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Development of a Combined Operational and Strategic Decision Support Model for Offshore Wind

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Abstract

This paper presents the development of a combined operational and strategic decision support model for offshore wind operations. The purpose of the model is to allow developers and operators to explore various expected operating scenarios over the project lifetime in order to determine optimal operating strategies and associated risks. The required operational knowledge for the model is specified and the chosen methodology is described. The operational model has been established in the MATLAB environment in order to simulate operating costs and lost revenue, based on wind farm specification, operational climate and operating strategy. The outputs from this model are then used as the input to decision support analysis by establishing Bayesian Belief Networks and decision trees at various stages throughout the project life time. An illustrative case study, which demonstrates the capability and benefits of the modeling approach, is presented through the examination of different failure rates and alternative electricity price scenarios.

Nomenclature

$\lambda(t)$	Failure intensity function	φ	AR coefficient
ρ	Weibull scale parameter	Y_t	Transformed time series
β	Weibull shape parameter	$\hat{\mu}$	Seasonal Fourier series fit
Δt	Time step size	Hs_t	Significant wave height
μ	Mean of data	R	Failure criteria random number
ε	Gaussian noise	Λ	Transform Coefficient

1. Introduction

In recent years, commercial offshore wind farms have become economically viable resulting in 4.5 GW of capacity deployed or under construction worldwide, principally focused in the North Sea[1]. These sites have predominantly developed within 50km of shore and in water depths of less than 30m. It has been possible to operate these wind farms using similar principles to traditional onshore wind farms. In this respect, maintenance has typically comprised of annual scheduled maintenance, which utilizes access vessels and helicopters for minor repairs and specialist vessels for major repairs after unpredicted failures of large components[2]. Even for these smaller, near shore sites, Operations and Maintenance (O&M) has been estimated at up to 30% of lifetime costs for offshore wind and there is a risk that this will make projects commercially unviable in the future as site conditions become more remote and challenging to operate in. In order to minimize the O&M costs, it is therefore necessary to explore different operational strategies and their cost effectiveness under different circumstances. Due to the limited experience of operating large offshore wind farms, computational modeling is required in order to explore the impact of wind farm design, operating environment and maintenance strategies on O&M costs. A review of different computational models for the offshore wind industry is presented in [3]. A modeling framework that links operational modeling to decision making was identified as requiring development and a framework for such a model is presented in this work.

In this paper, the focus of the modeling is on the repair of major failures of blades, gearbox, generator and drive train bearings that require the use of expensive jack-up type vessels. The cost of these specialist vessels is in the region of hundreds of thousands of euros per day compared to thousands for access vessels and therefore although less frequent have significantly higher impact. However, the methodology is applicable to any type of maintenance action. Strategies for more common, lower impact failures are an area identified for future research using the outlined model.

2. Methodology

The required methodology can be considered in three distinct areas; capturing expert knowledge of the market; operational modeling and decision support modeling. The elicited expert knowledge informs the operational model in order to ensure that assumptions are representative of the market and the outputs from the operational model feed into the decision support model so that system operators can make informed decisions.

2.1. Costs and operating regimes for heavy lift jack-up vessels

In order to perform the simulations, cost distributions of offshore jack-up vessels for different maintenance strategies were required. In this respect, a comprehensive list of jack-up vessel specifications, including the capital expenditures (CAPEX) of the vessels, was initially developed through utilizing University of Strathclyde NA-ME department's vessel database and various other sources. As a first step, an initial shortlisting of the vessels currently available in the offshore wind market was performed in order to exclude vessels with limited capabilities which would not be appropriate to employ in the field of extensive maintenance activities of offshore wind farms.

After the shortlisting of the suitable jack-up vessels, a calculation methodology for establishing the charter rates for a number of different vessel charter periods was performed. The chartering scenarios examined were identified as: fix on fail/spot market, charter of 6 months, charter of 1 year, and charter period of 20 years. The above were determined using the authors' extensive experience of the shipping market as well as through a number of meetings with experts from offshore wind turbine

companies/operators, applying expert judgment and thorough vessel market research. However, difficulties arising during the elicitation period were related to the availability of charter rate data associated with the identified vessel operational periods. More explicitly, charter rate data were extremely scarce due to the immaturity of the offshore wind market, while confidentiality of data sharing among stakeholders is another issue as well as the lack of purpose-built vessels for the offshore wind market. Furthermore, the vessel charter rates also depend on the negotiations between vessels owners and charterers/developers which is another crucial factor.

In order to overcome the above mentioned difficulties, a regression analysis model was developed as shown in the analyses presented by Kaiser and Snyder [4] and performed using the vessels which were identified in the first stage. The developed model was employed in order to estimate the vessel charter rates for the 20 years period, which depends on the relationship between the vessels' CAPEX and their equivalent charter rates.

In order to estimate the rates for the one year charter, the existing vessel database which includes the one year charter rates for a number of different types and sizes of bulk carriers from 2004 to 2012 was examined. In this respect, although the offshore wind vessel market does not explicitly operate in the same way as the maritime vessel market, there exist similarities in terms of the CAPEX of the vessels being used as well as their charter rates. The latter demonstrate a similar trend over the same trading/chartering scenarios for specific chartering periods as the ones used in the case of the vessels employed in the offshore wind industry for maintenance activities. This allowed the estimation of a series of different charter rates for the offshore wind jack-up vessels under different water depths and charter periods.
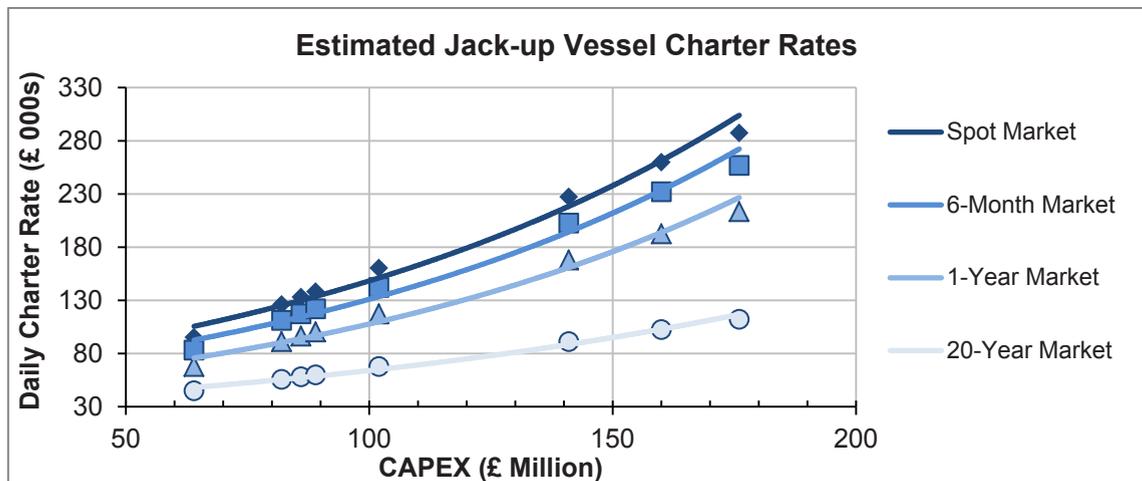

Fig. 1: Vessel charter rates under different operational regimes

In order to estimate the spot market charter rates, a different methodology was followed. In this case, a variety of combinations of different bulk carrier ships and equivalent charter rates were analyzed. Due to the similarity in high initial capital costs, capsize bulk carriers were employed in the regression analysis. In this case, the spot market rates between 2007 and 2010 were selected in order to include low and peak operational modes. The resulting vessel charter rates over a variety of CAPEXs and charter scenarios are displayed in Fig. 1. In this case, the improvements on the vessel capability influence the daily charter rates due to both increasing daily expenditures and decreasing number of vessels. Moreover, the variation of daily charter rates associated with the chartering periods becomes more obvious when the spot market

charting alternative is considered. For instance, the variation of CAPEX from £100 million to £150 million results an escalation of £30,000 for 20-year charter rates; on the other hand same variation can influence the charter rates of spot market almost £85,000.

In addition, it was noted that charter rates differentiate according to the seasonal availability of the jack-up vessels. As is expected, seasonal power ratings and capacity factors are higher in winter than summer [5]. Moreover, there is a higher probability that weather in winter can disturb the offshore maintenance operations which makes offshore maintenance operations more difficult to perform.. Consequently, jack-up vessel availability is higher and accordingly vessel demand is low during the winter season. Therefore, operators plan their maintenance activities during the spring and summer months, which accordingly increases the vessel demand and associated charter rates. Taking into account the above observations, in order to address the seasonality effect in the offshore vessel market, a similar seasonality trend was considered through the use of bulk carrier ships charter rates following a similar modelling process as mentioned before.

In this particular case, the data analyzed included the mean values for the charter rates of different types and sizes of bulk carrier ships. As a result, the seasonal ratios for charter rates for the vessels used in the offshore wind market were calculated as 0.940, 1.019, 0.991, and 0.992 for long-term charter rates in winter, spring, summer and autumn seasons, respectively. When spot market values are taken into account; winter, spring, summer and autumn seasonal ratios are calculated as 0.836, 1.130, 1.074, and 0.915 respectively. This allows the investigation of seasonal maintenance strategies to explore the trade-off of reduced vessel costs versus reduced accessibility. In this respect it needs to be mentioned that the results of the approximation method used in order to derive the charter rates for the maintenance activities in the offshore wind market were also validated by experts in the offshore renewable market, thus confirming the methodology followed. However, further development and improvement of the suggested methodology can be achieved by introducing additional vessel charter rate information as the market will get mature enough in the upcoming years.

In addition to the above, offshore wind farm operations also include mobilization costs, which can be described as the expenses related to preparatory work and operations, including the movement of personnel, equipment, supplies and incidentals to the project site, establishment of facilities necessary for work and operations which must be performed or cost incurred prior to beginning work on the various items on the project site. In this case, a mean value of £400,000 for each vessel commission was selected based on the observed heavy lift range and typical close proximity to shore of existing wind farms. The uncertainty and impact of changing mobilization costs on overall costs of O&M has been identified as an area requiring quantification in future work.

2.2. Operational Modeling

The failure behavior of mechanical systems can be represented mathematically using the Weibull distribution failure intensity function in Eq.(1) with wear in, normal life and wear out represented by altering shape parameter β from less than, equaling and greater than 1.

$$\lambda(t) = \rho\beta t^{\beta-1}, \text{for } t \geq 0 \qquad (1)$$

Eq. (1) can be applied to each individual subsystem to accurately represent failure behavior over the life time. The hazard rate can then be used to simulate the failure behavior of a repairable engineering system [6]. Each subsystem is represented with a binary state value of operating or failed. The failure methodology can be readily extended to represent intermediate states where a turbine is operating at a reduced capacity due to a failure [7] if sufficient system knowledge of offshore wind turbine failure behavior exists. The transition between states is governed by Eq. (1) and is determined by random number R in the interval 0-1 and comparing it to the failure criteria in Eq. (2), failure transition if:

$$R < \lambda(t) * \frac{\Delta t}{8760} \tag{2}$$

Repair times are considered to be deterministic in this work and are calculated using a time series simulation methodology which requires an adequate climate model.

2.3. Climate and Failure Simulation

Due to the dependency of operations on both wind and wave as well as the investigation of dynamic strategies, a time-series simulation approach with a correlated wind and wave time series is necessary. Various climate simulation approaches exist with different benefits and drawbacks. The modeling approach adopted in this work is a correlated, Multivariate Auto-Regressive approach (MAR) [8].

The wind model influences the cost of O&M per unit and is used to determine lost revenue associated with down time. It is also used to simulate aspects of the repair process when large components are replaced or a helicopter based strategy is implemented. The wave climate is used to determine down time associated with all repair actions. As large maintenance actions are dependent on both wind and wave climate, the requirement of a correlated wind and wave model is uniquely critical to offshore wind.

The general form for an AR model that is normalized by the mean of the data is described by Eq. (3)

$$X_t = \mu + \varepsilon + \sum_{i=1}^{p} \varphi_i(X_{t-i} - \mu) \tag{3}$$

Due to the inclusion of a Gaussian noise term, this equation is valid only for a process having a Normal distribution. Neither annual wind speed nor significant wave heights follow a normal distribution. A solution to this problem is to remove non-stationary trends and in the case of wave height, undergo a transformation so that Eq. (3) can be applied to a data set. By removing a fit of monthly mean and diurnal variation from observed wind speed data, the overall distribution approximates a Normal distribution. For significant wave height, it is necessary to remove a fit of monthly mean values and then apply a logarithmic transformation on the data as shown in Eq. (4) [9]. For the multivariate case presented in this work, a Box-Cox transformation has been used in place of a logarithmic transformation, shown in Eq. (5). The value of the transform coefficient, Λ, can be tuned iteratively to capture the observed level of correlation between the wind and wave values in the data while preserving individual wave climate characteristics.

$$Y\_t = ln(Hs\_t) - \hat{\mu}_{\ln(Hs\_t)} \tag{4}$$

$$Y\_t = \frac{Hs\_t^{\Lambda-1}}{\Lambda} - \hat{\mu}_{\frac{Hs\_t^{\Lambda-1}}{\Lambda}} \tag{5}$$

The two de-trended series are then simulated. Correlation is captured by substituting the Gaussian pseudorandom vector normally used for ε in Eq. (4) with the covariance matrix of the two de-trended series. The determination of AR coefficients and model generation is implemented using the *arfit* algorithm in MATLAB [10]. Order is chosen by optimizing Schwarz's Bayesian Criterion and coefficients using stepwise least squares estimation process. The simulation methodology maintains persistence characteristics, seasonality and correlation between wind and wave time series of the observed site.

Time to repair is then simulated based on the availability of vessel determined by strategy and access constraints based on the simulated climate time series. It is possible to represent the repair process by a probability where the repair behavior is well understood and this has been applied to the wind turbine case previously [11, 12]. However, due to the large uncertainty and dependency of maintenance actions

on a large number of operating decisions and resources this approach was not applicable. Due to the nature of large repairs, they are not performed cumulatively. Consequently, the system only returns to an operational state when a sufficient window is present. This is a conservative assumption representing the worst availability, in reality repairs may be able to be performed in several smaller visits.

The operational model allows a full range of operational configurations to be explored. Simulation results are output in terms of vessel costs and lost revenue in order to determine which strategy should be selected to minimize cost of energy. Operators may choose to base operational decisions on alternative metrics such as maximizing availability or minimizing the number of maintenance actions which are also captured by the model.

2.4. Decision Support Modeling

One limitation of the operational modeling is that a single strategy is chosen and the cost of that strategy is calculated over a specified time period. This modeling approach fails to capture that decisions are dynamic, can change over time and should be optimized at a global level for an operator rather than optimized at a site level. The modeling assumes a static maintenance approach without considering how uncertainties change over time. Long term strategic projects, such as managing O&M across a 25 year time period and across many different sites, are often naturally structured such there are 'option-like' flexibilities that allows decision makers to take advantage of opportunities or avoid losses as uncertainties become realized.

To capture these additional effects and to optimize decision making throughout the life of a wind farm, Bayesian Belief Networks (BBNs) are used to model the high-level uncertain variables; more specifically, to model high-dimensional probability distributions. A BBN is a Directed Acyclic Graph (DAG), comprised of nodes and edges, in which the nodes represent random variables (continuous or discrete), decision nodes or utility nodes, and the edges imply direct dependencies between the linked variables. For example, where we have two nodes X and Y with an arc from X to Y, we believe that Y is conditional on X. The full joint distribution for this is then $p(x, y) = p(x)p(y \mid x)$. BBNs allow a decision maker to specify the different strength of the dependencies through these conditional probabilities. To evaluate the BBN, an equivalent decision tree can be constructed and from this, standard dynamic programming can be used to solve the decision tree [13].

BBNs also give the decision maker a framework to update their beliefs once additional evidence becomes available. This is an important feature of the methodology within this problem. As we learn about the reliability of the system during its early life, we can begin to update our beliefs to reflect this. We can then change or modify our decision based on this evidence. Finally, BBNs use graphical representations, typically influence diagrams, to qualitatively structure the problem. Using a BBN, decision trees can be developed to capture that once a decision has been taken, this can narrow or expand the portfolio of decisions available to a decision maker in the future. By identifying the different utility associated with each decision and random outcome, the decisions that optimize the utility can be selected. For a detailed description of BBNs and its theory, see [14], [15] and in particular, [16].

Within this problem, BBNs can be used to assess the optimal decision for a single site when the maintenance strategy can change at different points in time. Fig. 2 illustrates the BBN representing this problem. In the diagram, square nodes represent decisions, oval nodes represent uncertain quantities and square nodes with rounded corners represent value variables. An arrow shows that the value taken by the node at the start of the arrow has a direct influence on the value taken by the node at the end of the arrow.

The early cost (i.e. the cost during the first 7 years or wear in period) is influenced by the failure intensity, the electricity price and the strategy adopted during the early strategy. The failure intensity variable is modeled as one of three different states corresponding to; target offshore, observed onshore and observed offshore. The electricity price variable is also represented as one of three states

representing potential changes due to an external cost driver. These inputs can be expanded or reduced depending on the level of complexity that an operator desires.

The late strategy is influenced by the output of the failure intensity and the electricity price, i.e. the strategy chosen takes into account the learning that has taken place in the first 7 years and changes to the operating environment. From that second strategy, a cost for the remaining life of the wind farm is used. Finally, the total cost is the sum of the early cost and the late cost. The advantage of using a BBN to model the decision is that it allows the operator to capture the learning that will take place in the first 7 years and how the optimal strategy may change over time. From the decision tree in Fig. 2, the distribution of costs over all the different scenarios for the optimal strategy can be estimated.
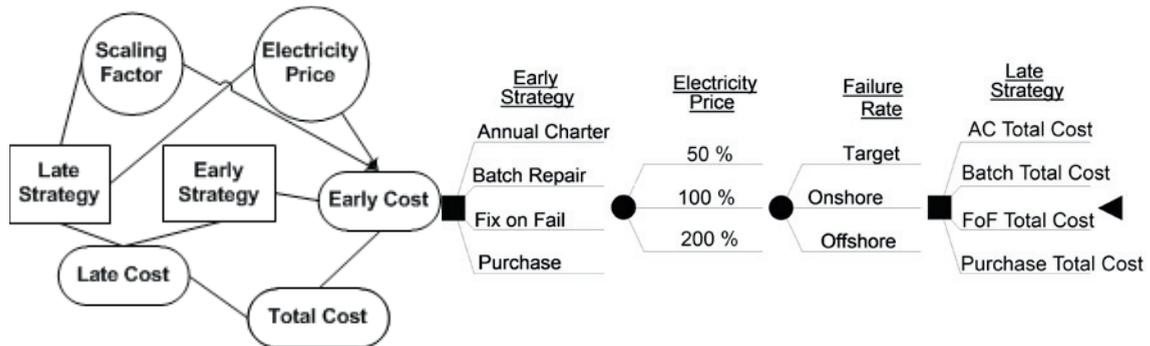
Fig. 2: BBN modeling a single site where the maintenance strategy can change and the resulting decision tree for single site

The modeling that has been presented here is sufficiently generic that it can be used if the output of the simulation models change. Alternatively, the model framework has been developed so that the operator can expand the modeling if they adopt more than two strategies during the 25 year life of the wind farm or if the strategy decision is expanded across multiple sites.

3. Case Study

In order to demonstrate the modeling methodology, a simple case study has been performed. The modeled wind farm comprised of 60 wind turbines based on the NREL 5MW model in 45m water depth [17]. Site conditions for both accessibility and lost revenue are based on data from the FINO 1 platform, representing typical North Sea conditions of future wind farms [18]. Baseline electricity prices were set as £120 MW/hr representing the combined wholesale electricity price and support mechanism in the UK market. Table 1 summarizes the failure rate input based on observed onshore major failure rates for components requiring jack-up vessels; gear box, generator, blade and bearings. The overall life failure rate of 0.2 was fitted to the 'bath-tub' curve described in Eq.(1) based on [19].

Table 1: Failure distribution parameters

Stage	Shape parameter β	Scale parameter ρ
Wear in	0.8	0.3
Normal Life	1	0.16
Wear Out	3.5	0.001

For simplicity, only two decision points were simulated corresponding to the simplest possible analysis. This represents the operator an early life strategy and then reviewing the strategy after 7 years of

operation and adopting a strategy for the remainder of the wind farm life. The methodology can be extended to any number of strategy decision points which in this case would be driven principally by length and flexibility of vessel and supply contracts. The operator may choose to adopt a service contract whereby the OEM takes responsibility for a fixed warranty period; this would effectively represent the early life strategy and such analysis would be relevant to only later life decision points. In addition, the analysis adopted in this case study is required in order to determine if such contracts represent the most cost efficient solution. In addition, the probabilities of each uncertainty which in this case are the failure rate and electricity price must be estimated to populate the BBN. This is demonstrated for the case study in Fig. 2. These values are shown in Table 2 and must be estimated using observed data and engineering judgment. As operators gain experience these values can be refined and the accuracy of decision making analysis will improve.

Table 2: Estimated uncertainty probabilities

Uncertainty	Improved λ / low electricity price	Onshore observed λ / current electricity price	Poorer λ / increased electricity price
Failure rate	0.3	0.6	0.1
Electricity price	0.1	0.7	0.2

Using the specified inputs a joint operational and decision making analysis was performed. The outputs of these analyses are shown in Fig. 3 and Fig. 4 identifying the optimal strategy choices and estimated costs the different scenarios.
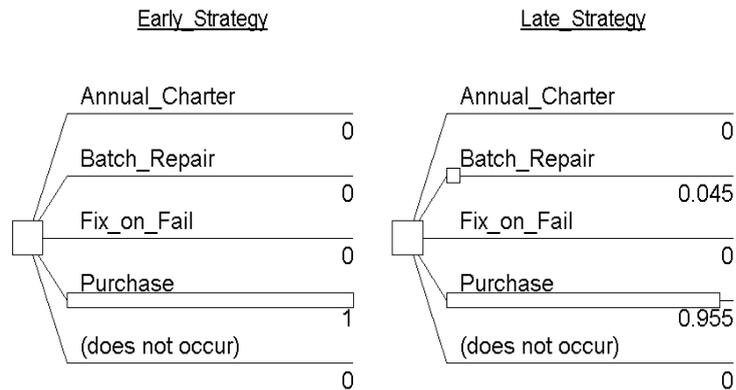

Fig. 3: Preferred early and late life strategies for given uncertainties.

In this case, the optimal early life strategy is to purchase a vessel, regardless of failure rate and electricity prices. However, given a low fail rate and a low or medium electricity price, the optimal later life strategy is batch repair. Based on Fig. 3 the likelihood of this scenario occurring is 4.5%. The associated risk profile plot identifying different calculated cost under the different operational choices and the probability of arriving at each cost is show in Fig. 4.

The risk profile in Fig. 4 illustrates the probability of an expected cost, assuming that the optimal decision has been chosen. From this, we see that the lifetime costs range from £158m - £340m depending

on the chosen strategy and the observed failure rate and electricity price with an expected value of £278m. Note that as the number of variables increase, the risk profile tends towards a cumulative probability curve. From Fig. 4, we see that, there are nine different 'steps'. These nine 'steps' represent the cost associated with each uncertain scenario, i.e. there are two uncertain variables, each with three states, i.e. $3^2 = 9$. From Fig. 4, we can see a clear jump in the risk profile at £280m – this is due to the two most likely scenarios, onshore failure rate and the electricity price remaining at the currently observed level. All the costs above this represent scenarios where at least one of the variables was in a 'higher' state, i.e. high electricity prices or offshore failure rates.

Currently, the selection of decision points and interaction between the operational and decision making models is done manually. It is hoped that future work will allow for this process to be integrated providing a single environment that allows developers and operators to more effectively investigate the wide range of operating uncertainties that exist.
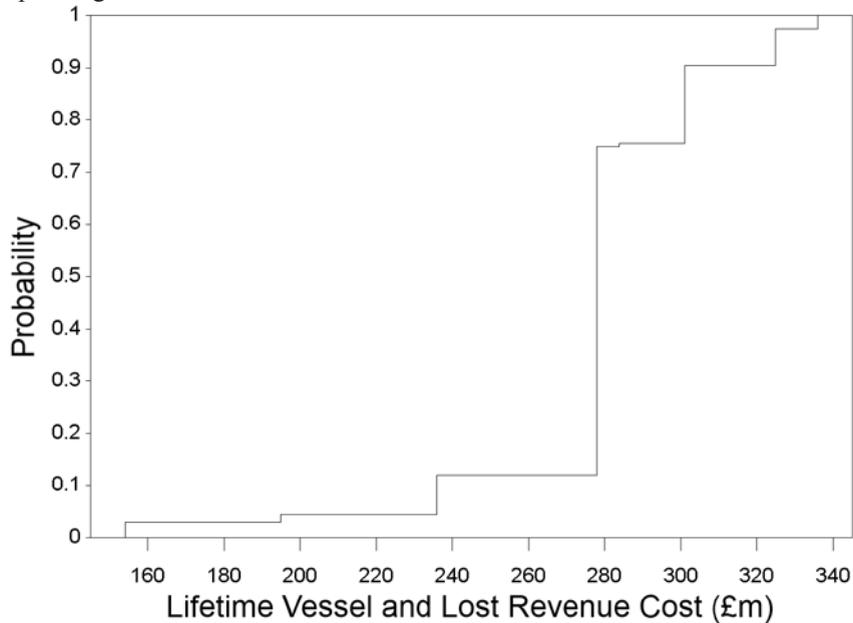

Fig. 4: Risk profile plot demonstrating different cost scenarios

4. Conclusions

This paper has demonstrated the required knowledge and an appropriate methodology for an offshore wind operational model. The approach used combines a Multivariate Auto Regressuve climate model with a Markov-Chain Monte Carlo failures and simulated repair process in order to output costs. This methodology is able to capture the impact of climate, wind farm specification and operational strategy on O&M costs while remaining computationally simple. In addition, by using the outputs of the operational models in order to inform decision making tools, their usefulness to developers and operators is greatly increased. The outputs have been used in conjunction with BBNs and decision trees in order to produce risk profiles that not only provide expected costs, but also allow a greater understanding of the likelihood of arriving at different costs and the uncertainties that represent the largest risks. Future work will aim to integrate the separate models more closely and apply the decision making tool to a wide range of wind farms. In addition, expanding the number of decision points and input variables will enhance the benefits of the presented methodology.

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