This is a peer-reviewed, accepted author manuscript of the following research article: Jadali, A. M., Ioannou, A., Salonitis, K., & Kolios, A. (2021). Decommissioning vs. repowering of offshore wind farms—a techno-economic assessment. *International Journal of Advanced Manufacturing Technology*, *112*, 2519-2532. https://doi.org/10.1007/s00170-020-06349-9

Decommissioning vs. Repowering of offshore wind farms – a techno-economic assessment

A.M. Jadali[1], A. Ioannou[1], K. Salonitis[2], A. Kolios[1*]

[1*] Department of Naval Architecture, Ocean & Marine Engineering, University of Strathclyde, Glasgow, United Kingdom

[2] Department of Manufacturing, Cranfield University, United Kingdom

*Corresponding author: Athanasios Kolios, athanasios.kolios@strath.ac.uk

Abstract:

Offshore wind turbines are normally designed for a nominal service life of 20 to 25 years; however, with a significant number of units approaching the second half of their service life, the discussion on selecting the most appropriate end of life scenario becomes ever more relevant. Scenarios to be investigated mainly include decommissioning, repowering or service life extension, while such decisions depend on a number of criteria which should be taken into account and should ultimately inform a techno-economic and risk assessment. This paper performs an initial comparative assessment between two of these scenarios, repowering and decommissioning, through a purpose developed techno-economic analysis model which calculates relevant key performance indicators. The economic model of risk aversion is further adopted to calculate the certainty equivalent of LCoE (Levelized Cost of Energy) based on each of the examined end of life scenarios and a stochastic expansion of the deterministic model. An application to a typical, hypothetical offshore wind farm, qualifies the full repowering scenario as the prevailing option, under the assumptions considered, with a lower amount of risk premium (1.136 £/MWh) and certainty equivalent (69.821 £/MWh) in comparison to other scenarios, reducing LCoE by nearly 35% compared to partial decommissioning and 36.5% compared to full decommissioning.

Keywords: Offshore wind farms; End-of-life scenarios; Repowering; Decommissioning, Levelized Cost of Energy, Risk Premium, Certainty Equivalent

1. Introduction

The offshore wind industry in Europe is a key driver towards achieving the EU set goals for sustainable power generation in the next few years, with more than 22GW installed from 5,047 grid-connected wind turbines across 12 countries by the end of 2019 [1]. The trend to move production into deeper waters and further offshore is based on the higher and steadier wind shear, increased availability of space and less social impact than onshore. Since the first offshore installation in 1991, the Vindeby Offshore Wind Farm (OWF), there has been a continuous trend to install more units of higher capacity within a wind farm; however, with many of the first generation installations approaching or having already exceeded their nominal service life, the discussion on the selection of the optimal end of life (EoL) scenario has become very relevant as such decisions can increase profitability, potentially reducing costs. Normally, decommissioning should be considered even at the planning stage of the wind farm; however, before this occurs, repowering or service life extension may be pursued, taking into account any residual capacity of key wind farm components, as suggested by Topham et al. [2].

The current academic literature about EoL scenarios is limited, forcing operators of wind farms to adopt their own practices when supporting relevant decisions. While in other industries systematic approaches have been established to support EoL decisions, this is not currently the case for OWFs [3–6]. Luengo and Kolios [7] have reviewed in detail the risks involved on service life extension based on a detailed failure mode identification and with a view to qualifying which are the key components to drive such decisions. It is claimed that extending efficient operation and increasing the overall energy production may significantly increase the return on investment and reduce the LCoE.

Topham and MacMillan [8] investigated key stages of the decommissioning phase, such as the disassembling procedure for the wind turbine and lifting, cutting methods for the removal process of foundations and cables, with a view to comparing various transportation strategies to reduce the decommissioning cost. Fowler et al. [9] studied the benefits of leaving offshore infrastructures in the ocean, mainly from an environmental point of view, while in a similar study Topham et al. have evaluated the environmental impact of recycling wind turbines [2]. Judge et al. have developed a life cycle financial analysis model for OWFs, exclusively investigating decommissioning [10], while Myhr et al. [11], proposed a framework based on Multi-Criteria Decision Analysis (MCDA) techniques to select the most appropriate decommissioning methods for OWFs. In addition to this, Gjødvad and Ibsen have introduced a tool to assign the decommissioning process to stakeholders [12]. Sun et al. have performed a study on OWF layout optimization based on the decommissioning strategy [13]. Beauson et al. studied offshore wind decommissioning regulations for the USA. Beauson and Brøndsted have focused on the fate of offshore wind turbine (OWT) blades, based on the first wind farm in the world that will undergo decommissioning [14] and Lichtenegger et al. have focused on the blade waste that OWTs are expected to generate, pointing out the significance of the problem [15]. In a different study Hou et al. [16], determined that repowering is considered a sustainable alternative solution to increase the OWT life. Cabboi et al. have analysed technical issues related to decommissioning, investigating novel methods for vibration-assisted decommissioning of a slip-joint [17]. Hinzmann et al. have summarised problems and solutions in typical problems related to decommissioning of offshore monopiles [18], while Topham et al. have summarised the challenges of decommissioning based on European best practice [19].

With respect to repowering, Hou et al. presented a method for optimization of OWF repowering through the selection of different ways of replacing wind turbines [20]. Himpler and Madlener, studied the economics and optimal timing of repowering, and presented a case study application in Denmark [21], while Sun et al. investigated OWF repowering for the context of Hong Kong [22]. Bezbradica et al.

applied multi criteria decision analysis for the ranking of a number of wind farm repowering scenarios for a case study in Gotland [23]. Finally, Safaei et al. presented a model for finding the best topology and optimal time for repowering systems based on cost and availability functions [24].

A number of studies have investigated the techno-economic feasibility of OWF with only a few considering in detail EoL scenarios [11, 25–31]. Kaiser and Snyder proposed a model to calculate the cost of decommissioning and installation based on data from European OWFs [32, 33]. Common key performance indicators (KPIs) to systematically assess the cost of OWFs include Net Present Cost (NPC), Life Cycle Cost (LCC) and Levelized Cost of Energy (LCoE). The NPC concept is used to show the total present value of cash flow, including the initial cost of all the components, any replacement cost, maintenance cost, investment cost and discount cost during the lifetime of the system [34]. LCoE is a common economic metric to compare different energy technologies [35]. The LCoE shows the cost of produced energy rather than determining the potential profit of an investment, which can be estimated through other economic metrics such as return of investment and internal rate of return [36]. LCoE is calculated in £/kWh or £/MWh and is used to evaluate commercially the feasibility of a power generation technology and compare its implementation with other technologies considering LCCs and power production. Net Present Value (NPV) aims to account for the time value of money, which is a particularly important factor, considering the length of these investments. A detailed techno-economic model incorporating both concepts has been presented by Ioannou et al. [31] and will stand as a basis for subsequent work in this paper.

It should be noted that a number of variables influence the LCC modelling of an investment and considering that the offshore wind energy market is still developing, considerable uncertainty can be introduced in the analysis [37, 38]. To this end, it is meaningful to transition from a deterministic to a stochastic assessment, expressing the calculated KPIs instead of single values in joint probability density functions, which accumulate the effects of randomness of specific variables [39–41]. This approach would allow the assignment of certain confidence levels to the results of the cost analysis.

This paper aims to develop a framework for a preliminary analysis and comparison of two key EoL scenarios: repowering and decommissioning, with a view to presenting the impact of key influencing factors from a deterministic and stochastic approach, also adopting the economic model of risk aversion to calculate the certainty equivalent of LCoE based on each of the examined EoL scenarios. To achieve this, results from a detailed techno-economic assessment have been extended to calculate the LCoE based on the Capital expenditure (CAPEX), Operational and maintenance expenditure (OPEX), Decommissioning and disposal (D&D) or Cost of repowering (REPOW), in order to inform the decision of the optimal strategy. The novelty of this approach lies in the fact that a high-fidelity cost model is applied and two of the EoL scenarios are compared directly, based on their NPV and LCoE. With a few hundreds of wind turbines expected to reach the end of their nominal service life in the next five years, outcomes of this work can inform current best practice on supporting decisions related to EoL scenario selection, and can stand as the basis for more advanced numerical studies which will account for higher fidelity calculations of the operations and maintenance (O&M) costs and also involve service life extension as an alternative EoL scenario. It should be noted here that service life extension has not been considered in this analysis, as the approach to quantification of the underlying costs would be different and would demand a fully integrated cost model with detailed modelling of the O&M phase requirements; further, this option highly depends on the current condition of the wind turbine units and representative component reliability data, which is beyond the scope of this paper.

The rest of the paper is organised as follows; Section 2 presents briefly the most common EoL scenarios and justifies the ones that are selected for this work; Section 3 presents the methodological framework; Section 4 provides the results and discussion; and finally Section 5 gives the conclusions and future recommendations.

2. End life scenarios

Once the 20-25 years of nominal service life of a wind farm lapse, a decision is required from the operator as to what would be the optimal EoL scenario and how it should be selected considering associated costs and risks. Operators need to evaluate the current condition of their assets, the state of the technology that was originally procured, and maximise the value of their initial investment. Similar decisions have been made over the past decades from the offshore oil & gas industry, with platforms originally designed for 20 years and eventually ceasing operations after 40+ years from commissioning [42]. Figure 1 presents the most common EoL scenarios for OWFs which will be further discussed in this section.

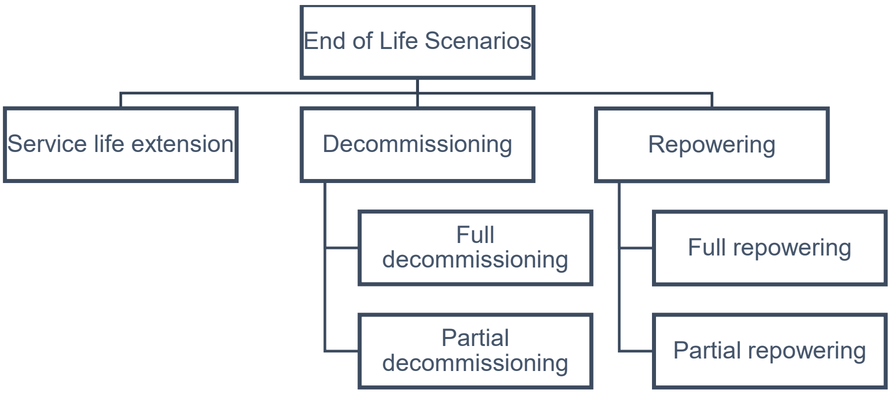


Figure 1: End of life scenarios of offshore wind farms

2.1. Decommissioning

The decommissioning process is known as the final stage of an OWF project as even if operations are extended, eventually the deployment area should return to its original, before-installation conditions [8, 20, 43]. Technically, the process is implemented reversely to the installation process, e.g. using vibrations to remove the piles from shallow water installations. Vindeby was the first wind farm to be decommissioned by Dong Energy, a process which was completed in September 2017 after 25 years of operation. The driver behind choosing this strategy was associated with the difficulty of finding spare parts as the technology was becoming obsolete and costs of repairs and upgrades were not sustainable [8, 20].

Planning of the decommissioning process is essential in order to reduce operational risks and reduction of costs. Weather and seabed conditions are crucial to this end. The type and number of foundations, capacity of the wind turbines and distance to port, are key factors influencing the process. Decommissioning starts with the turbine removal phase which includes disconnecting and de-energizing the wind turbine from the grid, dismantling of the blade, nacelle and tower [44] and transportation to shore for recycling or disposal, where appropriate. With respect to the foundation, two strategies can be considered: partial or full removal. The partial removal of the foundation can be done with external or internal cutting of the foundation, normally two metres below the mud line and is more relevant to heavy foundations deployed in deep waters. In this strategy, parts such as the cables and scour protection should be considered separately, taking into account the option that will cause the least disturbance to the environment [45, 46]. In full removal, the whole foundation is de-piled using vibrations and transferred to the port facilities on a barge.

2.2. Repowering

Current practice has shown that core components of an OWF, such as cables, foundations and offshore substations, do not have a similar service life to the turbines. This implies that after 20 years, there can still be some capacity in the OWF and the cost of harvesting its value should be investigated before making EoL strategy selection decisions. It should be noted here that the high cost of the decommissioning process raises an additional argument in favour of delaying this process for as long as possible.

Repowering can be applied to the whole wind farm or part of it, potentially with more modern turbines of higher capacity [16]. New generation OWTs have the technology of direct drive without gearbox, which produces more energy with an average capacity of 6MW [2]. Reducing the weight of the nacelle, as well as component failures, reduce loads and operational costs and hence increase the profitability of the initial investment. Repowering provides the opportunity for the OWF operator to use the existing foundation as well as the original electrical system, commonly known as the balance of plant (BOP). Installing higher capacity WTs, as well as modifying some key components, such as drive trains or electronic equipment to improve their efficiency, will extend the operational life of the OWF with limited additional cost of installation [43, 47, 48]. It should be noted here, that the extent to which repowering can take place can often be restricted by the capacity of the offshore substation and cable infrastructure.

2.3. Service life extension

Extending the life of assets is always an interesting option for OWF owners as they can continue to operate as usual, provided that they have sufficient information on the status of their integrity. Available data from monitoring schemes and inspection reports are a key requirement as the 20 years of operation often stipulates the design service life of major components, such as the drive train, and such repair or replacement activities bear significant costs to the operators; therefore, identifying the most critical parts such as the generator and blades could help reduce inspection and maintenance costs [49, 50]. Although operational data are not excessively available from operational wind turbines, it is expected that the failure rates and associated costs will increase during the second half of their service life and it is also anticipated that the costs for inspections, monitoring and maintenance will also increase during this latter part of their operation, and certainly within the extended period, especially related to the modification and replacement of critical components [51]. A failure mode-based, risk identification and evaluation exercise of the factors influencing operation and maintenance (O&M) costs are pertinent to optimizing service life extension strategies [7, 52, 53].

Service life extension can potentially add five or more years of additional operation, before deciding on repowering or decommissioning at the end of this period [16]. The rapid technological evolution of wind turbines' inspection and maintenance programmes and relevant certification schemes can enable service life extension, increasing the profits from existing OWFs with less investment [54, 55].

2.4. Boundaries of this study

This research focuses on the techno-economic comparison of decommissioning and repowering with the latter option depending on a higher level assessment of the technology rather than a detailed integrity assessment, even at a unit level, which is required for the service life extension option. Consideration of service life extension requires evaluation of failure rates of maintenance-significant components, e.g. drive train components, along with their variance throughout the service life of the asset, which are difficult to retrieve considering the lack of data from operational wind farms. This information is not normally required to the same extent for a repowering strategy and also, considering that technology has significantly advanced since the first generation of wind farms, this paper focuses on repowering as a competitive EoL scenario.

3. Methodology

3.1. Techno-economic analysis framework

This section documents the framework for the techno-economic evaluation of the two EoL scenarios: the foundation of the specific features that are included in the analysis and the KPIs that will be investigated. As mentioned earlier, the results of this analysis are based on an existing techno-economic model presented by Ioannou et al. [31], which also included a sensitivity analysis illustrating key influencing factors to standard KPIs, as presented in Figure 2, while Figure 3, presents in a flow chart the key concepts of the methodology developed in this research and how these will interact during the analysis.

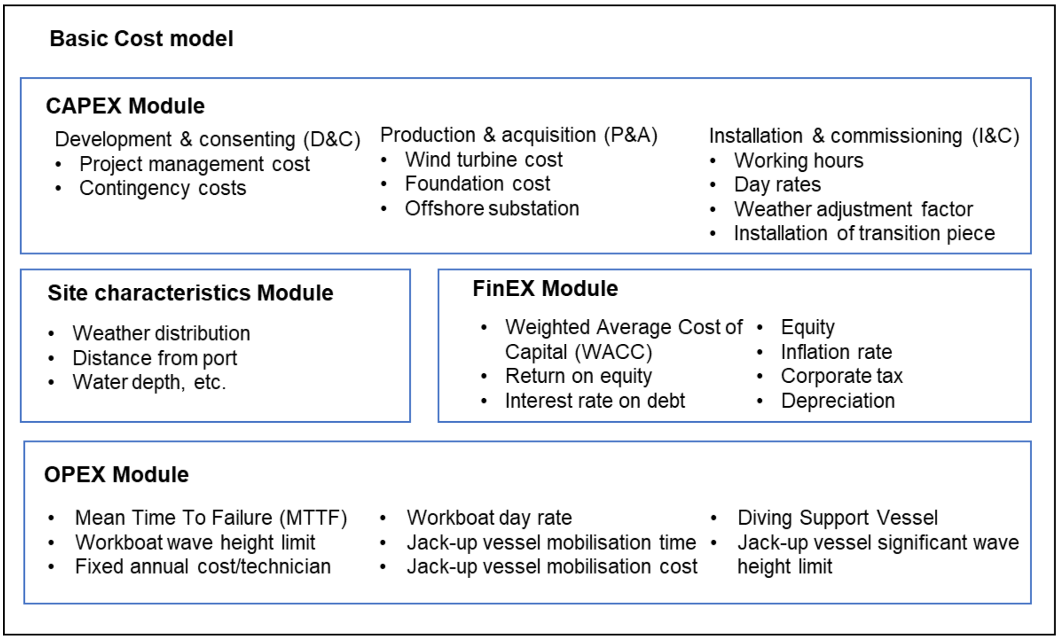


Figure 2: Structure of basic model and key influencing parameters

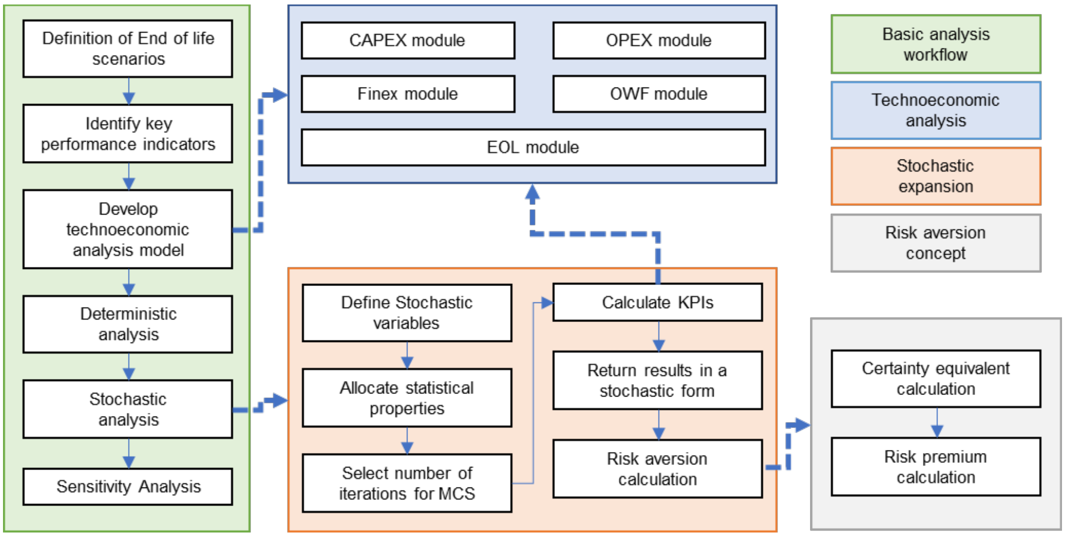


Figure 3: Overview of analysis framework

The analysis starts with the definition of the EoL scenarios, which for this case are the concepts of repowering and decommissioning. Next, the KPIs will be selected, as presented in the following subsection. The core techno-economic analysis framework which was presented in Figure 2 is then extended, with the inclusion of the EoL module which will calculate the additional costs of each alternative, in addition to the initial CAPEX (capital expenditure), OPEX (operational expenditure), FinEx (financing expenditure) and OWF (offshore wind farm) modules. The developed EoL module based on the KPIs, as well as the role of energy production based on the whole life of the asset, provide the deterministic result of LCoE and it will stand as a basis for the stochastic expansion of the initial model. For this, once the stochastic variables have been determined, appropriate statistical properties are assigned, together with the number of simulations that will run for the Monte Carlo Simulations (MCSs). Then, following an iterative algorithm, the KPIs are calculated and the results are expressed in the form of histograms which will allow the risk aversion parameters to be calculated. Once this has been completed, a sensitivity analysis will take place, to determine the impact of key variables on the selected KPIs.

3.2. Key performance indicators

3.2.1. Levelized Cost of Energy

The levelized cost of electricity considers the costs and power output throughout the whole life of an energy asset. The global weighted average LCoE for offshore wind in 2018 has been estimated at $0.127/kWh, according to IRENA [56]. For the accurate estimation of the cost of energy in this study, a high fidelity LCC analysis was performed, considering the different phases of the asset's development and operation: Development and Consenting (D&C), Production and Acquisition (P&A), Installation and Commissioning (I&C), Operation and Maintenance (O&M) and Decommissioning (DECOM).

The total levelized cost of electricity of the OWF can be calculated by levelling and discounting the investment as well as the O&M cost during its lifetime, and then dividing it by the annual electricity production technology [57]. Eq. (1) presents the fundamental definition of LCoE [58].

$$LCoE\ (\$/Wh) = \frac{\Sigma_{t=1}^{T} \frac{C_{tot,t}}{(1+r)^t}}{\Sigma_{t=1}^{T} \frac{AEP_t}{(1+i)^t}} \quad (1)$$

where, $C_{tot,t}$ is the total cost during year t ($), AEP_t is the electricity production during year t (Wh), i denotes the discount rate and T represents the design life of the asset. The discount rate is identified based on the market value of both equity and debt, the so-called Weighted Average Cost of Capital. It is necessary to consider the project risk as well as the return yield. Discount rate has been identified as a key parameter affecting the LCoE value in various studies [31, 37, 38]. The equation of LCoE can be modified based on the type of analysis. The deprecation tax shield and salvage value at the end of the asset life should be considered in the total life cost of an asset.

To accurately predict the LCoE, a life cycle cost model of an OWF has been developed and the sensitivity of important parameters such as availability, distance to the shore and load factor were considered in [11]. For the purpose of this paper, the initial model is expanded considering the EoL costs for each option, and an additional stochastic functionality is added through MCSs in order to allow for the stochastic calculation of the KPIs. Similar applications of the integration of MCS to compare the LCoE has been presented for coal-fired power plants as well as the generation of natural gas [59–61]. Further, the LCoE of various sources of energy has been stochastically calculated based on MCS in [62]. Even though there are studies associated with the cost estimation of partial and full decommissioning, the literature review has indicated that there is no research associated with the detailed economic consideration of the EoL scenarios based on the whole life of the OWF [58].

Based on various methods to calculate the LCoE, this paper also considers the concept of net present value (NPV) based on summing the discounted capital, operational expenditure in each year of the OWF's life and the associated expenditure, which depends on the examined EoL scenarios, taking into account the actual value of money which considers the timing of the transactions, as shown in Eq. (2)

$$NPV_{Total\ Cost} = \sum_{n=0}^{T} \frac{CAPEX_n + OPEX_n + DECOM}{(1+i)^n} \tag{2}$$

As mentioned above, to calculate LCoE, the discounted electricity output has to be estimated based on Eq. (3).

$$NPV_{Yield} = \sum_{n=1}^{T} \frac{AEP_n}{(1+i)^n} \tag{3}$$

As such, by dividing the NPV of the OWF lifetime cost shown in Eq. (1), into the NPV of produced energy in the OWT farm, the LCoE is calculated as:

$$\mathrm{LCoE} = \frac{NPV_{Total\ Cost}}{NPV_{Yield}} \tag{4}$$

LCoE is calculated in this study parametrically based on the different EoL scenarios for fixed-bottom OWTs. The LCoE can be estimated separately for each case, considering respectively OPEX, CAPEX, decommissioning or repowering cost and expected yield of the OWF.

3.2.2. Capital expenditure (CAPEX)

Capital expenditure covers the costs associated with the building and commissioning of the OWF. It is divided into three main categories: Development and consenting (D&C), Production and acquisition (P&A), Installation and commissioning (I&C). This is translated into the following equation:

$$CAPEX = C_{P\&A} + C_{D\&C} + C_{I\&C} \tag{5}$$

It should be noted that in order to improve the accuracy of the cost consideration, several critical factors, such as geographical location and meteorological conditions, capacity factor, reliability, availability and accessibility of transportation, should be taken into consideration [63].

3.2.3. Operational expenditure and maintenance (OPEX)

The costs during the O&M phase are associated with planned and unplanned maintenance and account for interventions which aim to ensure safety and reliability as well as the continuous operation of the OWF. Operational costs further involve rental payments, insurance costs, and project management.

$$OPEX = C_{repair} + C_{rent} + C_{insurance} + C_{Project\ management} \tag{6}$$

A detailed description of the key characteristics of O&M models and calculation tools can be found in [64], while multiple groups to date have proposed different approaches and have engaged in different comparative analyses [65–67].

3.2.4. Decommissioning and disposal cost

Decommissioning and disposal is the final stage of the wind turbine life cycle and is assumed to be the reverse of commissioning and installation processes. It covers the costs associated with the removal of the wind turbine (nacelle, tower, and transition piece) as well as the balance of the plant (foundations, scour protection, cables, and substations) ($C_{Removal}$), site clearance $C_{Site\ Clearance}$, transportation to the disposal sites $C_{Transportation}$, port preparation ($C_{Port\ preparation}$), disposal process $C_{Disposal}$, and finally hiring vessels costs $C_{Hiring\ vessels\ and\ personnel}$ [63]. The disposal process of an OWT depends on the waste management strategies and the main available disposal options include reuse, recycle, incineration with energy recovery and disposal in a landfill site [2].

$$DECOM = C_{Removal} + C_{Transportation} + C_{Disposal} + C_{Site\ Clearance} + C_{Hiring\ vessels\ and\ personnel} + C_{Port\ preparation} \quad (7)$$

For the purpose of this work, costs of full and partial decommissioning are calculated based on assumptions from [68]. More specifically, full decommissioning is assumed to be 30% more expensive than partial decommissioning and the ratio between partial decommissioning through internal and external cutting of the foundation is assumed to be 1.052. The difference between partial decommissioning through internal and external cutting is negligible, therefore the internal cutting of the foundation has been investigated in the subsequent parts of this work. In the case of decommissioning as the qualifying EoL strategy, the maximum value of T in $NPV_{Total\ Cost}$ and NPV_{Yield} would be based on the nominal life of the asset, i.e. 20 years. The total duration of the decommissioning process itself is assumed to be one year at the end of the 20 years.

3.2.5. Repowering Cost

When assuming repowering as the EoL strategy, the Repowering Cost (REPOW) is estimated instead of DECOM. An assumed initial service life of 20 years is considered, after which the OWF will be repowered, in this case with a turbine of the same capacity. Figure 4 illustrates this strategy and the calculation of LCoE for each part of the asset life in the repowering case. The maximum value of time T_1 in $NPV_{Total\ Cost}$ and NPV_{Yield}, which are the main parameters of $LCOE_1$, would be based on the nominal life of the asset which in this case is assumed to be 20 years. The total duration of the repowering process is assumed to be one year added at the end of the nominal service life of the asset. In the case of asset life extension for a further 20 years, the LCoE would be assumed for the next 20 years (T_2), which is denoted as $LCOE_2$.

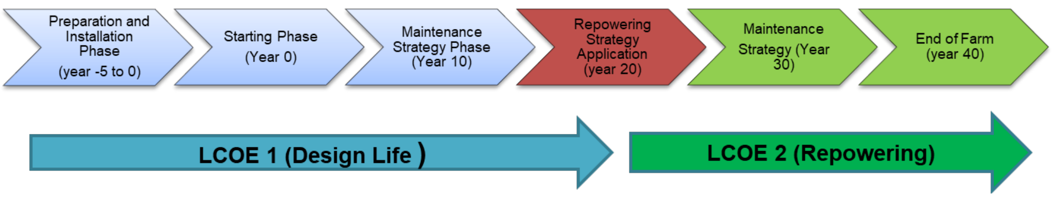


Figure 4: Repowering Strategy for an OWF

The costs of the repowering process of OWFs with same capacity turbines include the cost of removing the current wind turbine ($C_{Removal}$), transportation ($C_{Transportation}$), disposal ($C_{Disposal}$), new wind turbine acquisition ($C_{New\ WT}$), hiring vessels and personnel ($C_{Hiring\ vessels\ and\ personnel}$), operation ($C_{Operation}$) and maintenance ($C_{Maintenance}$), as shown below:

$$REPOW = C_{Removal} + C_{Installation\ new\ WT} + C_{New\ WT} + C_{Operation} + C_{Maintenance} \tag{8}$$

3.2.6. Energy production

The amount of energy produced depends on the technology type, capacity factor and the system scale. Energy performance is a key factor to compute the LCoE during the life of the wind farm. The capacity factor (CF) plays a crucial role in the energy performance estimation and is defined as the ratio of the real energy production to the maximum potential energy outcome. OWF reliability would influence the capacity factor indirectly, implying that a higher capacity of power plant would reduce the LCoE; however, it is important to consider the demand for energy from the power plant. To calculate the annual energy production (AEP) of the OWF, different power curve modelling techniques can be implemented [69]:

$$P_S(v) = \frac{1}{2}\rho\pi R^2 C_{p,max} v^3 \tag{9}$$

where, ρ is the density of air (1.225kg/m^3), R is the radius of the rotor, $C_{p,max}$ is the coefficient of the maximum effectiveness of power, and v is the instantaneous wind speed. The simulated power curve, $P_{sim}(v_a)$, is based on the mean wind speed as shown in Eq. (10). The $P(v, v_a)$ shows the probability distribution of wind speed, based on the turbulence intensity factor and v_a [70, 71].

$$P_{sim}(v_a) = \int_0^\infty P_S(v) P(v, v_a) dv \tag{10}$$

The AEP of the wind farm can then be calculated as:

$$AEP = Z\ (1 - \eta_w) h \eta_A \int_0^\infty P_W(v_a) P_{sim}(v_a) d_{v_a} \tag{11}$$

where, Z is the number of turbines, h is the number of hours in a year, η_w represents the factor accounting for wake losses, η_A is the availability of the wind farm and $P_w(v_a)$ signifies the Weibull distribution as a function of v_a. The AEP is assumed to be constant in this study. The net AEP, which is computed based on these inputs, is 1,734,792 MWh/year.

3.3. Stochastic expansion of the techno-economic model

As mentioned earlier, the input variables of the LCoE are often characterised by considerable uncertainties, which deterministic models are not able to handle systematically. Even adopting a scenario analysis including the assumption of upper and lower inputs for each variable, distinguishing conservative/unconservative scenarios for LCoE, this approach would not be able to support decisions under uncertainty. Therefore, to achieve a meaningful assessment, a systematic approach should be considered in order to quantify the cumulative impact of these uncertainties. Based on reviewing KPIs, the uncertain variables with significant impact on the LCoE can be modelled stochastically and then MCS can be employed to compute the LCoE through a joint probability distribution histogram. The MCS approach generates sets of inputs of the stochastic values which feed an iterative calculation loop of calculating output KPIs through the deterministic model. This approach can efficiently consider multiple stochastic variables; however, it becomes inefficient when calculating low probabilities of failure. Estimating LCoE through a stochastic analysis has proved to be more insightful than a deterministic approach since, instead of returning a deterministic value with limited context, it can provide an LCoE value with an associated confidence interval (CI).

The result as a stochastic distribution provides an opportunity for a quantitative analysis of the risk or uncertainty in comparison to average LCoE. The constant in relation to the risk aversion utility function is implemented in this research based on [72] and [62] to calculate the certainty equivalent of LCoE for each EoL scenario. The certainty equivalent indicates a fixed value of LCoE which the decision maker should be indifferent towards, relative to the uncertain LCoE that they face. Moreover, the uncertainty or risk premium (RP) indicates the amount of money that should be paid to reduce the uncertainty and is used as a method to monetize the risk of investment in terms of an uncertain outcome. To calculate a certainty equivalent LCoE for each EoL scenario, it is necessary to find the uncertainty or RP. Eq. (12) shows RP as function of risk aversion of LCoE, r as the number of iterations and the gamma value γ. The LCoE value is obtained based on each iteration within the MCS.

It is assumed that a gamma γ coefficient of relative risk aversion, equal to 2, is used in the analysis. The case of a more risk averse decision maker may be modelled through increasing the value of gamma [62]. After computing the RP for each EoL scenario, Eq. (13) is implemented to calculate the certainty equivalent C_{eq}.

$$RP = \frac{\sum_1^r LCOE}{r} - \left(\left(\frac{\sum_1^r \frac{(LCOE)^{1-\gamma}}{1-\gamma}}{r} \times (1-\gamma) \right) \right)^{(1-\gamma)} \tag{12}$$

$$C_{eq} = \frac{\sum_1^r LCOE}{r} + RP \tag{13}$$

The relative risk aversion is assumed to be constant due to being positive as well as decreasing the utility function of the LCoE. The higher certainty equivalent would be based on the higher risk aversion and the RP.

4. Results

4.1. Case Study

This section presents the assumptions and characteristics used in this paper, aiming to refer to a realistic but hypothetical OWF deployed in UK waters. The cost of labour and vessels, environmental conditions, wind turbine, monopile foundation and the capacity of the wind turbine are assumed to be the same as in [31], which is the basis of this study, and account for a 504 MW wind farm capacity, with a nominal service life of 20 years, five years of construction time, availability between 92.2-92.5% and an interest rate of 8%. The distance to the port is assumed to be 36 km, water depth 26 m, and the turbine characteristics are as follows: Rotor diameter 107 m, Hub height 77.5 m, Pile diameter 6 m, Rated power 3.60 MW, Cut-in speed 4 m/s and Cut-out speed 25 m/s. The key assumptions with respect to CAPEX (k£) and OPEX (k£/y) are presented in Tables 1 and 2. The reader is referred to [31] for the detailed methods and data that are utilised for the estimation of each field of the table; this information is not presented here in order to avoid repetition.

Table 1: CAPEX (k£) and OPEX (k£/y) estimation in OWF

Total D&C costs	205,750	**Total I&C costs**	305,742
Project management cost	42,327	Installation of wind turbines (tower, hub, nacelle and blades)	62,619
Legal cost	16,698	Installation cost of foundations	102,224
Environmental surveys cost	19,162	Installation cost of cables	115,070
Engineering cost	1,144	Installation cost of substation	3,991
Contingency cost	126,419	Installation cost of scour protection	873
Total P&A costs	1,040,230	Insurance cost during installation	20,966
Wind turbine cost	546,056	**Total O&M costs**	56,597
Foundation cost	212,699	Repair cost	28,403
Cables cost	120,525	Rent cost	5,040
Offshore substation (x2)	121,337	Insurance cost	7,338
Onshore substation	30,334	Project management cost	15,816
SCADA cost	9,278		

Table 2: Repowering Cost (k£)

The total cost of Repowering process	707,035
Turbine cost	546,056
Removal cost	41,763
Installation cost	62,619
Operation and maintenance	56,597

4.2. Deterministic analysis result

LCoE is calculated parametrically in order to allow multiple iterations to run in an efficient way. Results for the three scenarios that have been studied in this work, are presented in a stack bar chart in Figure 5. It is indicated that the repowering option has the lowest LCoE compared to the other scenarios. The output reduction of energy of the OWF after the installation is 1.6 ± 0.2% for each year [73]. The repowering strategy provides the opportunity to the owner of the wind farm to improve the efficiency of energy production by avoiding further energy losses with less investment cost (reduction of the maintenance cost, installation cost as well as existing current structure). More specifically, for the case where the same capacity of wind turbine is selected, the recalculated LCoE, which accounts for after the end of the nominal service period, becomes 65.8 £/MWh. The repowering strategy would reduce the LCoE of the OWF by nearly 35% compared to partial decommissioning and 36.5% compared to full decommissioning.

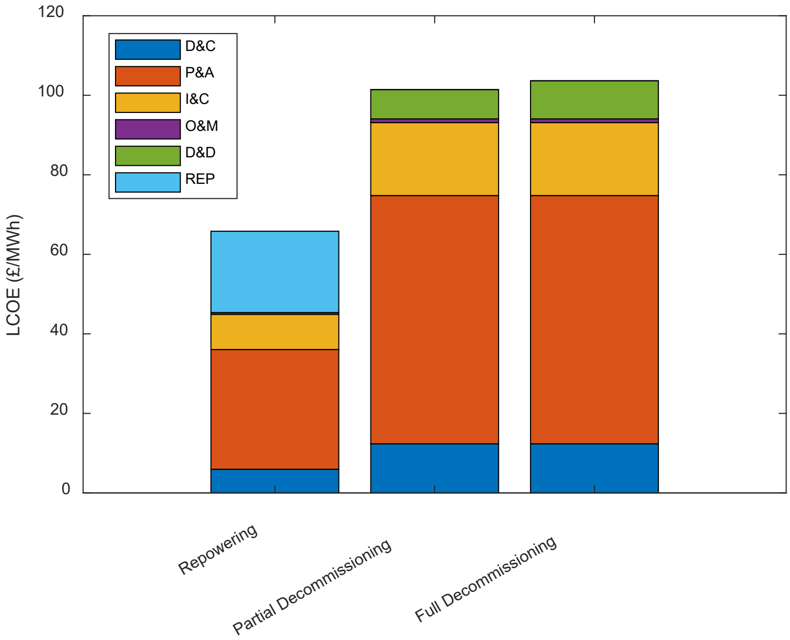


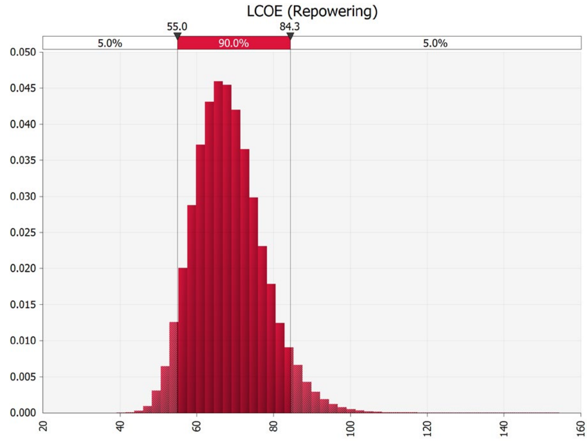
Figure 5: Estimated LCoE for EoL scenarios investigated

4.2. Stochastic analysis result

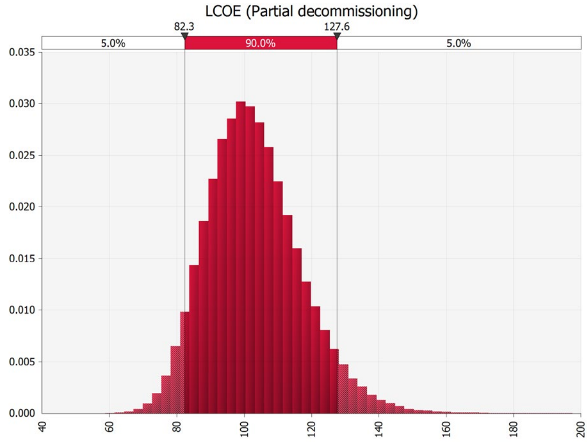
Following the expansion of the deterministic model to account for uncertain inputs, a total of 100,000 iterations was executed considering the statistical properties listed in Table 3. In the absence of real data, normally distributed variables were chosen; it should be noted, however, that the developed algorithm could equally easily treat statistical distributions of any type. A fixed CoV of 0.1 was chosen for this analysis. Figure 6 presents the probability normalized histograms of LCoE based on the different EoL scenarios which were investigated in this exercise.

Table 3: Mean values and standard deviations of variables

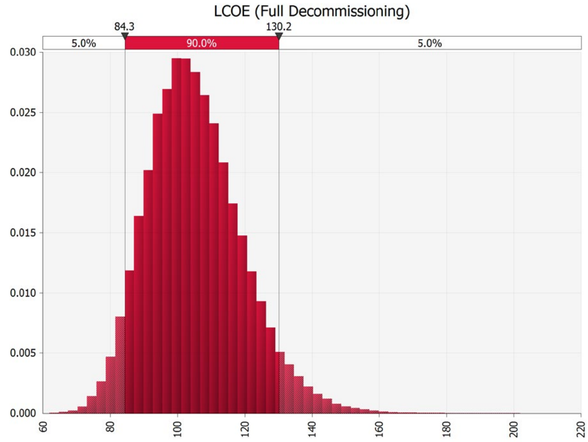
Variable	Distribution	Characteristic values
D&C costs (£000s/MW)	Normal	$\mu = 205{,}750,\ \sigma = 20{,}575$
P&A costs (£000s/MW)	Normal	$\mu = 1{,}040{,}229,\ \sigma = 104{,}022$
Total I&C costs (£000s/MW)	Normal	$\mu = 305{,}742,\ \sigma = 30{,}574$
O&M costs (£000s/MW/yr)	Normal	$\mu = 56{,}597,\ \sigma = 5{,}659$
Repowering process Cost (£)	Normal	$\mu = 707{,}035,\ \sigma = 70{,}703$
Full Decommissioning Cost (£)	Normal	$\mu = 159{,}718,\ \sigma = 15{,}971$
Partial Decommissioning Cost (£)	Normal	$\mu = 122{,}860,\ \sigma = 12{,}286$



(a)



(b)



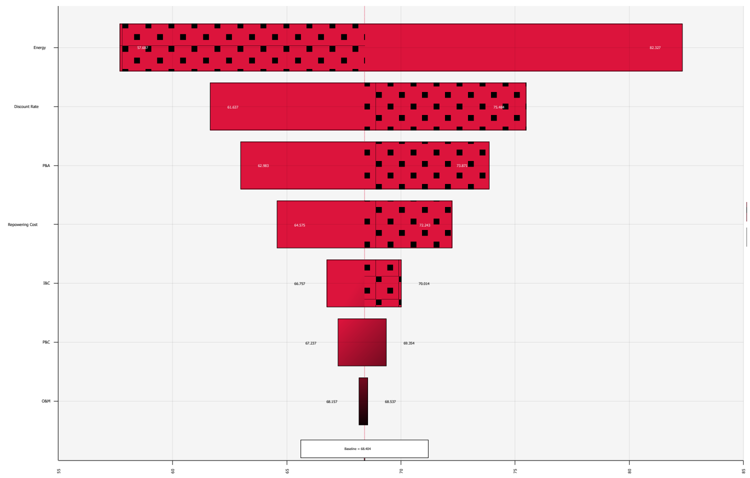
(c)

Figure 6: Stochastic assessment of LCoE: (a) Repowering, (b) Partial decommissioning, (c) Full decommissioning

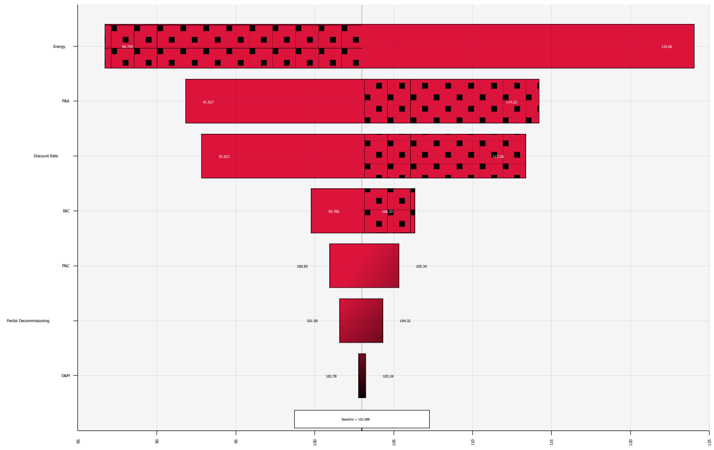
For the case of repowering, the mean value for LCoE is £68.4/MWh and is bound within a 90% CI from values £55-£84.3/MWh based on 20 years' additional service life. Similarly, for partial decommissioning, the mean value is £102/MWh and in the 90% CI within values of £82.3-127.6/MWh. Finally, the mean value for the case of full decommissioning is £105.2/MWh and in the 90% CI within values £84.3-130.2/MWh. The variance of repowering ($\sigma = 8.99$) is smaller compared to the others ($\sigma = 13.94$ and $\sigma = 14.12$ respectively) showing that the LCoE values are grouped closely around the mean (expected value). It can be observed that the results between partial and full decommissioning are very close to each other.

4.3. Sensitivity analysis

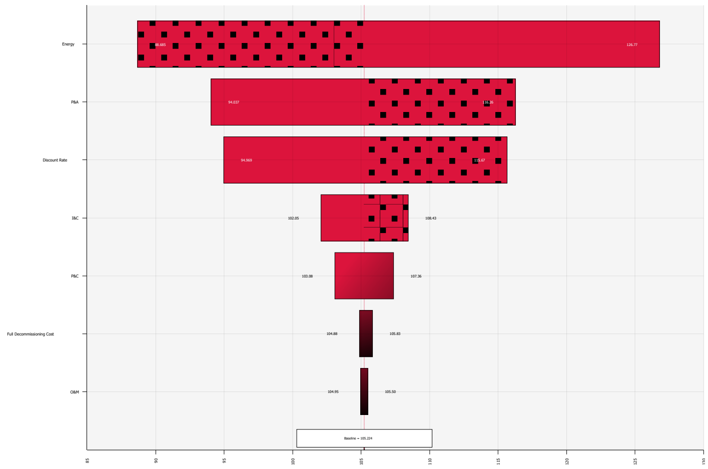
Due to the parametric nature of the model, a sensitivity analysis is performed in order to qualify the highest contributors to the stochastic calculation of LCoE. These factors are classified into the cost categories presented in section 3. Results are presented in a series of tornado plots in Figure 7 where inputs (influencing factors) are ranked accordingly. More specifically, for the repowering option, energy yield is found to have the highest impact followed by the discount rate and P&A costs. For partial decommissioning, energy yield again is found to be the prevailing option, followed by P&A and discount rate, and finally for the full decommissioning, energy yield is again the prevailing factor followed by P&A and discount rate values.



(a)



(b)



(c)

Figure 7: Sensitivity analysis LCoE, (a) Repowering, (b) Partial decommissioning, (c) Full decommissioning

4.4. Risk aversion concept

Table 4 presents the impact of LCoE variability on the risk averse decision maker. The uncertainty premium shows the amount of money that the decision maker must pay to reduce the uncertainty and shows the risk monetization of investment in the case of having an uncertain result. The distribution of LCoE based on various EoL scenarios was determined in the previous step. The wider distribution shows the higher uncertainty premiums and is calculated through C_{eq}. The certainty equivalent measures the price which the decision maker must pay due to being indifferent towards the related uncertainty. Repowering has the lowest RP and C_{eq} compared to the other options, with the amounts of 1.136 £/MWh and 69.821 £/MWh respectively.

Table 4: The RP and C_{eq} for EoL scenarios in OWT farm

End Life Scenarios	RP (£/MWh)	$\frac{\sum_1^T LCOE}{r}$ (£/MWh)	C_{eq} (£/MWh)
Partial Decommissioning	1.815	103.017	104.832
Repowering	1.136	68.685	69.821
Full Decommissioning	1.823	105.254	107.077

4.5. Discussion

Results from the deterministic analysis clearly show that the option of repowering is the prevailing one as, although it involves the cost of acquisition of the new turbine and critical components, it has a reduced P&A cost compared to the decommissioning option. The results of the stochastic analysis reveal that the AEP and the energy yield parameter play a significant role in the calculation of LCoE across the different scenarios. This implies that these parameters should be evaluated as accurately as possible and at the same time underlying uncertainties should be reduced, narrowing the scatter around the expected values. The certainty equivalent indicates a fixed value of LCoE which the decision maker should be indifferent towards, relative to the uncertain LCoE that they face, while the RP indicates the amount of money that should be paid to reduce the uncertainty. Among the different options, repowering again performs better with a lower value of RP as well as certainty equivalent.

The decision of the most appropriate EoL scenario should be based on risk and techno-economic assessment and the proposed approach considers both factors. There are, however, practical issues that the decision maker should consider. For repowering, the actual capacity of the critical infrastructure should denote the extent that repowering can be realised, both in aspects of number of positions considered as well as the maximum capacity that can be accommodated by the offshore substation. Decommissioning should ensure that partial or full removal should be based on sound reasoning and the process should be optimized so as to reduce operations and hence associated costs. Although the decommissioning process is considered as part of the D&D stage, the specificities of an investment and associated assets, which account for the deployment location and integrity of the structures, should inform the final decommissioning plan.

5. Conclusions and recommendations

In this study, repowering and decommissioning were investigated as possible EoL scenarios as OWFs approach the end of their nominal service life. The assessment is based on the extension of a techno-economic model that accounts for the specific activities and costs related for each of the two options investigated. LCoE has been the KPI that has been used to evaluate the resultant cost of each alternative. In addition to the deterministic results that are produced through the analysis, the model was extended to systematically account for uncertain inputs and the concept of RP was employed to quantitatively evaluate the impact of the results to the decision maker. Based on the analysis, and for the parameters of the case study investigated, repowering was found to be the optimal EoL strategy. RP and C_{eq} were found to have the lowest value in the repowering option in comparison to other scenarios, therefore, the investor would need to pay less to eliminate the risk of the investment.

This work benefits from high fidelity cost modelling for the assessment of the two scenarios, taking into account key influencing factors contributing to cumulative costs, rather than informing decisions through a qualitative assessment. This topic is very timely as the number of wind turbines approaching the end of their nominal service life is rapidly growing. Limitations of this work are the restricted literature on the topic of the techno-economic assessment of EoL scenarios, the scarcity of data related to service life extension and decommissioning processes, and the lack of accurate reliability data which would allow consideration of further scenarios. To this end, and in order to further advance the proposed concept, a number of additional topics can be investigated towards creating a more holistic impact assessment model:

- The analysis can also include service life extension as an alternative scenario, through a fully integrated techno-economic model, and reliability failure data which are currently not available.
- More representative modelling of stochastic variables considering more data becoming available from the first full scale wind farms to be decommissioned can add further value to the current findings and in addition serve the purpose of validating this approach.
- Investigation of the sensitivity of each EoL alternative to key influencing factors related to deployment location, such as distance from port, water depth and wind shear, can provide useful insights towards the most relevant strategies.
- Finally, the assessment can be complemented with a multi-criteria assessment framework [74, 75] to account for further aspects which inform decision making, such as certification, residual risks, opportunity cost, etc.

Nomenclature

$P_{sim}(v_a)$: simulated power curve

$P_w(v_a)$: Weibull distribution as a function of v_a

$C_{D\&C}$: Cost of Development and Consenting

$C_{Disposal}$: Cost of disposal

$C_{Hiring\ vessels\ and\ personnel}$: Cost of hiring vessels and personnel

$C_{I\&C}$: Cost of Installation and Commissioning

D&C: Development and Consenting

D&D: Decommissioning and disposal

DECOM: Decommissioning costs

EoL: End of life

FINEX: Financial expenditure

h: number of hours in a year

I&C: Installation and Commissioning

KPI: Key performance indicators

LCC: Life cycle cost

$C_{Installation\ new\ WT}$: Cost of new wind turbine installation
$C_{Maintanance}$: Cost of maintenance
$C_{New\ WT}$: Cost of new with turbine acquisition
$C_{Operation}$: Cost of operation
$C_{P\&A}$: Cost of Production and Acquisition
$C_{Port\ preparation}$: Cost of port preparation
$C_{Project\ management}$: Cost of project management
$C_{Removal}$: Cost of removal
$C_{Site\ Clearance}$: Cost of site clearance
$C_{Transportation}$: Cost of transportation
C_{eq}: Certain equivalent
$C_{insurance}$: Cost of insurance
$C_{p,max}$: coefficient of maximum effectiveness of power
C_{rent} : Cost of rent
C_{repair}: Cost of repair
$P(v, v_a)$: probability distribution of wind speed
η_A: availability of the wind farm
η_w: factor accounting for wake losses
CAPEX: Capital expenditure
CF: Capacity factor
CI: Confidence Interval
CoV: Coefficient of variance
LCoE: Levelized cost of energy
MCDA: Multi-criteria decision analysis
MCS: Monte Carlo Simulations
NPC: Net present cost
NPV: Net present value
O&M: Operations and maintenance
OPEX: Operational and maintenance expenditure
OWF: Offshore wind farm
OWT: Offshore wind turbine
P&A: Production and Acquisition
REPOW: Cost of repowering
RP: Risk premium
AEP: Annual energy production
R: radius of rotor
T: Design life of the asset
Z: number of turbines
i: Discount factor
n: Years in operation
r: number of iterations
v: instantaneous wind speed
ρ: density of air (1.225kg/m^3)

Ethical Approval: Authors confirm that this research complies to ethical standards of scientific research. No additional formal ethical approval is required based on the nature of this research.

Consent to Participate: This research does not involve participation of humans in any way so a relevant consent is not applicable.

Consent to Publish: This work exclusively belongs to the authors and all of them have given their consent for publication.

Authors Contributions: Ali Jadali has executed the work and written the first draft of the paper, Anastasia Ioannou has developed the initial numerical model, Konstantinos Salonitis has reviewed and edited the manuscript, Athanasios Kolios has supervised the work, developed the conceptual methodology and prepared the manuscript for submission.

Funding: This work has not received funding from external sources.

Competing Interests: Authors report no competing interests.

Availability of data and materials: No data is associated with this paper.

References

1. WindEurope (2019) Offshore Wind in Europe - Key trends and statistics 2019. https://windeurope.org/about-wind/statistics/offshore/european-offshore-wind-industry-key-trends-statistics-2019/
2. Topham E, McMillan D, Bradley S, Hart E (2019) Recycling offshore wind farms at decommissioning stage. Energy Policy. https://doi.org/10.1016/j.enpol.2019.01.072
3. Kafuku JM, Saman MZM, Yusof SM, Mahmood S (2016) A holistic framework for evaluation and selection of remanufacturing operations: an approach. Int J Adv Manuf Technol 87:1571–1584. https://doi.org/10.1007/s00170-016-8836-5
4. De Vin LJ, Ng AHC, Sundberg M, et al (2008) Information fusion for decision support in manufacturing: studies from the defense sector. Int J Adv Manuf Technol 35:908–915. https://doi.org/10.1007/s00170-006-0773-2
5. Lee SG, Lye SW, Khoo MK (2001) A Multi-Objective Methodology for Evaluating Product End-of-Life Options and Disassembly. Int J Adv Manuf Technol 18:148–156. https://doi.org/10.1007/s001700170086
6. Xu Y, Fernandez Sanchez J, Njuguna J (2014) Cost modelling to support optimised selection of End-of-Life options for automotive components. Int J Adv Manuf Technol 73:399–407. https://doi.org/10.1007/s00170-014-5804-9
7. Luengo M, Kolios A (2015) Failure Mode Identification and End of Life Scenarios of Offshore Wind Turbines: A Review. Energies 8:8339–8354. https://doi.org/10.3390/en8088339
8. Topham E, McMillan D (2017) Sustainable decommissioning of an offshore wind farm. Renew Energy 102:470–480. https://doi.org/10.1016/j.renene.2016.10.066
9. Fowler AM, Jørgensen A-M, Svendsen JC, et al (2018) Environmental benefits of leaving offshore infrastructure in the ocean. Front Ecol Environ 16:571–578. https://doi.org/10.1002/fee.1827
10. Judge F, McAuliffe FD, Sperstad IB, et al (2019) A lifecycle financial analysis model for offshore wind farms. Renew Sustain Energy Rev 103:370–383. https://doi.org/10.1016/j.rser.2018.12.045
11. Myhr A, Bjerkseter C, Ågotnes A, Nygaard TA (2014) Levelised cost of energy for offshore floating wind turbines in a life cycle perspective. Renew Energy 66:714–728. https://doi.org/10.1016/j.renene.2014.01.017
12. Gjødvad JF, Ibsen MD (2016) ODIN-WIND: An Overview of the Decommissioning Process for Offshore Wind Turbines. In: MARE-WINT. Springer International Publishing, Cham, pp 403–419
13. Sun H, Yang H, Gao X (2017) Study on offshore wind farm layout optimization based on decommissioning strategy. Energy Procedia 143:566–571. https://doi.org/10.1016/j.egypro.2017.12.728
14. Beauson J, Brøndsted P (2016) Wind Turbine Blades: An End of Life Perspective. In: MARE-WINT. Springer International Publishing, Cham, pp 421–432
15. Lichtenegger G, Rentizelas AA, Trivyza N, Siegl S (2020) Offshore and onshore wind turbine blade waste material forecast at a regional level in Europe until 2050. Waste Manag 106:120–131. https://doi.org/10.1016/j.wasman.2020.03.018
16. Hou P, Enevoldsen P, Hu W, et al (2017) Offshore wind farm repowering optimization. Appl Energy 208:834–844. https://doi.org/10.1016/j.apenergy.2017.09.064
17. Cabboi A, Segeren M, Hendrikse H, Metrikine A (2020) Vibration-assisted installation and decommissioning of a slip-joint. Eng Struct 209:109949. https://doi.org/10.1016/j.engstruct.2019.109949

18. Hinzmann N, Stein P, Gattermann J (2018) Decommissioning of Offshore Monopiles, Occuring Problems and Alternative Solutions. In: Volume 9: Offshore Geotechnics; Honoring Symposium for Professor Bernard Molin on Marine and Offshore Hydrodynamics. American Society of Mechanical Engineers
19. Topham E, Gonzalez E, McMillan D, João E (2019) Challenges of decommissioning offshore wind farms: Overview of the European experience. J Phys Conf Ser 1222:012035. https://doi.org/10.1088/1742-6596/1222/1/012035
20. Hou P, Enevoldsen P, Hu W, et al (2017) Offshore wind farm repowering optimization. Appl Energy. https://doi.org/10.1016/j.apenergy.2017.09.064
21. Himpler S, Madlener R (2014) Optimal timing of wind farm repowering: a two-factor real options analysis. J Energy Mark 7:3–34. https://doi.org/10.21314/JEM.2014.111
22. Sun H, Gao X, Yang H (2019) Investigation into offshore wind farm repowering optimization in Hong Kong. Int J Low-Carbon Technol 14:302–311. https://doi.org/10.1093/ijlct/ctz016
23. Bezbradica M, Kerkvliet H, Borbolla IM, Lehtimaki P (2016) Introducing multi-criteria decision analysis for wind farm repowering: A case study on Gotland. In: 2016 International Conference Multidisciplinary Engineering Design Optimization (MEDO). IEEE, pp 1–8
24. Safaei F, Tazi N, Chatelet E, Bouzidi Y (2019) Optimal Topology and Repowering Time for Offshore Wind Turbines. In: 2019 6th International Conference on Control, Decision and Information Technologies (CoDIT). IEEE, pp 1344–1349
25. Schweizer J, Antonini A, Govoni L, et al (2016) Investigating the potential and feasibility of an offshore wind farm in the Northern Adriatic Sea. Appl Energy 177:449–463. https://doi.org/10.1016/J.APENERGY.2016.05.114
26. De Prada Gil, Mikel , Domínguez-García JL, Díaz-González F, Aragüés-Peñalba M, Gomis-Bellmunt O (2015) Feasibility analysis of offshore wind power plants with DC collection grid. Renew Energy 78:467–477. https://doi.org/10.1016/J.RENENE.2015.01.042
27. Castro-Santos L, Filgueira-Vizoso A, Carral-Couce L, Formoso JÁF (2016) Economic feasibility of floating offshore wind farms. Energy 112:868–882. https://doi.org/10.1016/j.energy.2016.06.135
28. Satir M, Murphy F, McDonnell K (2018) Feasibility study of an offshore wind farm in the Aegean Sea, Turkey. Renew Sustain Energy Rev 81:2552–2562. https://doi.org/10.1016/j.rser.2017.06.063
29. Spinney PJ, Watkins GC (1996) Monte Carlo simulation techniques and electric utility resource decisions. Energy Policy 24:155–163. https://doi.org/10.1016/0301-4215(95)00094-1
30. Morthorst PE, Kitzing L (2016) Economics of building and operating offshore wind farms. In: Offshore Wind Farms: Technologies, Design and Operation. Elsevier Inc., pp 9–27
31. Ioannou A, Angus A, Brennan F (2018) A lifecycle techno-economic model of offshore wind energy for different entry and exit instances. Appl Energy 221:406–424. https://doi.org/10.1016/j.apenergy.2018.03.143
32. Offshore Wind Energy Cost Modeling: Installation and Decommissioning - Mark J Kaiser, Brian Snyder - Google Books
33. Kaiser MJ, Snyder BF (2013) Modeling offshore wind installation costs on the U.S. Outer Continental Shelf. Renew Energy 50:676–691. https://doi.org/10.1016/j.renene.2012.07.042
34. Ruddell AJ (2010) 11 - Flywheel energy storage technologies for wind energy systems A2 - Kaldellis, J.K. BT - Stand-Alone and Hybrid Wind Energy Systems. In: Woodhead Publishing Series in Energy. Woodhead Publishing, pp 366–392
35. Ioannou A, Angus A, Brennan F (2018) Parametric CAPEX, OPEX, and LCOE expressions for offshore wind farms based on global deployment parameters. Energy Sources, Part B Econ Planning, Policy 13:281–290. https://doi.org/10.1080/15567249.2018.1461150
36. (2015) Projected Costs of Generating Electricity 2015 Edition
37. Ioannou A, Angus A, Brennan F (2017) Stochastic Prediction of Offshore Wind Farm LCOE through an Integrated Cost Model. Energy Procedia 107:383–389. https://doi.org/10.1016/j.egypro.2016.12.180

38. Ioannou A, Angus A, Brennan F (2020) Stochastic financial appraisal of offshore wind farms. Renew Energy 145:1176–1191. https://doi.org/10.1016/j.renene.2019.06.111

39. Leimeister M, Kolios A (2018) A review of reliability-based methods for risk analysis and their application in the offshore wind industry. Renew Sustain Energy Rev 91:1065–1076. https://doi.org/10.1016/j.rser.2018.04.004

40. Kolios A, Mytilinou V, Lozano-Minguez E, Salonitis K (2016) A comparative study of multiple-criteria decision-making methods under stochastic inputs. Energies 9:. https://doi.org/10.3390/en9070566

41. Hanak DP, Kolios AJ, Biliyok C, Manovic V (2015) Probabilistic performance assessment of a coal-fired power plant. Appl Energy 139:. https://doi.org/10.1016/j.apenergy.2014.10.079

42. Kolios AJ, Martinez Luengo M (2016) Operational management of offshore energy assets. J Phys Conf Ser 687:. https://doi.org/10.1088/1742-6596/687/1/012001

43. Kaiser MJ (2015) Decommissioning forecast in the deepwater Gulf of Mexico, 2013-2033. Mar Struct. https://doi.org/10.1016/j.marstruc.2014.12.006

44. Ortegon K, Nies LF, Sutherland JW (2013) Preparing for end of service life of wind turbines. J Clean Prod. https://doi.org/10.1016/j.jclepro.2012.08.022

45. Smyth K, Christie N, Burdon D, et al (2015) Renewables-to-reefs? - Decommissioning options for the offshore wind power industry. Mar Pollut Bull 90:247–258. https://doi.org/10.1016/j.marpolbul.2014.10.045

46. Kaiser MJ, Snyder B (2010) Offshore wind energy installation and decommissioning cost estimation in the U.S. outer continental shelf. 340

47. Smith G, Michael D, Paul R, et al (2016) Assessment of Offshore Wind Farm Decommissioning Requirements. Ontario Minist Environ Clim Chang

48. Manago F PROCEEDINGS: PUBLIC WORKSHOP DECOMMISSIONING AND REMOVAL OF OIL AND GAS FACILITIES OFFSHORE CALIFORNIA: RECENT EXPERIENCES AND FUTURE DEEPWATER CHALLENGES

49. Hou P, Hu W, Soltani M, et al (2016) Optimization of decommission strategy for offshore wind farms. IEEE Power Energy Soc Gen Meet 2016-Novem:1–5. https://doi.org/10.1109/PESGM.2016.7741634

50. Ziegler L, Cosack N, Kolios A, Muskulus M (2019) Structural monitoring for lifetime extension of offshore wind monopiles: Verification of strain-based load extrapolation algorithm. Mar Struct 66:154–163. https://doi.org/10.1016/j.marstruc.2019.04.003

51. Martinez-Luengo M, Shafiee M, Kolios A (2019) Data management for structural integrity assessment of offshore wind turbine support structures: data cleansing and missing data imputation. Ocean Eng 173:867–883. https://doi.org/10.1016/j.oceaneng.2019.01.003

52. Scheu MN, Tremps L, Smolka U, et al (2019) A systematic Failure Mode Effects and Criticality Analysis for offshore wind turbine systems towards integrated condition based maintenance strategies. Ocean Eng 176:118–133. https://doi.org/10.1016/j.oceaneng.2019.02.048

53. Kolios AJ, Smolka U (2020) Risk-based Maintenance Strategies for Offshore Wind Energy Assets. In: 2020 Annual Reliability and Maintainability Symposium (RAMS). IEEE, pp 1–6

54. Shafiee M, Animah I, Simms N (2016) Development of a techno-economic framework for life extension decision making of safety critical installations. J Loss Prev Process Ind. https://doi.org/10.1016/j.jlp.2016.09.013

55. Animah I, Shafiee M (2018) Condition assessment, remaining useful life prediction and life extension decision making for offshore oil and gas assets. J Loss Prev Process Ind. https://doi.org/10.1016/j.jlp.2017.04.030

56. IRENA International Renewable Energy Agency (2018) Renewable Power Generation Costs in 2017

57. Tran TTD, Smith AD (2017) Evaluation of renewable energy technologies and their potential for technical integration and cost-effective use within the U.S. energy sector. Renew. Sustain. Energy Rev.

58. Colla M, Ioannou A, Falcone G (2020) Critical review of competitiveness indicators for energy projects. Renew Sustain Energy Rev 125:109794. https://doi.org/10.1016/j.rser.2020.109794

59. Vithayasrichareon P, MacGill I, Wen F (2010) Electricity generation portfolio evaluation for highly uncertain and carbon constrained future electricity industries. In: IEEE PES General Meeting, PES 2010

60. Hanak DP, Kolios AJ, Manovic V (2016) Comparison of probabilistic performance of calcium looping and chemical solvent scrubbing retrofits for CO 2 capture from coal-fired power plant. Appl Energy 172:323–336. https://doi.org/10.1016/j.apenergy.2016.03.102

61. Hanak DP, Kolios a. J, Biliyok C, Manovic V (2015) Probabilistic performance assessment of a coal-fired power plant. Appl Energy 139:350–364. https://doi.org/10.1016/j.apenergy.2014.10.079

62. Heck N, Smith C, Hittinger E (2016) A Monte Carlo approach to integrating uncertainty into the levelized cost of electricity. Electr J 29:21–30. https://doi.org/10.1016/j.tej.2016.04.001

63. Shafiee M, Brennan F, Espinosa IA (2016) A parametric whole life cost model for offshore wind farms. Int J Life Cycle Assess

64. Chiachío-Ruano J, Hermile M, Kolios A (2019) A Sensitivity Study for Operational Availability of Offshore Wind Energy Assets. In: Volume 3: Structures, Safety, and Reliability. American Society of Mechanical Engineers

65. Martin R, Lazakis I, Barbouchi S, Johanning L (2016) Sensitivity analysis of offshore wind farm operation and maintenance cost and availability. Renew Energy 85:1226–1236. https://doi.org/10.1016/j.renene.2015.07.078

66. Sperstad IB, Stålhane M, Dinwoodie I, et al (2017) Testing the robustness of optimal access vessel fleet selection for operation and maintenance of offshore wind farms. Ocean Eng 145:334–343. https://doi.org/10.1016/j.oceaneng.2017.09.009

67. Kolios A, Walgern J, Koukoura S, et al (2019) openO&M: Robust O&M open access tool for improving operation and maintenance of offshore wind turbines. Proc 29th Eur Saf Reliab Conf (ESREL 2019) 452–459. https://doi.org/10.3850/981-973-0000-00-0

68. Kerkvliet H, Polatidis H (2016) Offshore wind farms' decommissioning: a semi quantitative Multi-Criteria Decision Aid framework. Sustain Energy Technol Assessments. https://doi.org/10.1016/j.seta.2016.09.008

69. Pandit RK, Infield D, Kolios A (2020) Gaussian process power curve models incorporating wind turbine operational variables. Energy Reports 6:1658–1669. https://doi.org/10.1016/j.egyr.2020.06.018

70. Choukulkar A, Pichugina Y, Clack CTM, et al (2016) A new formulation for rotor equivalent wind speed for wind resource assessment and wind power forecasting. Wind Energy 19:1439–1452. https://doi.org/10.1002/we.1929

71. Carrillo C, Obando Montaño AF, Cidrás J, Díaz-Dorado E (2013) Review of power curve modelling for windturbines. Renew. Sustain. Energy Rev. 21:572–581

72. Pratt JW (1964) Risk Aversion in the Small and in the Large. Econometrica 32:122. https://doi.org/10.2307/1913738

73. Staffell I, Green R (2014) How does wind farm performance decline with age? Renew Energy 66:775–786. https://doi.org/10.1016/j.renene.2013.10.041

74. Martin H, Spano G, Küster JF, et al (2013) Application and extension of the TOPSIS method for the assessment of floating offshore wind turbine support structures. Ships Offshore Struct 8:. https://doi.org/10.1080/17445302.2012.718957

75. Kolios A, Collu M, Chahardehi A, et al (2010) A multi-criteria decision making method to compare support structures for offshore wind turbines. In: European Wind Energy Conference and Exhibition 2010, EWEC 2010