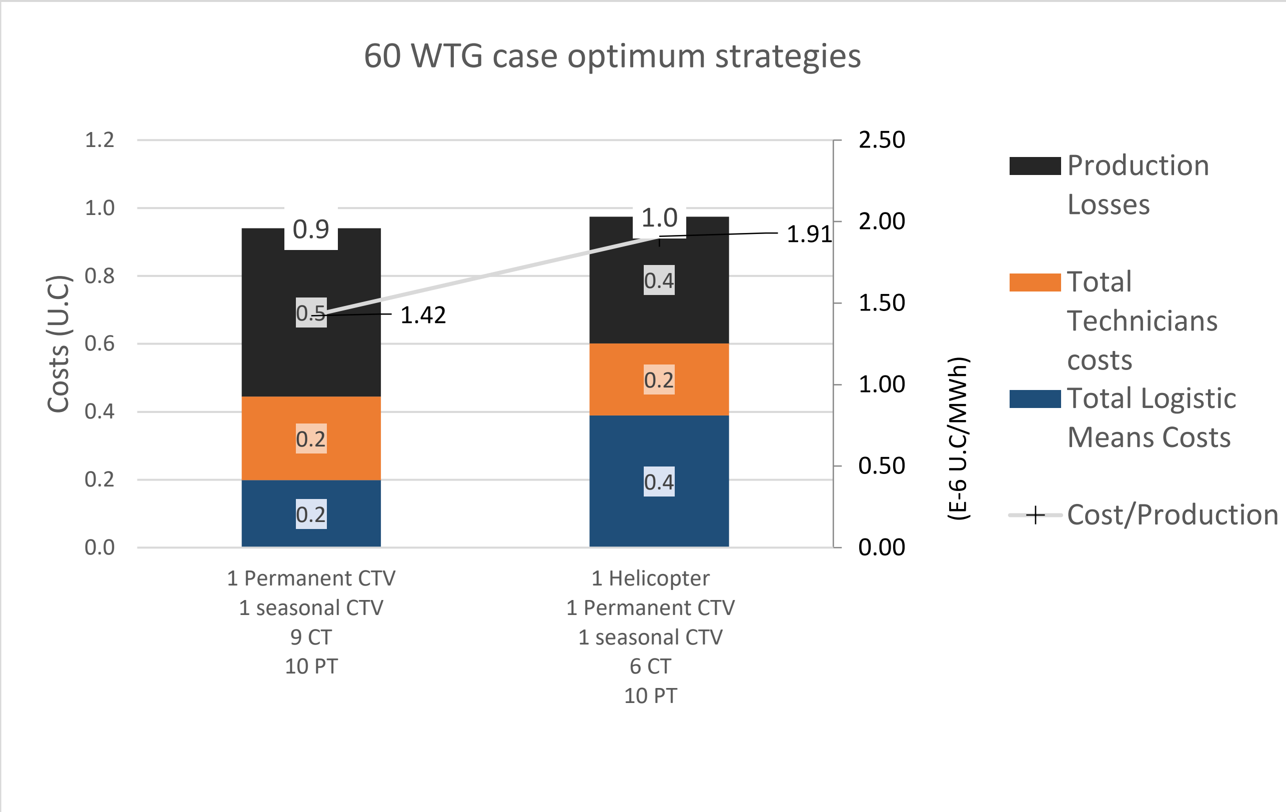

Figure 9: 60 WTG case strategies' total costs

3.2.2 90 WTG case

For the 90 WTG case, an onshore-based strategy is still clearly optimal, as could be deducted from the charts in Fig. 10.

SOV costs would need to decrease by 25% to be able to compete against an onshore-based strategy. If those 25% cost reduction costs could be achieved, SOV would decisively become the optimal strategy.

A solution based on one permanent CTV leads to a very low availability. This appears as a threshold effect, above a certain number of WTG, a CTV cannot manage to perform enough repair per operating day. This leads to an accumulation of untreated failures and therefore to an exponential downtime. At least a second CTV is required. This phenomenon appears during winter but not during summer due to the very high operability. Thus, the number of permanent CTV is oversized for summer and there is no more need for seasonal CTV.

We can note that, a divergence appears in the solution obtained with each objective function:

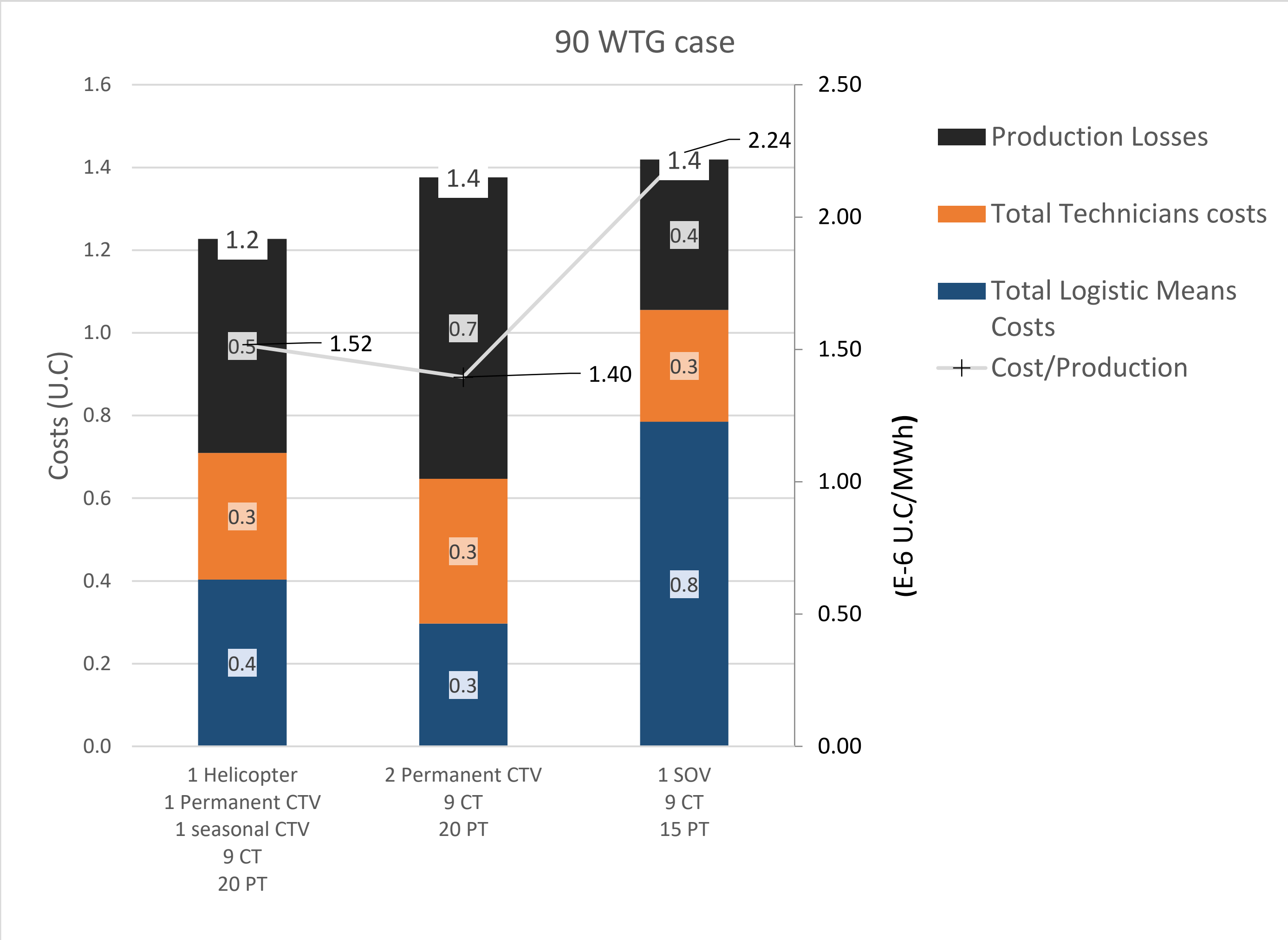

Figure 10: 90 WTG case strategies' total costs

When optimizing the profit of the project company, the PPA level enable the HLO to offset its costs and becomes the optimal strategy. Similarly, the SOV is highly retributed for the important availability it reaches. This tends to bring this strategy at a level of performance closer to the others.

However, studying the LCOE indicator leads to a totally different hierarchy. The LCOE indicator retributes less the production than the profit approach with the chosen PPA level. Thus, neither the HLO nor the SOV offset their costs with increases in production.

Finally, we can note that in this case, all optimal strategies mobilize the same number of technicians. If the weather constraints were the first limit to availability, the CTV would have less operable days per year than the SOV. The CTV would therefore have to carry more interventions per operable days than the SOV. Thus, the optimal number of technicians for a CTV-based strategy would be largely higher than the one for a SOV based strategy.

Therefore, this equal number of technicians among the optimal strategy indicates that the weather constraints are not the first limit on the availability.

3.2.3 110 WTG case

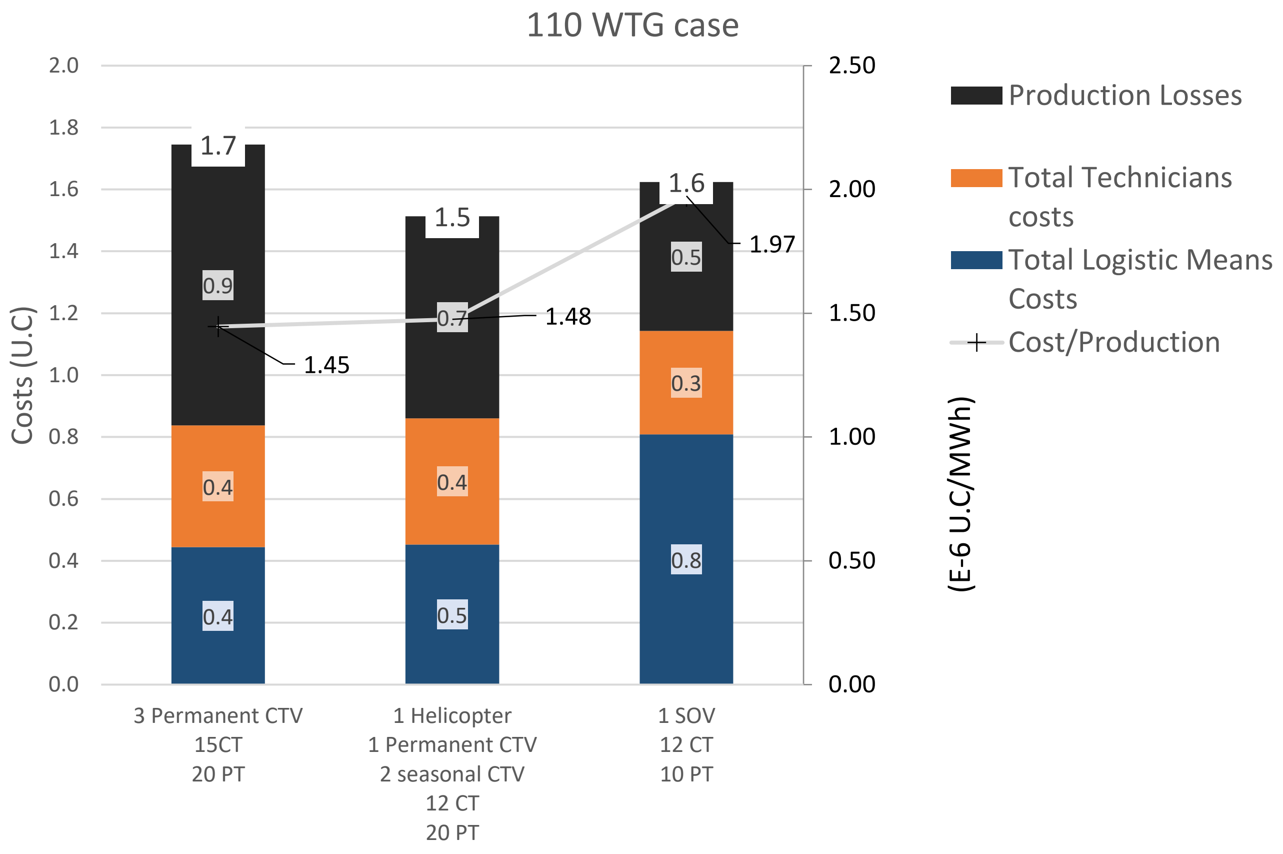

Figure 11: 110 WTG case strategies' total costs

This case is very similar to the 90 WTG case. The onshore strategy is still optimal although less clearly than in the previous case. A decrease in the SOV costs of 15% would lead to a SOV based strategy when maximizing profit. We are therefore close to the turning point where an offshore based strategy would become optimal.

For an LCOE approach however, a CTV-only solution remains optimal. The number of CTV is oversized to be able to face winter season where inoperable days lead to an accumulation of required intervention. We can note that the number of CTV has increased more importantly than the number of technicians. This is due to technicians' working hours, allowing them to spend no more than 12 hours at sea per day. With transit time between the windfarm and the port and between WTG, the fourth team on a CTV would not have enough time to perform any consequent action. Thus, the number of technicians per CTV is never above 9, i.e. 3 corrective teams.

On the contrary, the HLO can carry many teams per day on different WTG due to its high speed and absence of speed restrictions inside the windfarm. Therefore, only one permanent CTV and one HLO lead to the optimal CTV+HLO strategy. This illustrates how some constraints can create sizing threshold effects in the design of logistics strategies.

3.2.4 170 WTG case

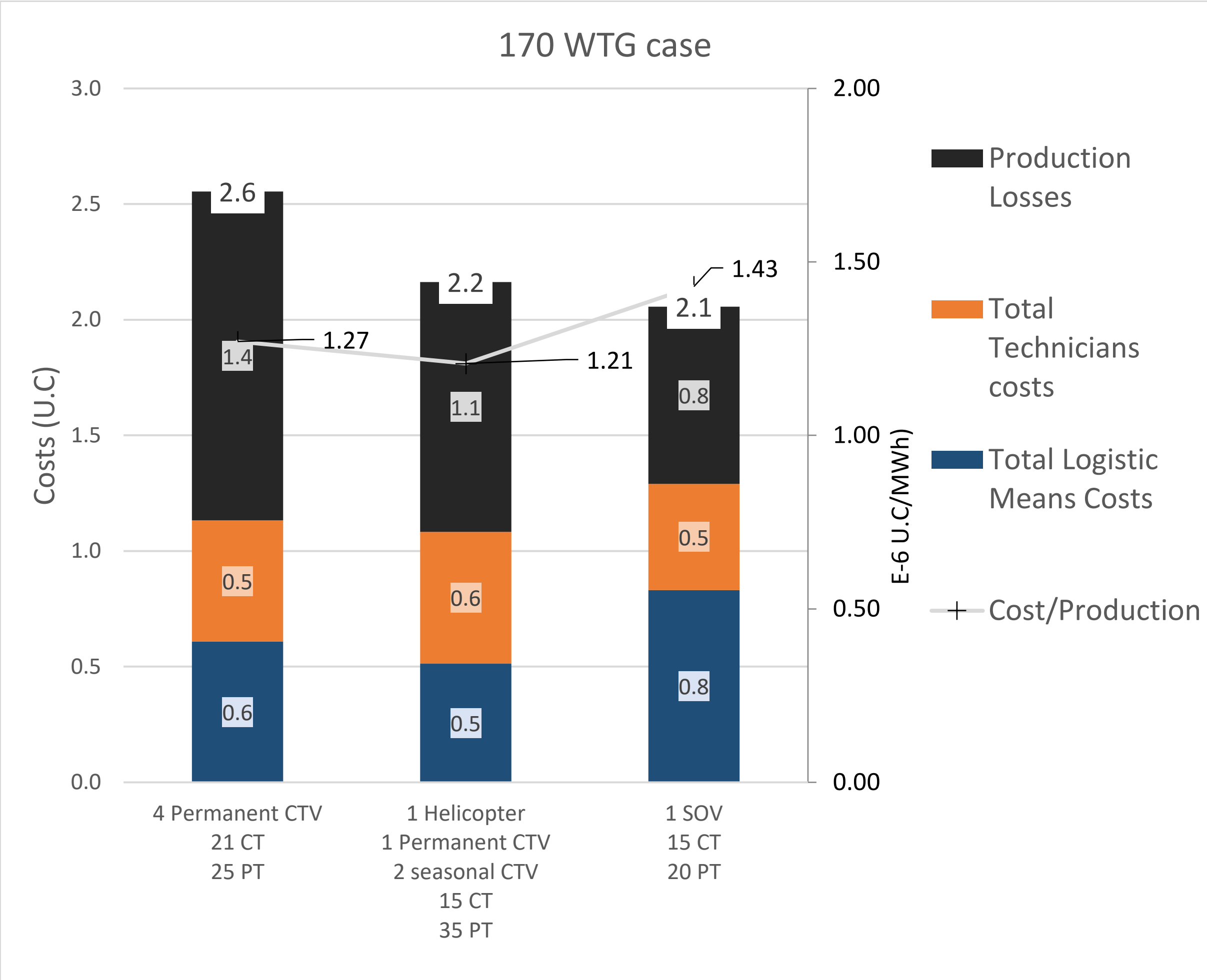

Figure 12: 170 WTG case strategies' total costs

The 170 case is interesting because the offshore-based strategy becomes optimal for a profit analysis. The cost of the SOV would need to increase by at least 13% to attain the second best-performing strategy. Therefore, the SOV strategy can be chosen confidently for this case.

CTV-based option is still possible if allowing a larger number of vessels and follows a permanent-only CTV strategy for the same reason as in the previous case. The strategy with one helicopter and one permanent CTV is promising if compared to adding another HLO or permanent CTV. However, the number of seasonal CTV needs to be increased in order to be able to perform the preventive maintenance campaign between June and September which are the months with the lowest production.

This result relies on the hypothesis that the HLO is limited only by the weather conditions. In reality, the HLO flying hours might be capped per year for contractual or legal reasons. Therefore, another HLO might be needed.

It could also be noted that with a LCOE approach the offshore-based scenario is still largely non-optimal and that the HLO+CTV strategy just becomes optimal.

3.3 Result analysis and discussion

3.3.1 Sensitivity analysis

In order to assess the validity of the results and assess the impact of variations of two other main parameters a sensitivity analysis is conducted on the 60 WTG case.

The total costs analysis is performed for different CTV wave HS performance values and for a varying PPA price level. The results are presented in Figures 13 and 14 further below.

In each case, both the profit and LCOE approach are applied in order to explore if variations of some parameters could change the strategy recommended by each approach.

Varying the HS it could be observed that for the two approaches the optimum strategy remains unchanged.

Secondly, we can note that a threshold effects appears for a CTV at 1.5m HS value. Above this limit, all the CTV options lead to approximatively the same production losses. This means that the availability attained when using a CTV at 1.75m HS value is very close to the one attained with a CTV at 2.5m HS.

On the contrary, the availability attained with a 1.5m CTV is significantly lower than the one attained with a 1.75m CTV. The same observation can be made for the LCOE approach.

As an HS value of 1.75m is rather conservative, this sensitivity study increases the confidence in the level of lost production predicted. Moreover, it would not be economically rational to increase the CTV cost in order to increase its performance.

Finally, it should be underlined that the HS performance apparently has no impact on the optimum number of technicians.

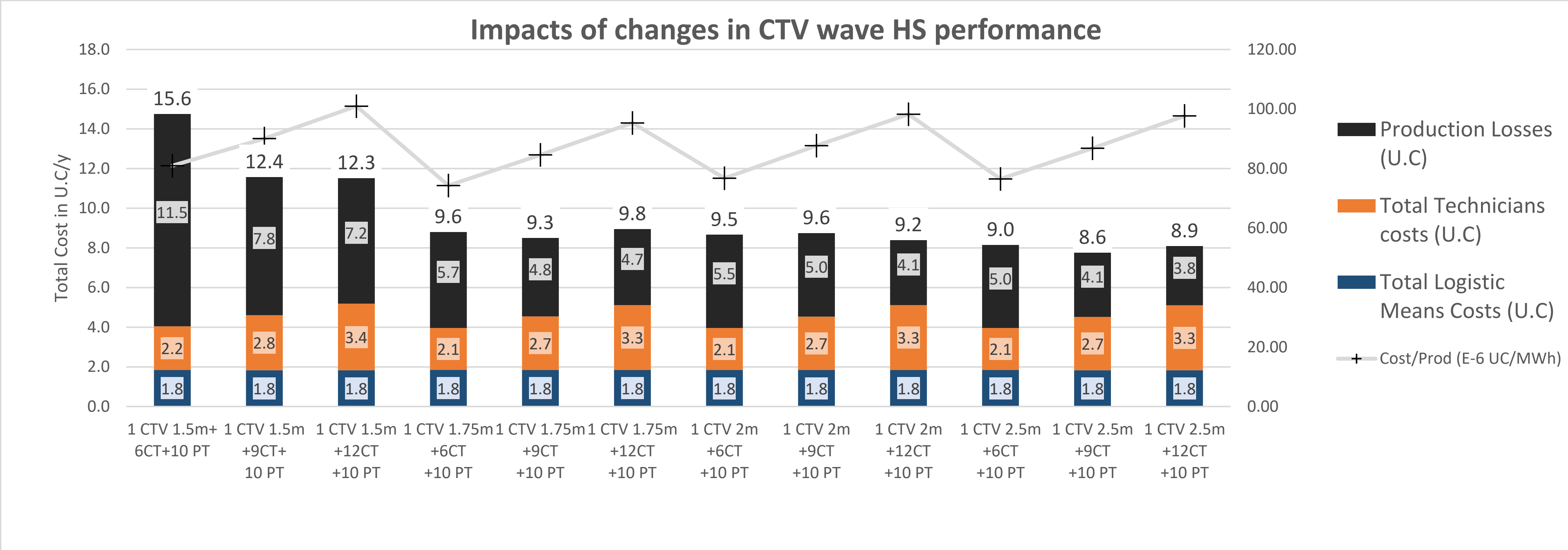

Figure 13: Influence of the maximum HS at which a CTV can transfer on the Cost-Benefits analysis

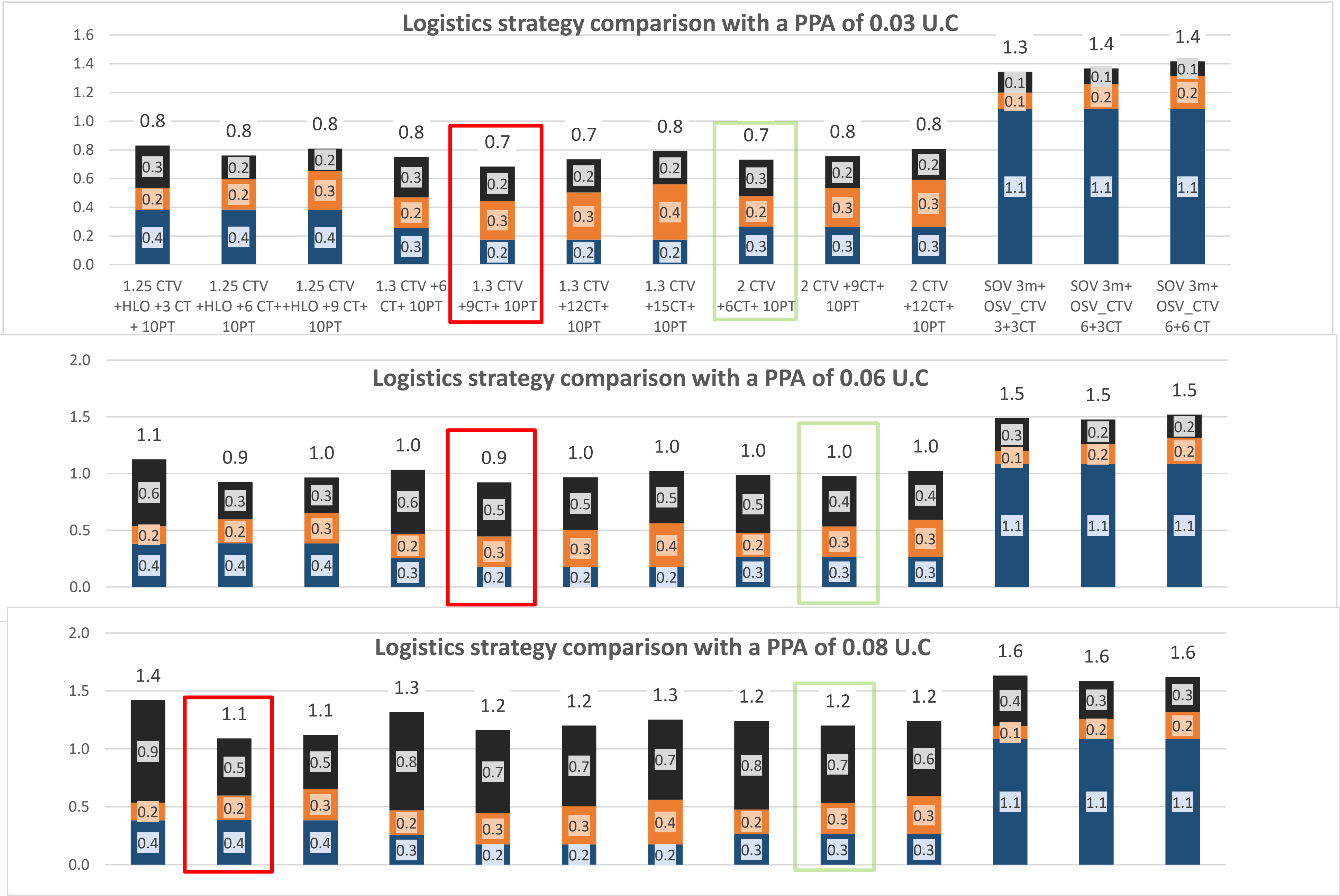

Figure 14: Costs benefits analysis on the 60WTG case with different value of the PPA

Concerning the PPA variability, two other values of PPA were studied, one below and one above the baseline power selling price of 0.06 U.C/MWh. The evolution of the total costs for three different PPA values, namely 0.03, 0.06 and 0.08 U.C/MWh, is summarized in Fig. 14. These values are deemed to cover a spectrum large enough to properly represent already installed and future offshore windfarms.

The results show that lowering the PPA does not change the optimal logistics strategy for performing maintenance on the windfarm (circled in red in Fig.14). However, increasing the PPA value to 0.08 U.C. leads to an optimal strategy of a CTV+HLO whereas the base case lead to a CTV-only strategy.

Also, it should be noted that lowering the PPA has an impact on the optimal number of technicians for a 2 CTV strategy (circled in green in Fig. 14).

The LCOE approach is by nature not affected by changes in the value of PPA. Therefore, it delivers results that are not submitted to uncertainty on the PPA level. This study shows that the plausible variations of the PPA value should however be quite substantial if they would lead to differences in the optimal strategy.

3.3.2 Discussion on the results

This case study showed that the maximum number of WTG below which an onshore-based logistics strategy is clearly optimal lies between 110 and 170 WTG, closer to 170. Securing a high PPA value leads the operating company to design its logistics strategy significantly differently than when maximizing the LCOE. In order to maximize the profit, the operator company invests more in the logistics solutions in order to increase the wind turbine availability and thus increasing the overall energy production by the windfarm.

SOV enables windfarms to reach a significantly larger availability than onshore-based strategy. However, the high costs of SOVs make them optimal only for very large windfarms or windfarms that are at a long distance from the closest harbor. Therefore, a reduction of SOV price is an interesting way to reduce the LCOE. As this study case shows, SOV would become beneficial also for very large windfarms close to shores if the costs could drop by approximately 25%.

Finally, it can be observed that the ratio of Operation Costs/Production decreases as the number of turbines increases. Thus, even if threshold effects exist, it appears that strategic logistics become more efficient as the number of turbines increases. This indicates that from an operation point of view it is economically more beneficial to establish larger windfarms.

4 CONCLUSIONS

Governmental auction is nowadays the most important scheme of installation of windfarm. These tenders create an important competition. O&M represent a major part of the total costs of an offshore windfarm projects. Furthermore, as the number of offshore turbine manufacturers is limited, windfarm owners are likely to have little action on the construction costs level. Thus, there is a need to optimize O&M costs. As logistics strategy for maintenance is a core component of an offshore windfarm's O&M, it also needs to be optimized.

Designing and optimizing a logistics strategy involves choosing and sizing logistics means that are to be allocated to perform maintenance of the windfarm. In order to design and optimize the logistics strategy, maintenance needs and windfarms performance must be assessed.

As all industrial systems, offshore wind turbines require preventive (predictable) and corrective (unpredictable) maintenance. Unlike some other systems, weather conditions often prevent access to the WTG. The interactions between this two stochastics phenomena need to be modeled in order to assess the windfarm's availability and therefore its energy production. The methodology presented in this study is based on an offshore wind farm modelling software called OSPREY. OSPREY is able to generate stochastic times-series of weather parameters such as wind speed and wave height, obtained with a neural network trained on measured data.

The modelled time-series lead therefore to similar operating conditions to the one observed and allow for testing a lot of different weather conditions patterns. OPSREY also models stochastics failures and actions that are needed to restore the energy production. Different logistics scenario can therefore be tested and their associated electricity production to be derived. This allows for costs-benefits analysis of each logistics strategy and thus for reliable optimization.

The case study presented herein shows that choosing to consider LCOE or gross profit metric can lead to different optimum in some cases. This difference is explained by a level of PPA important enough to induce difference between marginal cost of production of a MWh and profit by producing a MWh. The profit approach tend to favor larger logistics fleet and thus higher availability than an LCOE approach. Threshold effects regarding the use of vessels and number of technicians are important. This is another reason to rely on a modelling tool rather than using ratios or simplest derivations.

Key parameters in designing a logistics strategy are the distance to shore, number of turbines and transfer capacity of vessels. The diversity of hypothesis and results of scientific literature is important. Offshore wind can therefore be considered as a still immature industry and is still evolving at a fast pace.

This study points out that inoperable windows due to bad weather conditions are a very important challenge for offshore wind maintenance. Reducing the number of unplanned intervention on the WTG is therefore a strong lever to reduce the LCOE. Two approaches are currently gathering momentum: predictive maintenance and robotization. Predictive maintenance is the use of a large amount of data to identify WTG components on the edge of failure and replace those components before they fail. This allows to reduce the downtime and the number of interventions by grouping the replacements. Robotization, or automation, aims at increasing the number of failures that can be managed remotely.

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