CRANFIELD UNIVERSITY

Anastasia Ioannou

Risk-based methods for the valuation and planning of sustainable energy assets

School of Water, Energy and Environment and School of Management
Renewable Energy Marine Structures Centre for Doctoral Training (REMS-CDT)

EngD
Academic Year: 2014 - 2018

Supervisor: Professor Feargal Brennan
Associate Supervisor: Dr Andrew Angus
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This thesis is submitted in partial fulfilment of the requirements for the degree of Engineering Doctorate

“…Ithaca gave you the delightful voyage:
without her you would never have set out:
and she has nothing else to give you now.

And though you should find her wanting, Ithaca
will not surprise you; for you will arrive
wise and experienced, having long since perceived
the unapparent sense in Ithacas.”
K.P. Kavafis, 1911

ABSTRACT

This research project aims to develop and apply appropriate methods dealing with risk and uncertainty at a technology and energy system level providing decision support to the various stakeholders involved in the planning, development and operation of sustainable energy investments. The thesis comprises a portfolio of research activities fulfilling the set research objectives. Outcomes of this research portfolio have been either published or are under the peer review process.

More specifically, following a systematic literature review to identify the state-of-the-art in risk-based methods for sustainable energy systems planning and feasibility studies, a cluster analysis was applied based on data from existing offshore wind energy installations in the UK, to distinguish investment strategies followed by equity investors. This study has identified three distinct clusters of investors, namely the late entry, pre-commissioning and build-operate-transfer investors. Subsequently, a high-fidelity lifecycle techno economic model was developed allowing for the temporal valuation of a renewable energy investment. This integrated model has allowed for a set of parametric equations to be developed through appropriate selection of approximation models linking global design parameters to key performance indicators. Furthermore, a stochastic extension of the financial appraisal model has allowed for a transition from the conventional deterministic terminology to a stochastic one, assigning confidence levels to key performance indicators (KPIs). Additionally, the development of a purpose-specific tool for the evaluation of the operational phase KPIs, such as the availability, operating cost and energy production losses due to planned and unplanned maintenance has allowed for the development of better-informed risk control policies. Finally, having analysed uncertainties at a technology level, a stochastic optimisation framework was developed for deriving optimal national power generation technology mixes taking into account uncertainties for a series of scenarios linked to national energy strategies through appropriate constraints in the analysis.

Keywords:

Renewable energy, risk, advanced stochastic methods, systematic literature review, Monte Carlo simulation, nonlinear regression, lifecycle cost revenue model, O&M cost modelling, parametric expressions, multi-stage stochastic optimisation, cluster analysis.

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LIST OF EQUATIONS

LIST OF ABBREVIATIONS

ANN	Artificial Neural Network
ARIMA	Autoregressive Integrated Moving Average
BOT	Build Operate and Transfer
CfD	Contracts for Difference
D&C	Development and consenting
D&D	Disposal and decommissioning
DCF	Discounted cash flow
EPCI	Engineering, Procurement, Construction and Installation
FinEX	Financing Expenditures
I&C	Installation and commissioning
IPPs	Independent power producers
IRENA	International Renewable Energy Agency
IRR	Internal Rate of Return
KPIs	Key performance indicators
LCC	Lifecycle cost
LCOE	Levelised cost of electricity
LE	Late entry
MC	Monte Carlo
MCDA	Multi-criteria decision analysis
MRJD	Mean-reverting jump-diffusion
MSP	Multi-stage stochastic programming
MTTF	Mean Time To Failure
MVP	Mean variance portfolio
NPV	Net Present Value
O&M	Operation and Maintenance
OEMs	Original Equipment Manufacturers
OW	Offshore wind
P&A	Production and acquisition
PC	Precommissioning
PO	Planning option
PPA	Power Purchase Agreement

RE	Renewable energy
ROA	Real Options Analysis
ROI	Return on Investment
SDEs	Stochastic differential equations
WAAC	Weighted Average Cost of Capital
WTG	Wind turbine generator

Part I: Overview of the research project

1 INTRODUCTION TO THE THESIS

1.1 Background on uncertainty modelling of sustainable energy systems

Over recent decades, the European electric energy system has been undergoing a transition from a centralised paradigm to a competitive decentralised one, driven not only by energy security but also climate change mitigation targets. Political pressures to reduce carbon dioxide emissions and policy incentives to increase the share of renewable energy (RE) technologies in the power generation mix have rapidly increased the value of investments in RE over the last decade.

Indeed, at a global level, at the Paris climate conference (COP21), 195 countries adopted the first-ever universal and legally binding global climate deal to limit warming to well below 2^{o}C and to pursue efforts to limit it to 1.5^{o}C. The EU climate and energy 2030 package requires member states to increase the share of energy produced from renewables by 27% by 2030 (in comparison to 1990 levels), along with the limitation of greenhouse gas emissions (40% reduction) and energy efficiency (27% improvement). The target set at the UK level mandates the reduction in GHG emissions of at least 80% by 2050 [1].

As a result of the political incentives, an estimated cumulative £37bn was invested in RE generation between 2010 and 2014, reaching an average of £7bn per year in the UK [2]. Global investment in renewable energy (RE) in 2017 amounted to $279.8 billion, with China being the leading location for the installation of renewable energy investments (approximately 45% of global investments). Increasing investment activity in low carbon energy projects has induced the need for an improved valuation framework both at a technology and at an energy systems level.

In this study, at a technology development level, offshore wind has been selected as the reference technology to be analysed further, as it is a very well-established technology, with the UK being a recognised world leader. Europe's total installed offshore wind capacity amounts to 15,780 MW, 43% of which is installed in the UK [3]. From a commercial viewpoint, offshore wind is widely accepted by institutional investors as a sensible portfolio component, with a constantly expanding supply chain. A diverse pool of investors operates in the offshore wind industry: Utilities, Original Equipment Manufacturers (OEMs), Independent Power Producers, Japanese Trading Houses, Pension Funds and Banks are some of the major investors.

Broadly speaking, investors can be segmented based on their risk appetite (technology, country, and asset stage), return expectations (IRR and yield), holding length, and level of engagement [4]. It is often encountered that equity investors buy and sell their stakes at different stages of the offshore wind farm depending on the strategy followed. For instance, an investor may act as a turn-key developer, bearing the construction risks through building the offshore wind farm, run it for 4 or 5 years, then sell the asset –once its operation can be safeguarded by warranties, with a risk premium- and exit the market. The latter type of investor has the flexibility to consider building a higher-CAPEX asset (more conservative designs through higher material factors in accordance to Industrial Standards) aiming at reducing the OPEX associated with inspections and maintenance (by increasing the intervals between consecutive inspections) and accordingly increase the value of the asset with the purpose of selling at a higher price (such an exercise has been conducted in the Conference paper [5]).

Strike prices awarded through the second 2017 Contracts for Difference (CfD) auction for offshore wind energy projects, have fallen by nearly 50% since the first UK's CfD auction in 2015. Indicatively, the average price awarded during the first CfD round (in 2015) for offshore wind was £117.14/MWh, while in the 2017 CfD auction, Dong Energy was awarded a CfD deal amounting to £57.50/MWh for the development of Hornsea Project II, while Innogy secured the development of Triton Knoll project at the price of £74.75/MWh [6]. Not to mention the three zero-subsidy bids in the German auction delivered by Dong and EnBW, receiving only the market price of electricity paid out per unit of eligible electricity produced.

The above figures reflect the significant drop in offshore wind costs – rendering the technology more competitive than gas and nuclear energy. Nevertheless, it should be noted that the above bids were enabled by a number of circumstances. As such, in the zero-bid contracts, the realisation window is expanded to 2024, allowing developers to apply next generation wind turbine technologies of between 13-15 MW capacity (with currently operating turbines up to 8.25 MW); hence, the reason for low bids might be the expectation of a disruptive innovation, which will drive down costs. Furthermore, the grid connection costs were excluded in the specific cases [7].

In existing literature, there is controversy regarding the actual costs of offshore wind energy and although long-term projections foresee a reduction in the levelised cost of electricity (LCOE), the reduction in total installation costs has been reported to incur in a slower pace. As such, the latest IRENA report suggests that between 2010 and 2017, total average LCOE was reduced by 13%, while the total installation costs only by 2% over the same period [8]. Figure 1-1 and Figure 1-2, gather ranges of CAPEX and OPEX cost estimates for offshore wind installations based on historic data of installed projects and surveys of project developers. These figures suggest that there is significant scatter of data between different sources denoting a high degree of uncertainty across the industry. This is mainly caused by the ongoing development of the supply chain, upscaling of new generation offshore wind farms, increased demand of new assets pushing upwards the CAPEX and reduced confidence in the assessment of Operation and Maintenance (O&M) costs of aging assets.

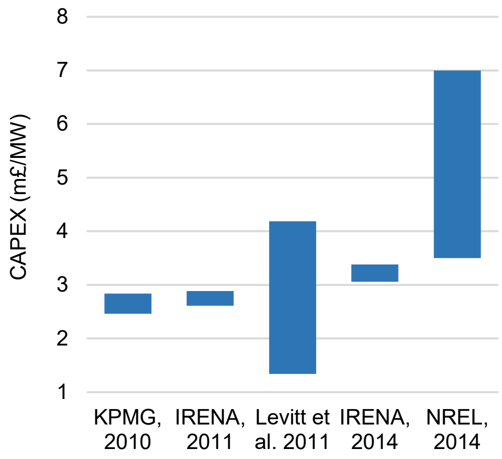


Figure 1-1 Range of capital costs (£m/MW) (Sources:[9]–[13])

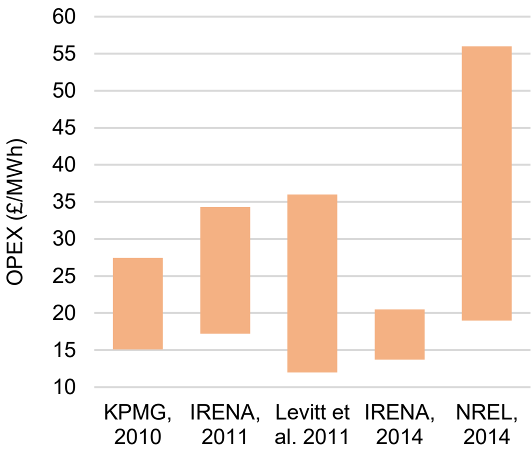


Figure 1-2 Range of operating costs (£/MWh) (Sources:[9]–[13])

Although deterministic models can support decisions pertinent to the development and operation of an offshore wind farm, they lack the ability to systematically account for the inherent uncertainty of input parameters when predicting the economic feasibility of a wind power project. To this end, a probabilistic/stochastic approach can significantly increase the value of the outputs of the analysis, assigning confidence levels to the predictions towards better informed decisions.

At an energy system development level, decision makers seek to develop methods that assist the power generation system planning through deriving optimal technology mixes. Optimising a performance indicator (such as minimizing the energy system cost), while at the same time satisfying a set of conditions related, for example, to the security of supply, the limitation of resources, the energy diversity, the environmental impact as well as the renewable technology capacity factors and the evolution of their costs, is a common method towards deriving optimal power generation mixes. It is apparent that numerous parameters included in the problem may be uncertain. Following this line of thinking, their uncertainty needs to be integrated in the analysis, and reflected in the results.

As the number of RE investments increases, so does the need to measure and account for the associated risks. Most relevant decisions throughout planning, construction and operation of offshore wind energy assets made by market agents involve a significant level of risk due to technical conditions and project externalities. According to ISO 31000, risk is defined as the effect of uncertainties on objectives [14].

Risk in renewable power generation investments is multi-dimensional and depends on the perspective of different stakeholders and maturity level of technological options. Table 1-1 summarises the most cited risks by employing a structured political, economic, social, technology, legal and environmental (PESTLE) approach.

Table 1-1 Risks in renewable energy investment sector

Risk Category	Sub-category	Risk factors/Events
Political	Country	Changes in the national economy
		Political stability
	Regulatory	Changes in policy support schemes
		Liability to third parties
		Contracting risk
	Bureaucracy	Complex approval processes/Delay of permits
Economic	Market	Variability of revenue due to electricity price
		Demand fluctuations
	Financial/Fiscal	Generating costs (CAPEX, fixed and variable OPEX, pre-development costs)
		Interest rate swings
		Financing risks (insufficient access to investment and operating capital)
		Taxation regime
		Transaction costs
	Strategic/business	Damage to reputation
Social	Lack of public acceptance	Delays in the licence acquisition
	Health risks	Accidents
Technological	Project development	Revenue loss due to project delay for the commercial operation date (COD)
		Failure to obtain all required licences
		Failure to obtain grid access
	Construction	Damage during transport or construction
		Damages due to natural hazards
		Unreliability of components (e.g. damage to turbines)
		Unavailability of skilled labour
	Operation/maintenance	Damages caused by natural hazards
		Technological/innovation risk
		Higher OPEX (due to critical failures of components)
		Unscheduled plant closure due to the lack of resources
		Risk of components generating less electricity over time than expected
		Sabotage, terrorism and theft risk
	Resource risk	Revenue because of the intermittent generation capacity
	Infrastructure	Variability of revenue due to grid availability
	Decommission	Decommission costs
Legal	Energy and climate change policy	Changes in the national energy and climate change policy
Environmental		Risk of environmental damage
		Carbon footprint and life cycle assessment

1.2 Aim and Objectives

In this context, this research project aims to qualify appropriate methods for dealing with uncertainty at a technology and energy system level providing decision support methodologies to different stakeholders. It develops high-fidelity risk-based valuation frameworks specifically for low carbon energy technologies and approaches the same research question from different stakeholder perspectives and at different levels of analysis.

To fulfil this aim, the following activities/objectives were distinguished:

- Assemble a state-of-the-art literature review of risk-based methods for sustainable energy systems planning and technology feasibility studies.
- Distinguish different investment strategies followed by investors in the offshore wind energy industry.
- Develop an integrated, high-fidelity lifecycle techno-economic model that allows for the temporal evaluation of a renewable energy investment, integrating (and developing) most relevant cost expressions.
- Formulate relevant parametric equations through appropriate selection of approximation models for the conceptual design and analysis of offshore energy assets.
- Expand the financial appraisal model to take into account uncertainties of key input parameters through selection and implementation of appropriate methods.
- Evaluate weather uncertainty during the operational phase and visualise cost performance and production losses through scatter plots.
- Develop and apply a stochastic optimisation framework for deriving optimal national energy technology mixes taking into account uncertainties of the system.

1.3 Structure of the thesis

This thesis comprises a portfolio of activities that reflects the objectives of the project and have been documented as stand-alone studies, which have been published or submitted at the time of writing. Following the submission-by-paper format, the thesis has been divided into two parts.

Part I includes five chapters: starting with an introduction to the thesis, followed by the methodological framework that has been developed and providing justification of the methods chosen. Then, key outcomes of the research are summarised and are, then, critically discussed. Finally, the conclusions and statement of contribution is included, commented on how the objectives of the project have been met and how original contribution has been achieved in aspects of novelty, scientific soundness and value of the findings.

Part II is a collection of the publications authored throughout the EngD period, including the following papers:

- Paper A assembles and analyses risk-based evaluation methods for low carbon energy technologies through employing a systematic literature review approach.
- Paper B systematically maps key investor behaviours in the offshore wind energy market by employing a statistical cluster analysis.
- Paper C develops an integrated, high-fidelity lifecycle techno economic model which allows for the temporal evaluation of the investment, taking into account (and develop) most suitable cost expressions.
- Paper D extends the previous model to a series of parametric expressions for CAPEX, OPEX and LCOE as a function of key deployment parameters, aiming to assist investors, researchers and other stakeholders to undertake an initial estimate of CAPEX, OPEX and LCOE values for offshore wind farm projects with varying design parameters, as well as use them as reference for estimating the effect in the change of one of the selected design parameters.
- Paper E reports the stochastic expansion of the techno-economic model to take account for the stochastic nature of certain variables using advanced numerical methods.

- Paper F investigates uncertainties present during the operation phase of offshore wind energy assets through developing and applying a parametric framework across a number of different locations in the south east coast of the UK, so as to demonstrate the effect of weather conditions and resulting downtime on a number of operational key performance indicators (KPIs).
- Paper G investigates the problem of the development of an energy system, through developing a multi-stage stochastic optimization model that determines the medium-to-long term optimal electricity generation mix, taking into consideration the uncertainty in electricity demand, capital cost reduction for renewable technologies and fuel prices along the planning horizon.

The references of the papers outlined above are as follows:

- **Paper A:** A. Ioannou, A. Angus, and F. Brennan, “Risk-based methods for sustainable energy system planning: A review,” Renewable and Sustainable Energy Reviews, vol. 74, pp. 602–615, Jul. 2017.
- **Paper B:** A. Ioannou, C. Vaienti, A. Angus, and F. Brennan, “A cluster analysis of investment strategies in the offshore wind energy market,” in 2017 6th International Conference on Clean Electrical Power (ICCEP), 2017, pp. 362–369.
- **Paper C:** A. Ioannou, A. Angus, and F. Brennan, “A lifecycle techno-economic model of offshore wind energy for different entry and exit instances,” Applied Energy, vol. 221C, pp. 406–424, 2018.
- **Paper D:** A. Ioannou, A. Angus, and F. Brennan, “Parametric CAPEX, OPEX, and LCOE expressions for offshore wind farms based on global deployment parameters,” Energy Sources, Part B Economics, Planning, and Policy, vol. 13, no. 5, pp. 281–290, May 2018.

- **Paper E:** A. Ioannou, A. Angus, and F. Brennan, “Stochastic valuation of offshore wind farms through the application of advanced numerical methods”. Under review in Renewable Energy Journal.
- **Paper F:** A. Ioannou, A. Angus, and F. Brennan, “Informing parametric risk control policies for operational uncertainties of offshore wind energy assets”. Submitted to Ocean Engineering Journal.
- **Paper G:** A. Ioannou, G. Fuzuli, F. Brennan, S.W. Yudha, A. Angus, 2018. “Multi-stage stochastic optimization framework for power generation system planning integrating hybrid uncertainty modelling”. Accepted with revisions in Energy Economics Journal.

Finally, the submitted/published conference papers are included in Appendices A-C.

2 METHODOLOGICAL FRAMEWORK

2.1 Approach of the thesis

This section provides an overview of the thesis approach and how each part of the portfolio of studies combines to fulfil the aim of this research. As outlined above, this thesis does not focus either on employing one single methodology, or on solving one single problem; rather, it combines different methods and approaches to solve at a technology and energy system/market development levels the problem of systematic consideration of uncertainties in the valuation of energy investments, as shown in Figure 2-1.

The research project started with a review of risk-based methods for sustainable energy systems planning by means of a systematic literature review (paper A). The approach that was adopted allowed for a clear understanding of the relevant methods and an appreciation on how extensively and for what problems they have been employed in previous studies. To obtain a better understanding of the market trends and the identification of key investor behaviours in the offshore wind energy market, a statistical analysis of existing wind farms across the UK was carried out, resulting in the identification of three distinct investor clusters distinguishing their behaviours by means of their entry and exit strategies (paper B). For this study real data from operational wind farms were obtained through databases and project records to result in a meaningful analysis.

At a technology level, and with a focus on offshore wind energy technology, a high-fidelity lifecycle techno-economic model for different entry and exit instances was developed (paper C). The model compiled the most up-to-date expressions to predict costs throughout all phases of an offshore wind energy project's lifecycle (design and consent, production and acquisition, installation and commission, operation and maintenance and, decommissioning and disposal), as well as developed new expressions when latest data were available. The commercial ECN O&M Tool was utilised for the accurate prediction of the operation and maintenance phase costs incorporating latest reliability data from literature. Discounted cash flow analysis was employed to evaluate the cash flows of the asset and sensitivity analysis to identify the main drivers of the asset's value. The paper also combined results of paper B to apply the developed model to different entry and exit strategies, along with the respective cost of financing representing the different investors in the market. It should be noted, that the approach followed during developing the tool is generic and can be adopted for other types of high value energy investment.

Next, the model developed in paper C was applied to generate a series of parametric expressions linking key global deployment variables, such as water depth and distance from port to financial KPIs (key performance indicators), such as LCOE (paper D). These parametric equations were derived through nonlinear regression from a number of simulations of the integrated cost model aiming to map the cost performance across the multi-dimensional domain of the independent variables. The expressions will be particularly useful for the preliminary assessment of available deployment sites, offering cost estimates based on global decision variables.

In paper E, the stochastic expansion of the techno-economic model was undertaken to account for the stochastic nature of certain time dependent variables, such as the market price of electricity as well as some time independent parameters, such as the vessels' significant wave height limit. Advanced numerical methods, namely the ARIMA for forecasting and ANNs for model approximation, were employed to allow the conversion of the deterministic model to its stochastic expansion in order to enhance the value of the model's outputs through assigning confidence levels to the predicted values of the chosen KPIs.

Next, an efficient model for the calculation of operational phase KPIs was developed with the aim to investigate the effect of uncertainties present during operation of offshore wind energy assets (i.e. related to the deployment conditions such as the wind and wave profile) on the actual potential revenue losses that an operator might face due to disruption of their activity. This allowed the visualisation of potential revenue losses around the UK offshore locations, which is an important element in the choice of the preferred risk control strategy from operators/investors through quantifying their exposure to certain hazards.

Finally, at an energy system development level, a multi-stage stochastic optimisation of the power generation system at a national level was developed by taking into account stochasticity of selected variables such as the volatility of fuel prices, as well as constraints related to energy security and climate change targets, among others. Uncertainty is modelled through an integrated scenario-tree configuration with Monte Carlo simulation, deriving probabilistically the optimised energy mix under certain policy scenarios.

The remaining subsections of this section will introduce the fundamentals of the methods employed, together with a critical discussion reasoning why specific methods are the most suitable for the problem investigated as well as how their application was validated (where relevant).

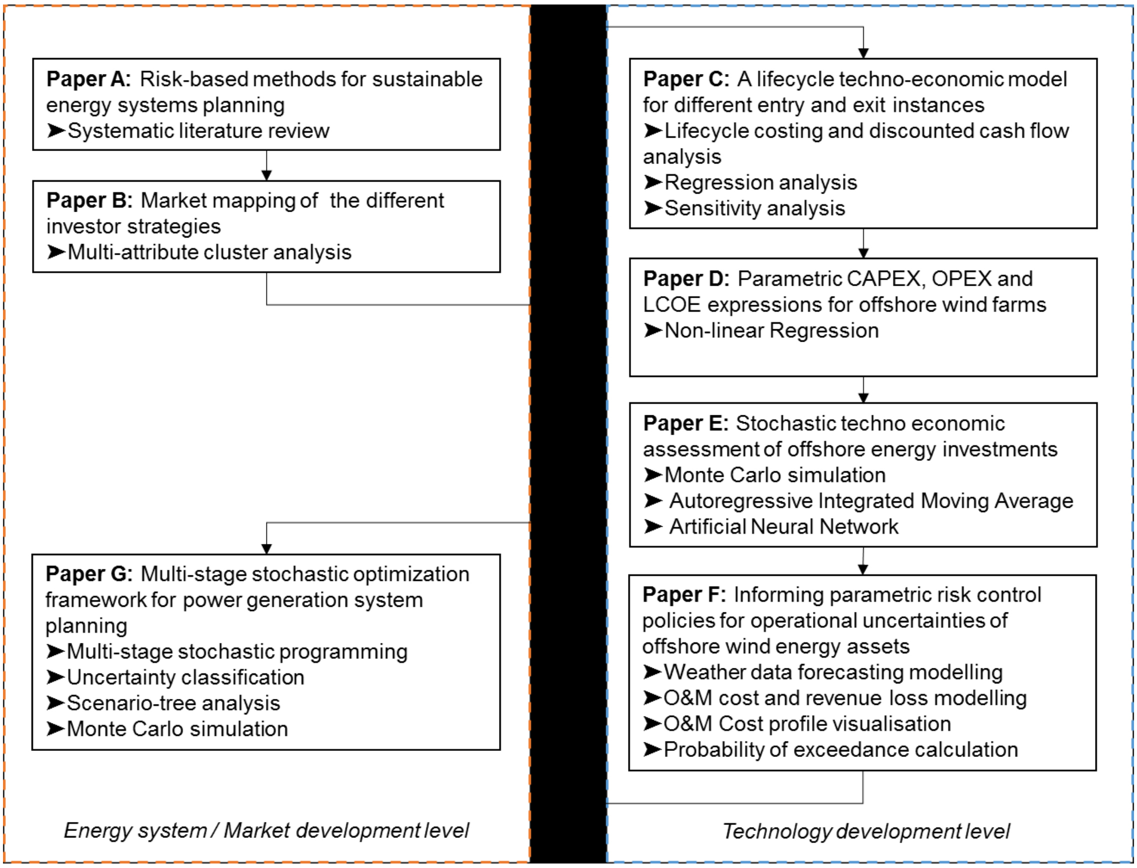


Figure 2-1 Structure of research

2.2 Research methods

This section provides a brief introduction to the research methods employed in this thesis for the investment decisions in low carbon energy investments under risk and uncertainty. The main approaches used in the methodological framework presented earlier comprise mainly quantitative/semi-quantitative models and methods (discounted cash flow analysis, Monte Carlo, stochastic optimisation, cluster analysis, advanced optimisation methods and time series forecasting) and a systematic literature review which was adopted to distinguish the most relevant methods to meet the objectives of this research project. A relevant critical discussion on how each method was selected is also included at the end of this section.

2.2.1 Systematic literature review

The literature review was conducted on the basis of a systematic literature review (SLR) approach, which provides the synthesis of the research in a systematic, transparent, and reproducible manner, while also restricting the researcher's bias [15]. To this end, a literature review protocol was developed to frame the research methodology. The literature review protocol outlines the aim and questions underlying the review, the search strategy, the inclusion and exclusion criteria and the plan for data extraction. Important criterion when selecting the keywords of the research was to be as inclusive as possible in order to avoid missing important studies.

The review was conducted on the basis of five major stages: (1) Formulation of the research question, (2) Locating of studies, (3) Selection, analysis and appraisal of studies, (4) Analysis and synthesis of results and (5) Reporting and dissemination of results.

Initially, a preliminary scoping study was conducted to identify the main domains of literature in the field and gain a better understanding on the contributions and identified gaps in knowledge in the research area of interest. Following the preliminary scoping study and the formulation of the research question, the research strategy was defined, namely the search strings of the review, as well as a number of inclusion/exclusion criteria of the papers retrieved to eliminate papers that fall outside the scope of the research topic. The search was limited to scientific peer-reviewed papers to ensure a collection of robust and validated works. Papers were retrieved through the Scopus search engine, while the final inclusion of papers considered for full-text analysis was determined following a quality assessment process (Figure 2-2).

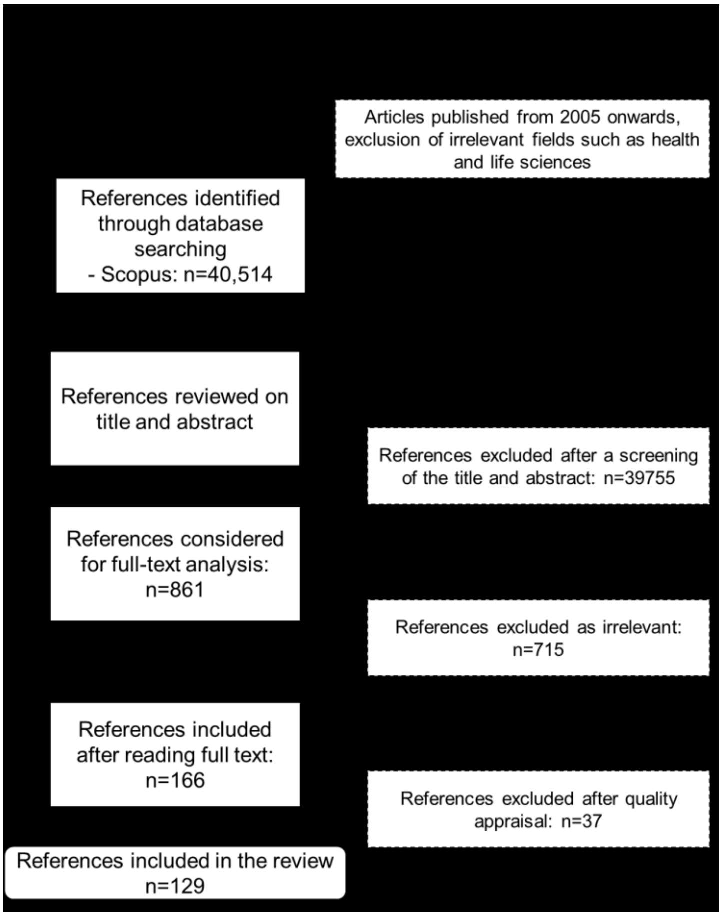


Figure 2-2 Summary diagram of the systematic literature review process

The initial literature was supplemented with additional works through a bespoke process, when further information to cover a particular topic was needed, or a key text in the literature had been omitted by the systematic review.

2.2.2 Cluster analysis

Equity owners of offshore wind energy projects tend to have different asset holding strategies according to their investment profiles. With the view to group the different behaviours in terms of the entry, exit, purchased and sold equity percentages, a statistical analysis of the relevant data was deemed appropriate. For the purposes of the analysis, data from 83 cases of investors investing or divesting part (or entirety) of their stake from a total of 27 operating wind farms, located in the United Kingdom, were collected through desktop research (e.g. 4C Offshore online database and market reports/online announcements such as: Centrica Company news).

The market mapping of the offshore wind energy sector was realised by means of a hierarchical cluster analysis. The cluster analysis groups cases of data based on the similarity of responses to different variables. The Euclidean Distance, d, is used as a measure of similarity between the cases.

$$d_{ij} = \sqrt{\sum_{k=1}^{p} \left(x_{ik} - x_{jk}\right)^2} \tag{2-1}$$

Equation (2-1) indicates the expression of the Euclidean distance between the scores of cases i and j on a variable k. Differences between scores of cases for each variable k are squared before their summation, in order to avoid the cancelling out of positive and negative differences. Then, the summation is square rooted to revert back to the original units of measurement. With Euclidean distances the smaller the distance, the more similar the cases. However, this measure is sensitive to variables with large size or dispersion differences. So, if the variables being tested have very different variances, the Euclidean distances will be inaccurate. It is, therefore, important to standardise scores before proceeding with the analysis.

Once a similarity measure has been determined the next step is to identify the grouping method based on the similarity coefficients. In this analysis, Ward's Method has been used, which aims to join cases so that variance within clusters is minimised. To this end, each case begins as its own cluster. Clusters are then merged so as to reduce the variability within a cluster. More specifically, two clusters are merged if this results in the minimum increase in the error sum of squares. To this end, the average similarity of the cluster is measured at each stage and the difference between each case within a cluster and the average similarity is calculated and squared. The sum of squared deviations is used as a measure of error within a cluster. A case is allowed to enter the cluster if its inclusion results in the cluster's least increase in error.

Figure 2-3 illustrates a typical cluster Dendrogram. The distance between merged clusters increases with the level of the merger, while the height of each node in the graph is proportional to the intergroup dissimilarity between its two children.

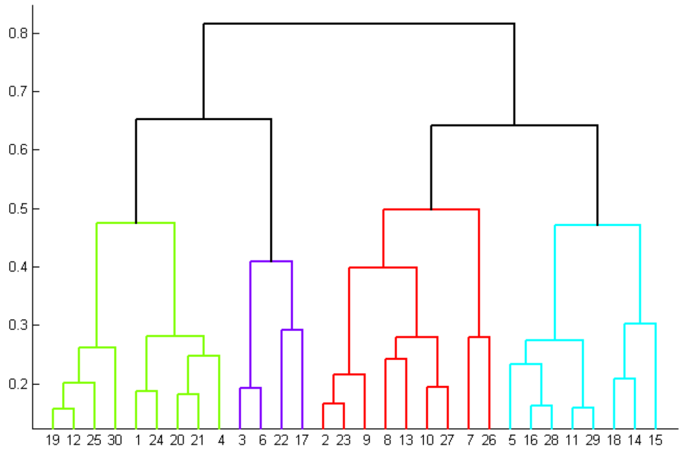


Figure 2-3 Example of Dendrogram

2.2.3 Lifecycle costing and discounted cash flow analysis

The development of a high-fidelity lifecycle techno-economic model for different entry and exit times was carried out in paper C through a discounted cash flow (DCF) analysis taking into account the lifecycle phases of an offshore wind investment (from the predevelopment and consenting to the decommissioning and disposal phases). For the modelling of O&M costs, the commercial ECN O&M Tool was used.

The discounted cash flow (DCF) valuation approach provides a basis for assessing the value of the cash flows of a project. Other valuation approaches are: the relative valuation, which estimates the value of the asset by comparing the pricing of similar assets in relation to a common variable, such as earnings, cash flows, or sales; and the contingent claim valuation using option pricing model to measure the value of assets that share option characteristics [16]. DCF is the foundation on which all other valuation approaches are built. To perform relative valuation and apply option pricing models to value assets, we often begin with a DCF valuation. DCF is based on assessing the costs and revenues over the lifetime of the investment through discounting expected future cash flows to estimate the present value of the asset. The formula for calculating DCF is typically the following:

$$NPV = -CF_0 + \sum_{t=1}^{N} \frac{CF_t}{(1 + WACC_{real})^t} \tag{2-2}$$

where, N is the lifetime duration of the investment, CF_0 is the cash flow in year 0, CF_t are the free cash flows of time period t, namely the difference between costs and revenues including taxes, depreciation, etc. Inflation and interest rates are used to account for the time value of money. Inflation accounts for the reduction in the purchasing power of a unit of currency between two time periods, while the interest rate is the rate earned from a capital investment. In financial analysis, the nominal interest rate is the interest rate quoted by the banks, stock brokers etc. which includes both the cost of capital and the inflation. Real discount rate (or else real WAAC) integrates the inflation adjustment and the discount of cash flows according to Fisher Equation [17]:

$$WACC_{real} = \frac{1 + WACC}{1 + R_{infl}} - 1 \approx WACC_{nom} - R_{infl} \tag{2-3}$$

The discount rate is determined by the source of capital as well as the estimation of the financial risks associated with the investment. Projects gather their capital by raising funds through debt and equity. These sources of financing demonstrate individual risk-return profiles; hence their costs also fluctuate.

Weighted average cost of capital (WACC) corresponds to the weighted average of cost of its equity and debt, with weights determined by the amount of each financing source. The weighted average cost of capital is calculated by the following expression [18]:

$$WACC = \frac{E}{V} \cdot RoE + \frac{D}{V} \cdot Rd \cdot (1 - tc) \tag{2-4}$$

Where, E: Market Value of Equity, D: Market Value of Debt, V=E+D, RoE: Return on equity, IR: interest rate on debt. The risk of the project significantly influences the amount of return on investment required by the investor. External capital is cheaper and thus it is often desirable to obtain the highest possible amount of debt; however, the cost of debt depends on the specific investment risk, namely the highest the investment risk, the lower the amount that banks will be willing to lend.

Another key performance indicator widely used for calculating the profitability of the investment is the internal rate of return (or IRR). This is defined as the interest rate at which the net present value of the cash flows of an investment equals to zero and is calculated by the following expression:

$$0 = -CF_0 + \sum_{t=1}^{N} \frac{CF_t}{(1 + IRR)^t} \tag{2-5}$$

The efficiency of an investment can also be measured by the Return on Investment (ROI), which equals to:

$$ROI = \frac{Gain\ from\ Investment - Cost\ of\ Investment}{Cost\ of\ investment} \tag{2-6}$$

As such, the Project analysis using the Discounted Cash Flow (DCF) method follows a three-step process:

1) Estimation of the amount and timing of future cash flows for each year of the project's life
2) Identification of a risk-appropriate discount rate
3) Calculation of the present value of future cash flow and derive NPV along with other performance indicators to conclude on the valuation of the project.

This approach provides a deterministic estimate of the project's value and is an analysis that usually incorporates numerous assumptions in the inputs based on available knowledge. Hence, the initial DCF analysis should be viewed as the first level of the valuation process, followed by an exploratory analysis, which accounts for uncertainty and explores the main drivers on the value of the investment. To this end, sensitivity analysis and Monte Carlo simulation methods are later employed. The whole valuation model was modelled in an integrated Matlab code.

2.2.4 Nonlinear regression

Nonlinear regression aims to find a nonlinear relationship between the dependent variable and a set of independent variables. A nonlinear regression model can be expressed as:

$$Y_i = f(x_i, \beta) + \varepsilon_i \tag{2-7}$$

Where Y_i represents the expected responses, which are nonlinear functions of the parameters, $f(x_i, \beta)$ is the regression/response function, x_i is the vector of predictors (or independent variables), β is the vector of unknown parameters, while ε_i is an error term. In nonlinear models at least one of the derivatives of the expectation function with respect to the parameters depends on at least one of the parameters.

In paper D, nonlinear regression was used to develop a series of parametric expressions for Capital Expenditure, Operational Expenditure and Levelised Cost of Energy as a function of key global deployment parameters of the wind farm such as the wind turbine rating, water depth, distance from port and wind farm capacity. Nonlinear regression was realised through SPSS software. After creating plots of each individual independent variable vs the CAPEX, OPEX and LCOE values, the most appropriate regression expressions were determined. Next, a set of overall relationships were developed for each of the dependent variables and the nonlinear coefficients were estimated through application of the maximum likelihood method for a pre-determined shape of the target equation.

2.2.5 Monte Carlo simulation (MCS)

MCS involves the random sampling of probability distributions of the model's input parameters with the purpose of producing numerous random output values. The sampling from each parameter's probability distribution is realised in a way that reproduces the shape of the resulting distribution; hence, the distribution of the output values deriving from the application of the method reflects the joint probability distribution of the outcomes [19]. It is a standard mathematical procedure, where random inputs are sampled and the output values are recorded for later processing through calculation that a desired event is realised in a number of occasions across the total iterations. Basic steps required to perform Monte Carlo simulation are as follows:

1) Definition of the problem, evaluation of available data and outcome expectations,

2) Definition of the system and creation of the parametric model, $y = f(x_1, x_2, \dots x_q)$,

3) Definition of probability distributions for each of the inputs, number of simulations to accomplish the desired accuracy,

4) Generation of set of random inputs $x_{i1}, x_{i,2}, \dots, x_{iq}.$,

5) Execution of the deterministic model with the set of input parameters and recording of output value y_i.

6) Repeat steps 4 and 5 for $i = 1$ to m.

7) Compilation of the joint probability distribution of the outputs y_i.

There are numerous statistical distributions that can be utilised for engineering approximations and random number generations. Three basic distributions are the normal, uniform and the triangular distribution.

The probability density of the Normal distribution is given by:

$$f(x) = \left\{ \frac{1}{\sigma\sqrt{2\pi}} \exp^{-}(x-\mu)^2/2\sigma^2 \right. \tag{2-8}$$

The continuous uniform distribution (also called rectangular distribution) is a distribution that has constant probability on the interval [a;b] and it is expressed by the following:

$$f(x) = \begin{cases} \dfrac{1}{b-a} & a \leq x \leq b \\ 0 & \text{otherwise} \end{cases} \tag{2-9}$$

The triangular distribution is used when a random variable can be defined by the minimum, the maximum and the most likely value, with values close to the most likely value having a higher probability of occurrence. The probability density distribution (PDF) of the triangular distribution is defined as follows:

$$f(x) = \begin{cases} \dfrac{2(x-a)}{(b-a)(c-a)} & a \leq x \leq c \\ \dfrac{2(b-x)}{(b-a)(b-c)} & c \leq x \leq b \\ 0 & \text{otherwise} \end{cases} \tag{2-10}$$

Other PDFs commonly used are: binomial, Poisson, Pert, Geometric, Weibull and Gamma, among others.

2.2.6 Advanced Stochastic Processes

Advanced numerical methods such as the ARIMA for forecasting and ANNs for model approximation, were employed to allow the conversion of the deterministic model to its stochastic expansion. Both methods were integrated in the Matlab main code.

2.2.6.1 Time series forecast model

This section looks at the forecasting method that was used to model electricity market prices, towards incorporating the uncertainty and variability in the cash flow model of the analysis. Time series techniques are usually based on extrapolating a set of historic observations to predict their behaviour in the future. In [20], electricity price forecast techniques are categorised into: multi-agent, fundamental methods, reduced-form models, statistical approaches and computational intelligence techniques. Statistical methods forecast the current value of a time series by applying a mathematical correlation of the previous values with the current values.

Geometric Brownian motion

Financial time series are most commonly based on stochastic differential equations (SDEs) which are the most general descriptions of continuously evolving random variables. Geometric Brownian motion is the simplest and most common financial time series model, according to which the logarithm of the randomly varying quantity follows a Brownian motion with drift.

Brownian motion (also called Wiener process) with drift parameter μ and volatility σ is a kind of Markov stochastic process $\boldsymbol{W} = \{X_t : t \epsilon\ [0, \infty)\}$ of the form:

$$X_t = \mu t + \sigma W_t \tag{2-11}$$

The Wiener process satisfies the following properties: a) The process starts from 0 $X_0 = 0$ (with probability 1), b) $\boldsymbol{W}$ has Gaussian increments, i.e. for $h \geq 0$, $X_{t+h} - X_t$ is normaly distributed with $\mu = 0$ and variance σ (same distribution as X_h), c) $\boldsymbol{W}$ has independent increments; that is, for $t_1, t_2, .., t_n\, \epsilon [0, \infty)$ with $t_1 < t_2 <, .., < t_n$, the random variables $X_{t_1}, X_{t_2} - X_{t_1}, \dots, X_{t_n} - X_{t_n - 1}$ are independent, d) X_t has a normal distribution with mean t_n , e) $\boldsymbol{W}$ has continuous paths, namely with probability 1, X_t is continuous on $[0, \infty)$.

Using Itô's lemma and integrating over time, the relationship between an initial value S_t and a later value S_{t+T} is the following:

$$S_{t+T} = S_t \cdot \exp\left[\left(\mu - \frac{\sigma^2}{2}\right)T + \sigma W_t\right] \tag{2-12}$$

Above equation represents the GBM model. This process has the advantage that it always remains positive and it can represent the characteristics of many variables. Geometric Brownian method has been used to stochastically assess the impact of volatile market electricity prices on the profitability assessment of offshore wind farms in a Conference paper accepted from the WindEurope Conference in October 2018, in Hamburg (see Appendix C).

Mean-reverting jump-diffusion (MRJD) process

The jump-diffusion model can be expressed by the following general stochastic differential equation for the increment of the electricity price (after removing seasonality and trend from the dataset):

$$dX_t = \mu(X_t, t) + \ \sigma(X_t, t)dW_t + dq(X_t, t) \tag{2-13}$$

where, dW_t represent the increments of a standard Wiener process (i.e. Brownian motion) and $dq(X_t, t)$ are the increments of a jump process.

When there is a high electricity demand, more expensive power generation technologies need to be brought online to cover the electricity load. During these periods, electricity prices exhibit jumps. In general, spot electricity prices are characterised by high volatility, seasonal cycles and occasional spikes. In mean-reverting jump-diffusion processes, the drift term $\mu(X_t, t)$ can force reversion to long term mean levels. The Ornstein-Uhlenbeck process, which is the most applied mean-reversion process (initially introduced in finance to model interest rate dynamics [21]), is expressed as:

$$dX_t = (\alpha - \beta X_t)dt + \ \sigma dW_t \tag{2-14}$$

where, β is the mean-reversion speed and $\frac{\alpha}{\beta}$ is the long term mean reversion level.

Autoregressive Integrated Moving Average (ARIMA)

ARIMA or Box-Jenkins model [22] is a statistical method standing for autoregressive (AR) integrated (I) moving average (MA) and is a generalisation of the Autoregressive Moving Average model (ARMA), where “I” (standing for Integrated) is a differencing step that is used to remove trend or seasonality from the time series. ARIMA models use standard notation of ARIMA (p,d,q) and (P,D,Q) for their seasonal counterparts. In power systems applications, ARIMA models have been used for load forecasting [23], [24], with good results, as well as to model and forecast day-ahead electricity prices [25], [26] and weekly prices [27]. ARIMA method was deemed appropriate for this study considering the ability of the method to take into account the seasonal trend of the dataset of electricity prices.

- The Autoregressive part (p) specifies which previous values from the data series are used to predict the current values or else the number of autoregressive orders.
- The Difference part (d) specifies the order of differencing of the time series before the application of the model. To apply the ARIMA model, the dataset is required to be stationary; if not, a transformation of the series to the stationary form needs to take place. Differencing is one of the simplest ways to achieve this. Box and Jenkins (1976) introduced a model that contains not only the autoregressive and moving average parts, but also the differencing part [22].
- The moving average part (q) specifies the order of moving average orders in the model, namely how the mean values deviation of the previous time series is used to predict the current values.

As such, the mathematical formulation of the ARIMA(p,d,q) model can be described using a lag operator notation (defined as $L^i X_t = X_{t-i}$) as follows:

$$\varphi(L)(1-L)^d X_t = c + \theta(L)\varepsilon_t \tag{2-15}$$

where, X_t is the price at time t, c a constant term, d the differencing order, ε_t is the random error at time t; further, $\varphi(L)$ are the parameters of the AR model formulated as:

$$\varphi(L) = 1 - \varphi_1 L - \ldots - \varphi_p L^p \tag{2-16}$$

where, p refers to the autoregressive terms, while $\theta(L)$ are the parameters of the MA(q) model expressed as:

$$\theta(L) = 1 + \theta_1 L + \ldots + \theta_q L^q \tag{2-17}$$

where, q refers to the moving average terms [28].

2.2.6.2 Artificial Neural Network (ANN) modelling approach

An Artificial Neural Network (ANN) is a powerful data modelling tool able to capture and simulate complex input/output relationships [29]. It comprises a large number of interconnected neurons with linear and nonlinear transfer functions and can be even used to predict the nonlinear behaviour of a system [30]. In general, the structure of ANNs consists of an input layer, one or more hidden layers and an output layer. Conventional mathematical models, such as common approximation models, use an algorithmic approach following a set of steps to solve a problem; unless these steps are known, the problem cannot be solved, restricting problem-solving capability of conventional models, often pre-assuming the shape of the response surface. ANN 'learns' the relations between the inputs and outputs by training.

The input to each neuron can be the network input from the input layer, the output of the neuron in the previous layer, and an externally applied bias [31]. The output of each neuron is the function of the weighted sum of the neuron inputs, with the hyperbolic tangent sigmoid transfer function (Eq. (2-18)) used in the hidden layer and the linear function (Eq. (2-19)) used in the output layer. The weights and bias are determined in the training process by minimising the error between the ANN outputs and the design matrix [32].

$$f(\varphi) = \frac{2}{1 + \varepsilon^{-2(\sum_{i=1}^{k} w_i \cdot u_i + \theta)}} - 1 \tag{2-18}$$

$$f(\varphi) = \sum_{i=1}^{k} w_i \cdot u_i + \theta \tag{2-19}$$

where, φ is the Neuron output; θ is the ANN layer bias; w_i is the ANN node weight and u_i is the stochastic variable.

In this analysis, the MATLAB Neural Network Fitting toolbox was used, with a two-layer feed-forward ANN with ten sigmoid hidden neurons and linear output neurons, to map the system response generated from the process model (based on the design matrix inputs).

To ensure an accurate prediction by the ANN, the data in the design matrix were divided between training (70%), validation (15%) and testing (15%) samples. Neural network training was performed to adjust the weights of all the connecting nodes until the desired network performance was reached. The evaluation of network performance is essentially an optimisation process and the objective function involves minimisation of an error function, e.g. mean squared error (MSE). In this study, the Bayesian Regularisation training algorithm was used as it can provide a better solution than other available algorithms for smaller problems to obtain the optimal values of the adjustable parameters, weights and biases. The MSE performance function (Eq. (2-20)) was used to assess the network performance.

$$MSE = \frac{1}{N} \sum_{i=1}^{N} (z_i - y_i)^2 \rightarrow min \tag{2-20}$$

Where, z_i: the targets, y_i: network outputs and N:data size.

2.2.7 Efficient model for calculation of operational KPIs

Accordingly, in paper F, a parametric framework was developed for the investigation of uncertainties present during the operation of offshore wind energy assets and calculation of operational KPIs. An overview of the integrated O&M analysis framework formulated in paper F is illustrated in Figure 2-4. The model consists of the following modules: (1) the failure modelling module, (2) the weather modelling module, and (3) the cost modelling module.

The failure modelling module is divided into the mean time to failure estimation (uptime) and the mean time to repair estimation throughout the planned and unplanned maintenance operations (downtime). The mean time to failure calculation is based on the annual failure rates, while the planned and unplanned maintenance operations require data related to the resources required for the repairs. Resulting downtime depends on the availability of the required resources for the repair, mission organisation time, duration of navigation and repair, as well as the required number of technicians' shifts.

The weather modelling module enables the prediction of the future sea states, namely future significant wave heights and wind speeds. Weather conditions play an important role in the total downtime of the wind farm, as when the related parameters surpass the set wave height and wind speed limits of the vessels, travelling to wind turbines and accessing them becomes impossible. Therefore, unfavourable weather conditions will delay repairs, thus increasing downtime and decreasing the wind farm's availability.

The cost modelling module takes into account the actual duration of all stages required to perform the repair and maintenance operations and uses vessel and crew day-rates, along with material costs to predict the total O&M cost. Outputs of the model are the availability, operating cost and the power production losses, among others.

A high-level validation based on the results of published cases has been performed, while further calibration of the model for more accurate results can take place through a specific case study.

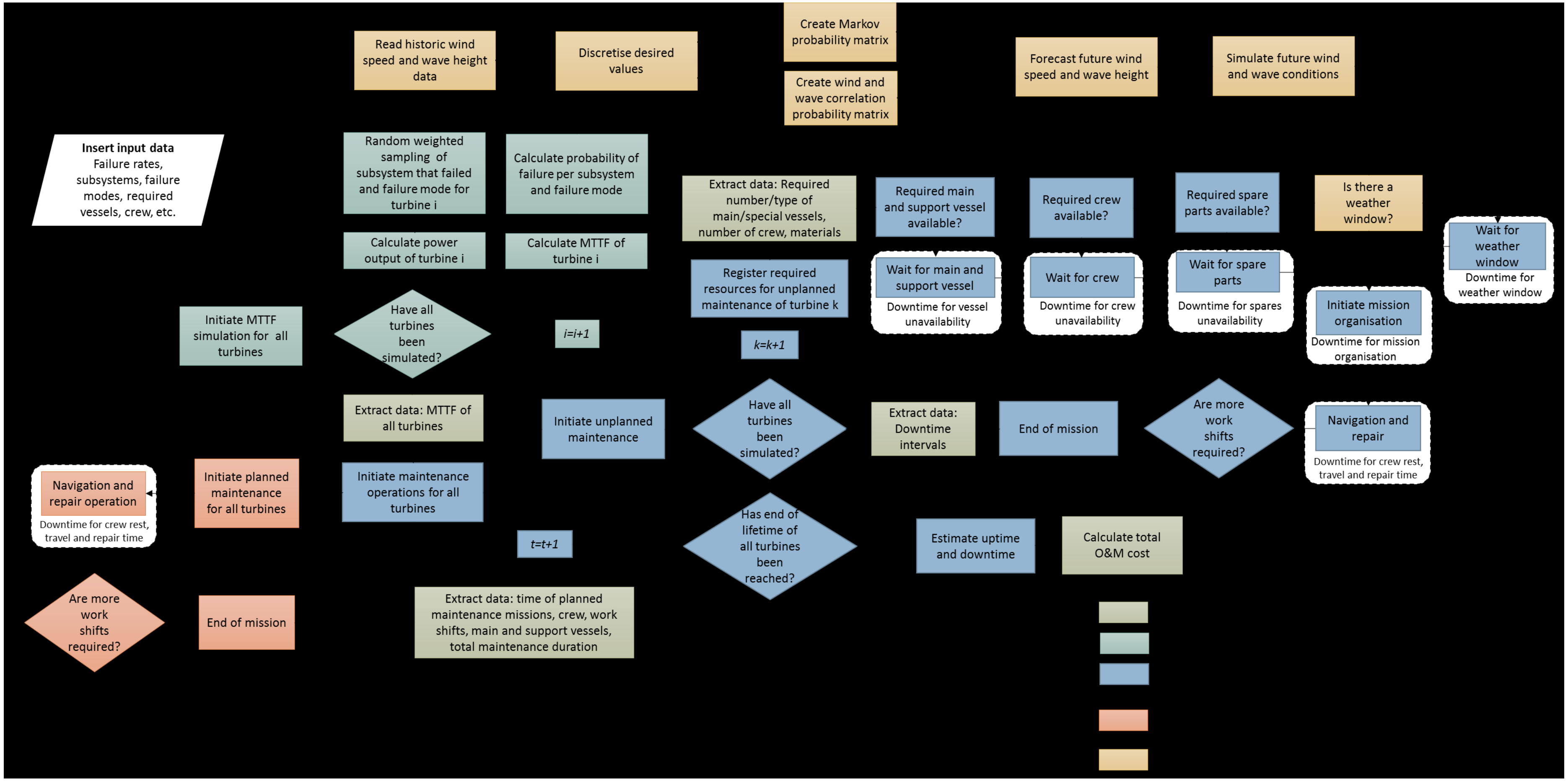


Figure 2-4 Flowchart of O&M cost model

2.2.7.1 Failure modelling module

In this thesis, the repair categorisation of Reliawind project [33] was adopted which classifies repair classes of subsystems into minor repairs, major repairs and major replacements. A total of 19 subsystems of the wind turbine were considered, while data used for the application of the model on failure rates, average repair times, average material costs and number of required personnel were retrieved from [34]. Assuming that the reliability of the turbine follows an exponential distribution, the probability of failure (PoF) can be expressed as:

$$PoF = 1 - Reliability = 1 - e^{-\lambda_{turb} \cdot t} \tag{2-21}$$

$$t = MTTF = -\frac{1}{\lambda_{turb}} ln(1 - PoF) \tag{2-22}$$

where, λ_{turb}=$\sum_{i=1}^{Subsyst} \lambda_i$, is the sum of the failure rates of each turbine's subsystems in series. Monte Carlo simulation is, then, performed to generate numerous random PoFs and subsequently returns an average MTTF value for each wind turbine. Once, MTTFs are calculated, Equation (2-21) can be used to estimate the probability of occurrence of each subsystem's failure, as:

$$PoF_{subsyst} = 1 - e^{-\lambda_{subsyst} \cdot MTTF_{subsyst}} \tag{2-23}$$

where, $\lambda_{subsyst} = \sum_{k=1}^{Repair\ class} \lambda_i$ is the sum of the failure rates of the different repair classes of the subsystems. Once the probabilities of each subsystem's failure is known, the model performs random weighted sampling to determine which subsystem will fail once the MTTF has elapsed along with the repair class, which is also randomly selected following the same logical process. Along with the MTTF calculation, the model calculates the absolute time set of the simulation, which is interpreted as the actual time from the beginning to the end of life of the wind farm. The duration of the individual activities is added to the absolute time set, enabling the calculation of the uptime and downtime of the turbine and registering the time when a certain failure happens.

Unplanned (corrective) maintenance is carried out following the occurrence of a failure on the turbine or the BOP, which may affect several turbines. The procedure after the occurrence of a new failure is illustrated in Figure 2-5. Once a failure has occurred on the first turbine, the availability check of the required main and support vessels takes place. It is assumed that a predetermined number of vessels will be continuously operating in the wind farm, hence they will be available to access the wind turbine that failed if the weather conditions allow so and the same applies for a predetermined number of personnel and the spare parts needed for the repair. If, however, all available vessels are occupied, the failure remains unresolved and the check is repeated once the required number of vessels are released from the previous mission. All required resources can also be inserted by the user as per each subsystem and repair class. Once the required vessels, crew and spare parts are available, the weather conditions are checked. Subsequently, the organisation of the mission, including the mobilisation of the vessel(s) (if required), take place. Once the crew accesses the subsystem that failed, the repair is carried out; it is assumed that one work shift lasts for up to 12 hours, which includes the total repair time, transitioning from harbour to the site and vice versa, as well as a mid-shift break. In case that more than one shifts are required, the crew returns to harbour and the mission restarts 12 hours later. When the damage is restored, the wind turbine starts producing power again, and the MTTF of the subsystem is reset to its original value. Finally, the transit back to the harbour and the demobilisation time are added to the total downtime of the wind farm. The durations of all unplanned maintenance activities are registered and added to the absolute total time set. Once the absolute total time set equals the service life of the wind farm, the simulation stops.

Planned maintenance (else calendar-based maintenance) operations are carried out periodically and deal not only with one subsystem of the wind turbine, but with groups of subsystems or the entire wind turbine. Planned maintenance can be scheduled ahead of time, to take place during periods of favourable weather conditions when delays to missions due to exceedance of vessels' safety limits (weather window downtime) are not likely to occur. The same applies for vessels, crew and spare parts unavailability downtimes. Calendar based maintenance is assumed to take place once every year with a deviation of ±1 month, to simulate the real life operations. Downtime due to planned maintenance is assumed to originate exclusively from the navigation and repair time, together with the potential downtime due to crew rest. It is, thus, expected that unplanned maintenance will incur higher downtimes in relation to planned maintenance considering the longer expected downtimes and types of maintenance activities.

2.2.7.2 Weather modelling

Commonly used methods for generating sea state time series comprise Gaussian and Langranian approaches for short term wave modelling, Autoregressive Moving Average (ARMA) methods and Markov-based models which work well for long term forecasting and can capture persistence of sea state parameters [35], [36].

In this thesis, the discrete time Markov chains was chosen as the weather forecasting method. To this end, historic weather datasets from 1992 to 2017 with a 3-hour time step were retrieved from BTM ARGOSS database [37]. Discrete time Markov chains method is based on having a finite number of states in a system and estimating the probability, $p_{i,j}$ of state *i* to evolve into state *j*. Markov probability matrices are generated for each month, to account for seasonality, as shown below:

$$P(sea\ state\ parameter)_{month} = \begin{pmatrix} p_{11} & p_{12} & \cdots & p_{1n} \\ p_{21} & p_{22} & \cdots & p_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ p_{n1} & p_{n2} & \cdots & p_{nn} \end{pmatrix}_{month} \tag{2-24}$$

where, $p_{i,j}$ equals the number of transitions of sea state parameter *i* to *j*, divided by the total number of times, state *i* appears. As such, initially, the weather data is discretised with a resolution of 0.2 m for wave height and 1 m/s for wind speed data, resulting in a finite number of possible values, namely 23 and 25 values, respectively. A time step of 3 hours is also considered for the forecast, during which wind speed and wave height are assumed to remain constant. Based on the probabilities of each transition matrix, the wave height for the starting month is randomly selected, successively all sea state conditions are predicted as a function of the previous state and the transition probability.

2.2.7.3 Cost modelling

The cost modelling module gathers the data recorded during each iteration, required to estimate the O&M cost. For unplanned maintenance of wind turbines, the time that a failure occurs is registered with reference starting point the beginning of operation of the wind farm. Further, the subsystem that failed and the type of failure will define the required main and support vessels (to match the correct day rates) and the number of crew members required for the repair. Downtimes of crew unavailability, spare parts unavailability, weather window, navigation time and demobilisation time are accounted to estimate the total cost of vessels and crew.

2.2.8 Multi-stage stochastic programming

Finally, in paper G, the optimisation of the power generation technology mix was carried out through a multi-stage stochastic optimisation. The proposed model was developed using the constrained solver fmincon of MATLAB R2017a optimization toolbox, which is based on sequential quadratic programming [38]. The optimisation problem is schematically presented in Figure 2-5.

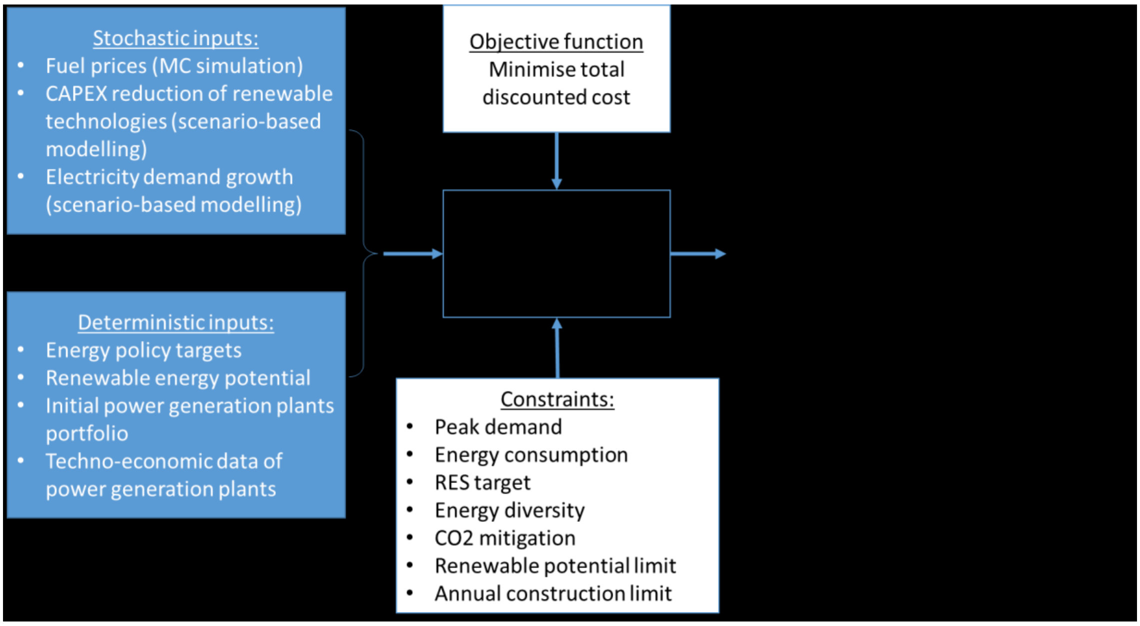


Figure 2-5 Schematic representation of the optimisation model

The study system covers a time horizon of 4 periods and 3 stages of 4, 5 and 5 years duration, respectively. Figure 2-6 demonstrates the multistage scenario tree that is developed by the three uncertainty variables (electricity demand, capital cost reduction and fuel price). The uncertainty of future demand and capital cost reduction is modelled by means of a scenario-tree configuration, whereas the uncertainty of fuel prices is approached through Monte Carlo simulation. Both the uncertainty of electricity demand and capital cost reduction are represented by three nodes: “Low”, “Medium” and “High” with assigned probability values 0.3, 0.5 and 0.2, respectively, as shown in Figure 2-6. Furthermore, each MC simulation sample is considered as a separate node with $1/n$ probability. The integration of MC simulation to model the stochasticity of fuel prices was a methodological contribution of this study converting the possibilistic scenario-based uncertainty modelling to a probabilistic approach. A scenario (s) is a route from the root node to a leaf node and the probability of scenario s (p_s) equals the product of probability of occurrence realized from root node to leaf node:

$$p_s = p_{s,t1} \cdot p_{s,t2} \cdot \ldots \cdot p_{s,T} \tag{2-25}$$

Hence, the probability of scenario s is the joint probabilities of all uncertain variables. The sum of corresponding joint probabilities of all scenarios is equal to 1. After reaching the leaf node at each stage, key decisions (installed capacity for each technology) from a set of n scenarios are averaged to provide the input value for the next node. Hence, in each stage, $n \cdot 3^{2 \cdot t}$ optimizations are performed, where n is the set of random fuel price MC sample, assumed to follow a normal probability distribution and t is the number of stages. Since fuel prices volatility is hard to model accurately by following a three-scenario-tree pattern, MC simulation was used to generate a random set of fuel prices based on their mean and standard deviation values of each technology's fuel price. It should be highlighted that increasing the size n of the MC generated samples can provide more robust results; however, it significantly increases the processing time. To identify the minimum sample size, a convergence study was implemented which indicated that results started to converge for $n = 150$.

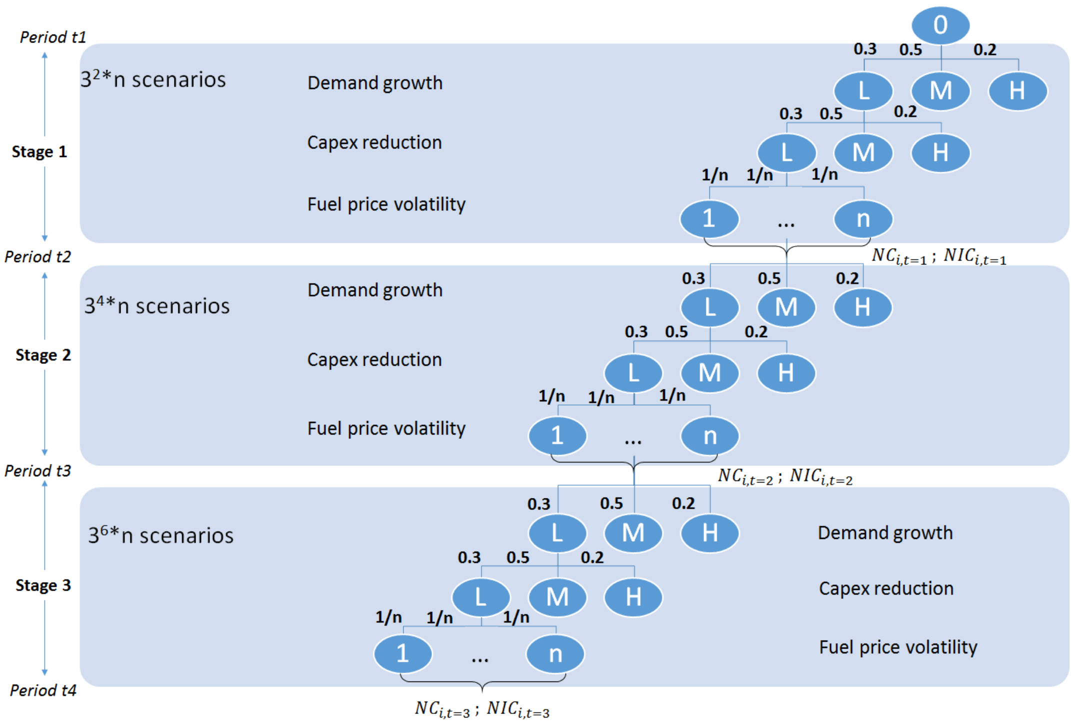


Figure 2-6 Uncertain inputs represented by scenario tree with assigned probabilities under the baseline scenario

2.3 Critical discussion on the methods selected

As described in the previous sections, this thesis encompasses a number methodologies and types of analysis, aiming at approaching the same research question from different stakeholder perspectives and at different levels of analysis. This section substantiates on the chosen methods and provides a critical discussion on alternative methods, advantages of the ones chosen, limitations of the methods and of the analysis. Finally, verification/validation approaches (where applicable and possible) are discussed.

Hierarchical cluster analysis is a statistical method that seeks to identify patterns within the data. Its aim is to reduce the number of observations by finding groups of observations with minimum within-group variabilities and maximum among groups variability. This method was considered appropriate for identifying investors following similar asset holding strategies. Hierarchical clustering has a logical structure, is easy to read and interpret [39]. However, it may be regarded mostly as a descriptive technique. The solution is not unique and it strongly depends upon the analyst's choices. In general, cluster analysis results should not be generalized bearing in mind that cases belonging to the same group are similar only with respect to the variables cluster analysis was based on. Data for cluster analysis don't have to comply with all strict conditions for statistical testing. They only have to be defined on a numerical scale (rational, ordinal or even dichotomous). Cluster analysis is easily administered, primarily as a descriptive technique. Alternative methods considered were principal components analysis and factor analysis, which are variable reduction techniques, reducing the number of observed variables to a smaller number of principal components which account for most of the variance of the observed variables. Validity of the derived clusters was checked manually, confirming that investments within a defined cluster were linked through similar investors' patterns across certain criteria.

The lifecycle costing and DCF analysis model developed is a fully parametric model, allowing the prediction of total costs of investments of multiple scales. As mentioned in section 2.2.3, alternative valuation approaches could be the relative valuation or the option pricing model; however, DCF is the foundation on which all other valuation approaches are built. The lifecycle overarching structure of the model is a comprehensive way to summarise all costs of the wind farm project. The high-fidelity parametric model is suited to accommodate different entry and exit strategies of investors. The model adopted the most up-to-date parametric equations found in the literature, while where latest data were available new parametric equations were developed. However, this is a deterministic model, unable to account for inherent uncertainties in the analysis, assuming mostly constant parameters (i.e. not accounting for volatility of WACCs, fluctuating electricity prices, cost of components, etc.). The parametric model was verified by the comparison of results with three different references namely [40]–[42]. Alternative approaches to the valuation of wind farm could include reliance on data from past investments however for an industry/application which is still maturing and the supply chain is not fully developed and costs depends on demand and deployment location, such approach would be inefficient.

The shortcomings of the deterministic DCF approach highlighted above were addressed through paper E, where the stochastic valuation of offshore wind farms, through the application of advanced numerical methods, is carried out. To this end, time dependent and independent stochastic variables were simulated by means of an Autoregressive Moving Average and an Artificial Neural Network (ANN) approximation model integrating a Monte Carlo simulation framework to derive the joint probability distributions of the output variables. The derived models were verified through a number of bespoke cases where costs were analytically calculated through the high-fidelity cost model.

On the one hand, Monte Carlo simulation is a widely used, versatile method to capture uncertainty, while it can conveniently expand deterministic models. On the other hand, it does not capture less likely outcomes and very low probabilities and it requires considerable data volume (definition of probability distribution functions) for random input variables or uncertain and predicted input parameters [43], and it cannot capture extremities [44]. As the problem investigated does not face such risks, Monte Carlo simulation approach was chosen as suitable.

Alternative methods considered were first and second order reliability methods which could derive results of low probabilities of occurrence. However, they are analytical methods and involve a further layer of approximation in the analysis reducing the accuracy of the results of nonlinear systems. Further, a detailed analytical expression is in most cases required for the calculations.

Artificial Neural Network is a surrogate modelling method able to capture nonlinear relationships as a black box function, which can be easily integrated into a Matlab code. However, if number of available input data and the quality of data do not fulfil certain criteria, it can lead to overfitting and hence poor approximation. For the problem of generalising the outputs of the O&M costs, where nonlinear behaviour is expected in the input/output relationship, an ANN approach is highly effective. Alternative methods that could be considered include regression models, which, are unsuitable when the relationship between the dependent and the independent variables is nonlinear, complex and its shape cannot be pre-assumed. The interpolating capability of the ANN model that was derived was quantified through the calculation of R^2 coefficients comparing actual and calculated values through the testing and training set, as well as an extra set of cases that were run through the commercial tool and approximated with the derived model, showing satisfactory results, as discussed later on in this thesis.

To identify the best forecasting method for modelling the energy market prices, one has to determine the scope of the analysis. The present thesis focuses on stochastically calculating the long-term electricity market prices to estimate the profitability and planning of the offshore wind energy investment beyond the expiration of the CfD strike price support mechanism. Statistical methods, such as the Autoregressive Moving Average, have a strong underlying mathematical and statistical theory, accommodating temporal correlations between past observations and current prices; as such, they can attach some physical interpretation to their components. Nevertheless, they are often criticized for their limited ability to capture nonlinear behaviour of electricity prices and they have been reported to perform better for short-term predictions (i.e. forecasts from a few minutes up to a few days ahead) [20].

Electricity prices exhibit seasonality on a daily, weekly and seasonal level basis, which can be captured through the ARIMA process. However, statistical methods cannot capture the presence of spikes in the dataset, especially for price-only models, but also for models using fundamental variables. Mean-reverting jump-diffusion (MRJD) processes are more appropriate to reproduce patterns of spikes and reversion to a long term mean level. However, they are considered to give a simplified picture of the price dynamics and are not expected to provide accurate results on an hourly basis, but rather recover main characteristics of the electricity prices at a daily time scale. Other available methods, such as Computational Intelligence techniques can be considered as they produce more accurate results (especially for day-ahead predictions of spot electricity prices), handling complexity and nonlinearity. Nevertheless, their application usually requires a larger dataset (in comparison to the price-only models) of fundamental drivers, including the system forecasted demand, weather related data, fuel costs, etc. Considering that an accurate prediction of short-term electricity prices is not under the scope of the present thesis, the accuracy criterion is more relaxed and therefore an ARIMA approach was considered efficient to predict the future electricity prices.

3 OUTCOMES OF THE RESEARCH

This section reports and discusses the highlights of the research undertaken as part of the EngD thesis as per an energy system and a technology development level.

3.1 Energy system development level

3.1.1 Outcomes of review on risk-based methods for sustainable energy system planning

Paper A reviews the risk-based methods employed for the planning and feasibility analysis of sustainable energy systems. It also aims to critically assess which risks have been analysed by which methods, what are the common outputs of these methods and which have been the target stakeholders. Methods have been classified into quantitative and semi-quantitative as shown in Figure 3-1. Quantitative risk-based evaluation methods deal with (statistical) risk factors that can be represented by probability distributions. Semi-quantitative methods have the flexibility to take into consideration statistical and non-statistical risks. Methods that were identified through the SLR are: MCDA and scenario analysis.

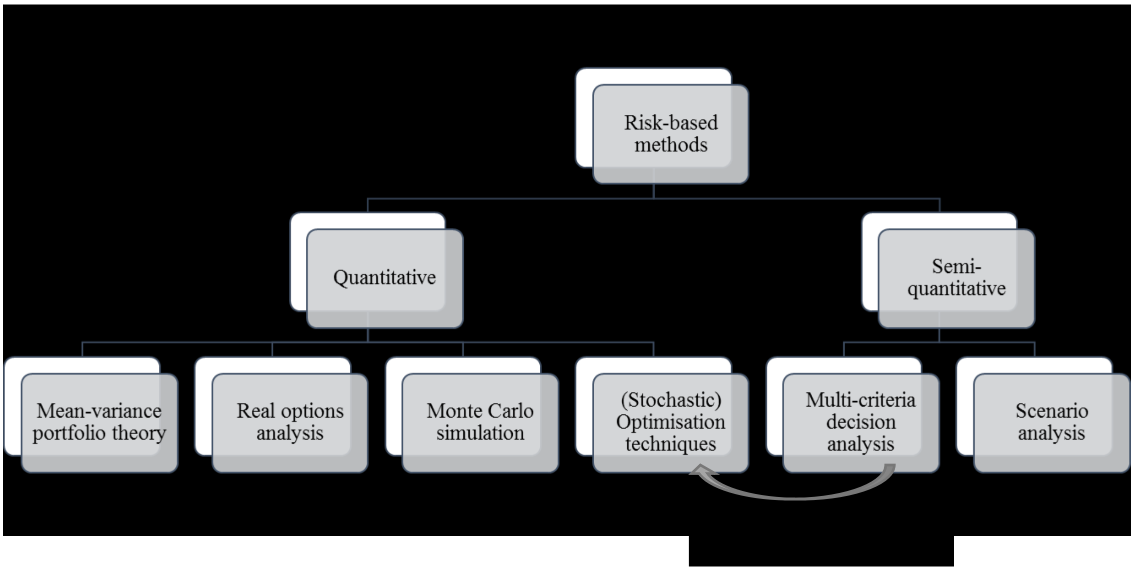


Figure 3-1 Classification of the risk-based methodological approaches implemented in the field of sustainable energy planning and feasibility

The paper also matches the risk-based methods with the risks/uncertainties identified by the systematic review providing guidance as to what methods are most suitable to address/model the specific risk and uncertainty factors listed.

A comparative overview of the most significant outputs of each method are summarised in Figure 3-2.

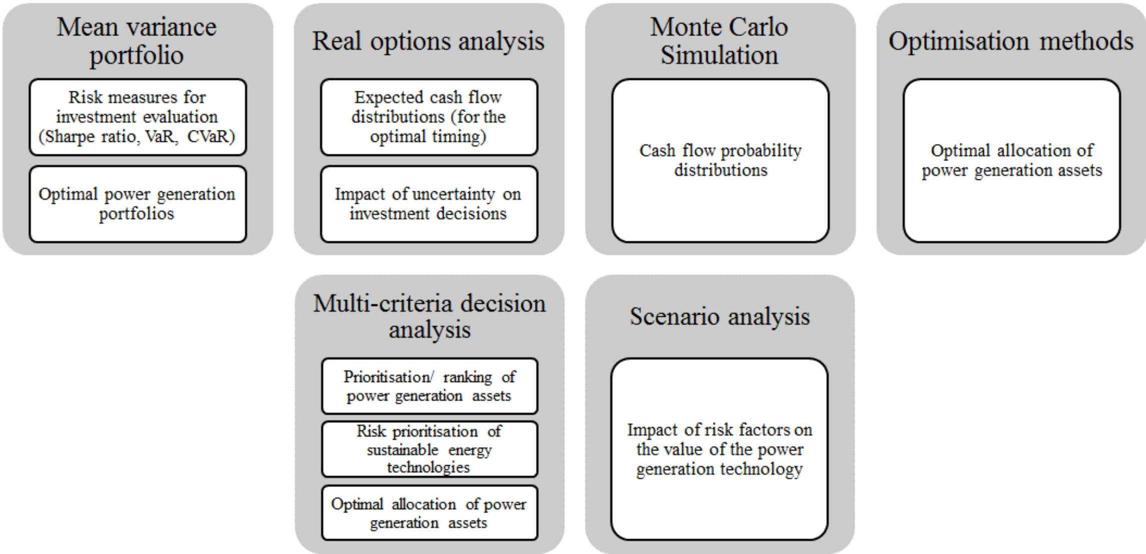


Figure 3-2 Common outputs of risk-based methodologies in energy planning and feasibility studies

Paper A served as a basis for the further research in the thesis, providing an understanding of which methods have been applied to address the uncertainty in the valuation and planning of sustainable energy systems, as well as to identify untapped issues on relevant areas of research.

3.1.2 Outcomes of cluster analysis of investment strategies in offshore wind energy market

In paper B, results of the cluster analysis method applied to operating installations indicated the formation of three distinct clusters of investors following similar strategies in terms of their entry, exit, purchase (of equity stake of the investment) timing, as well as the stake purchased. Figure 3-3 illustrates the resulting Dendrogram which shows the sequence by which the observations and clusters were merged.

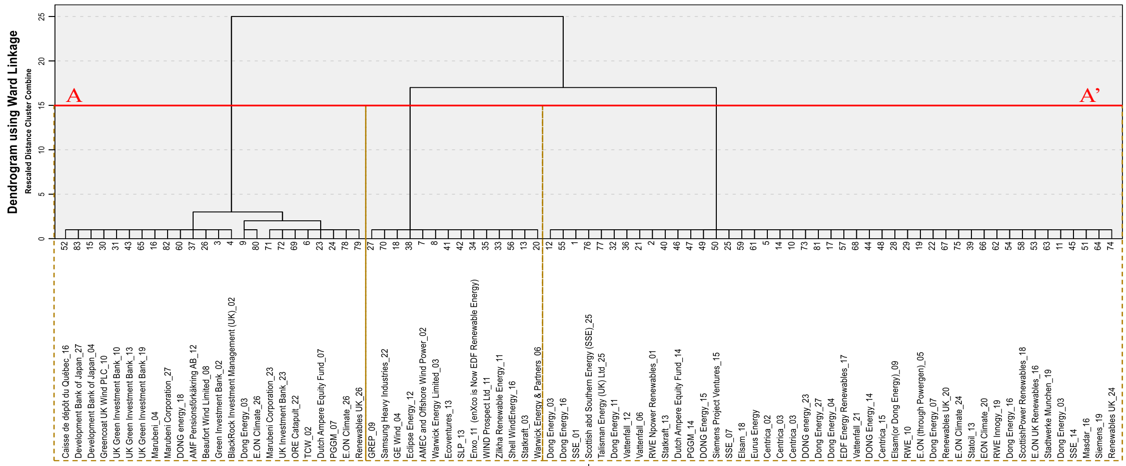


Figure 3-3 Dendrogram of the hierarchical clustering

Key characteristics of each cluster are summarised in Figure 3-4. From a financial point of view, each investor has a different risk profile, which is reflected through different WACCs, which in turn accounts for the profitability of an investment. The first cluster includes third party investors usually comprising institutional investors and infrastructure funds typically managing very large amounts of money (mostly in the scale of billions of £). Institutional investors are interested in owning projects during their operating life, maintaining a low risk profile reflecting costs of capital in the region of 6%-12% [45]. The second cluster comprises mostly independent power producers and OEMs/ECPI providers. Independent power producers (IPPs) develop, construct and operate offshore wind energy projects; accordingly, they usually sell the generated energy to the grid or to large scale power providers through Power Purchase Agreements (PPAs). They usually do not have as strong balance sheets as Utility companies and their cost of capital lies in the region of 10-20% (except for IPPs with a background in the offshore oil & gas industry). Finally, the Build-Operate-Transfer (BOT) cluster is dominated by major Utilities, able to finance the project from their own reserves or through corporate finance at a relatively low cost of capital (~8-10%). It should be noted that most offshore wind farms are less than 10 years' old and the first wind farm was only decommissioned last year, so it is possible for a further cluster to be formulated in the future with investors aiming to profit from the service life extension stage.

Cluster 1: Late entry investors	Cluster 2: Pre-commissioning investors	Cluster 3: Build-Operate-Transfer investors
• Third party capital investors • Corporate investors, infrastructure funds and institutional investors • Undertake exclusively operational risks and avoid construction risks, retaining a low risk profile with stable returns • Purchased stakes are in general minority stakes • Long exit timing • Cost of capital in the region of 6%-12%	• Independent energy companies, EPCIs contractors, and OEMs • Entrance: beginning of the project • Exit: prior the commissioning of the wind farm • Turnkey developers entering the venture at an early stage of its lifecycle, in order to get involved in the construction and installation stage, and following the commission, they tend to sell the stake they own exiting during the operating stage of the asset. • Cost of capital lies between 12-14%	• Build the asset • Keep the operating assets in their balance sheet • Divest part of their stake (minority stakes) during the operating stage of the asset • Major Utilities and Independent power producers • Low cost of capital (~8-10%)

Figure 3-4 Key characteristics of three investor clusters

3.1.3 Outcomes of stochastic optimisation of the power generation mix

Outcomes of the next study carried out at an energy system development level were derived from the application of the multi-stage stochastic optimisation framework (presented in section 2.2.8) to the Indonesian power generation mix (paper G). Indonesia was selected as the reference case study for determining the optimum power generation expansion planning due to the availability of data on the existing installed power plants as well as because it is a rapidly developing economy with projected electricity growth of 8.5% per year until 2025 and significant renewable energy resource potential [46].

The proposed model was initially applied to determine the optimal power generation mix under a baseline case and accordingly to another three representative cases calling for: the "Least cost option", the "Policy Compliance option" and the "Green Energy Policy option". The different sets of constraints that were imposed for each planning option (PO) are summarised in Table 3-1.

Table 3-1 Set of constraints for each PO

Constraint	Baseline case	Least cost option	Policy Compliance option [a]	Green Energy Policy option
Peak demand	√ [b]	√	√	√
Consumption demand	√	√	√	√
Renewable potential limit	√	√	√	√
Annual construction limit	√	√	√	√
Minimum proportion [c]	x	x	Coal: 30% in 2025 29% in 2030 NG: 22% in 2025	x
Maximum proportion [c]	45% for each technology	x	Oil: 25% in 2025 24% in 2030 Rest of technologies: 45%	45% for each technology
Renewable penetration target	16% in 2020 23% in 2025 25% in 2030	x	16% in 2020 23% in 2025 25% in 2030	24% in 2020 35% in 2025 38% in 2030
$CO_{2,eq}$ emission limit	750 m ton in 2020 1000 m ton in 2025 1250 m ton in 2030 of $CO_{2,eq}$/year	x	26% $CO_{2,eq}$ reduction in relation to 2020, 2025 and 2030 BAU	30% reduction in relation to 2020, 2025 and 2030 Baseline case
Carbon pricing	x	x	x	$ 30 /metric ton of $CO_{2,eq}$

[a] Source: [47], [48].
[b] "√" means that the constraint is included in the simulation, "x" means constraint is excluded.
[c] Proportion of each technology within the total power generation mix.

It should be noted that for the derivation of the planning options, location-specific literature has been studied in depth through a review of national and international regulations and communications with key stakeholders in the Ministry of Energy and Mineral Resources of Indonesia, who provided detailed data on the installed capacities per different technology and per different plant. To this end, this dataset also constitutes original contribution as high-fidelity analysis cannot be achieved only with data available within the public domain.

Under the baseline case, the optimised stochastic power generation mix for all leaf nodes run for the planning period 2025 is shown in Figure 3-5 and it includes coal 20.0–45.0% of total power generation mix, natural gas 9.0–32.0%, oil 3.5–17.5%, hydro 9.0-12.5%, geothermal 8.8–12.3%, biomass 2.3-11.9%, onshore wind 2.7–4.1%, offshore wind 0%-0.14% and solar PV 0%-8.0%. It has to be noted that results shown in this figure do not depict the likelihood of occurrence of each scenario. To identify the weighted mean proportion of power generation produced from each technology, τ, during time period, t, each observation is multiplied by the probability of occurrence of its originating scenario s_k (where k is a specific combination of s_D, s_C and s_F scenarios) and the products are, then, summed up. For instance, the weighted mean proportion of power generation derived from technology τ_1 is calculated as:

$$\bar{x}_{\tau_1} = \sum_{k=1}^{K} \left(p_{s_1} x_{\tau_1,s_1} + p_{s_2} x_{\tau_1,s_2} + \cdots + p_{s_k} x_{\tau_1,s_k} \right) \quad (3\text{-}1)$$

In Figure 3-6, the optimised stochastic power generation mix across the whole simulation period is illustrated. Total weighted mean power installed capacity was calculated 72.2 GW in the 2020 baseline case, increasing to 166 GW in 2030 because of growing energy demand. Outliers have been removed from the box plot representation, while the weighted mean proportions of the different technologies in the power generation mix are denoted by a red asterisk. The central red mark in the whisker charts represents the median, while the bottom and top edges of the blue boxes indicate the 25th and 75th percentiles, respectively. The black whiskers cover the non-outliers that represent the most extreme data points. Constraints imposing the renewable technologies contribution, as well as lower carbon emission levels appear to enforce the decrease of fossil-fuels-based technologies over time. In fact, coal, NG and oil installed capacities are reduced by 11%, 45% and 34% from 2020 to 2030 time periods, while hydro, geothermal, biomass and onshore wind are increased by 58%, 117% and 112%, respectively (as shown in Figure 3-7). Furthermore, the new weighted installed capacity was estimated 80.5 GW, weighted RES share was 35%, $CO_{2,eq}$ emissions 570 million tons and weighted total discounted cost $ 471 billion in year 2030. The model failed to find an optimum solution for around 5% of the total uncertainty scenarios, meaning that not all constraints could be satisfied under these scenarios. Results illustrated here were, thus, cleansed and their probabilities were readjusted to sum up to one.

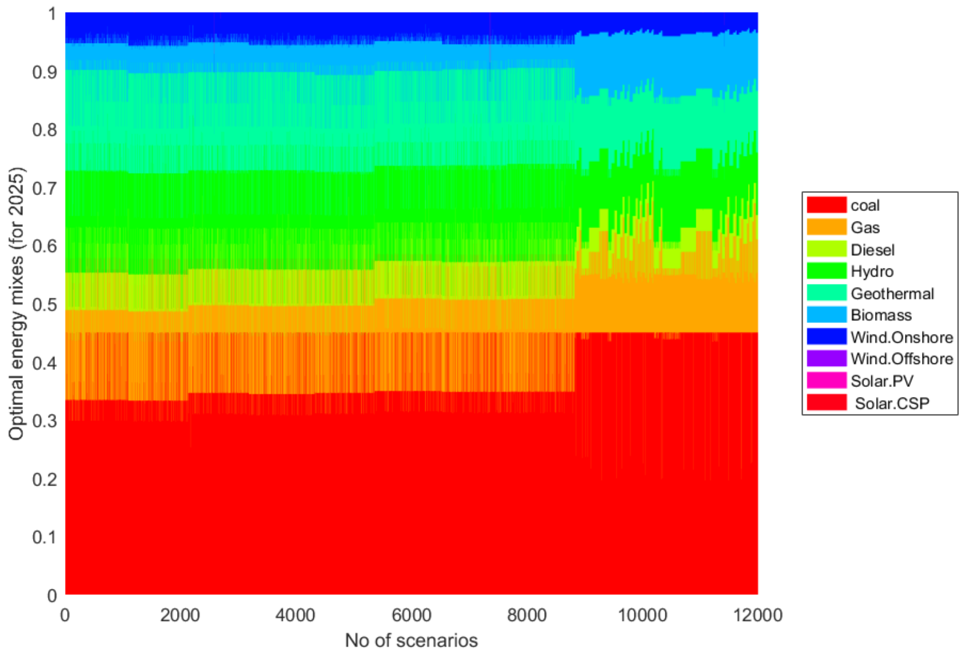


Figure 3-5 Power generation mix across different scenarios (for year 2025)

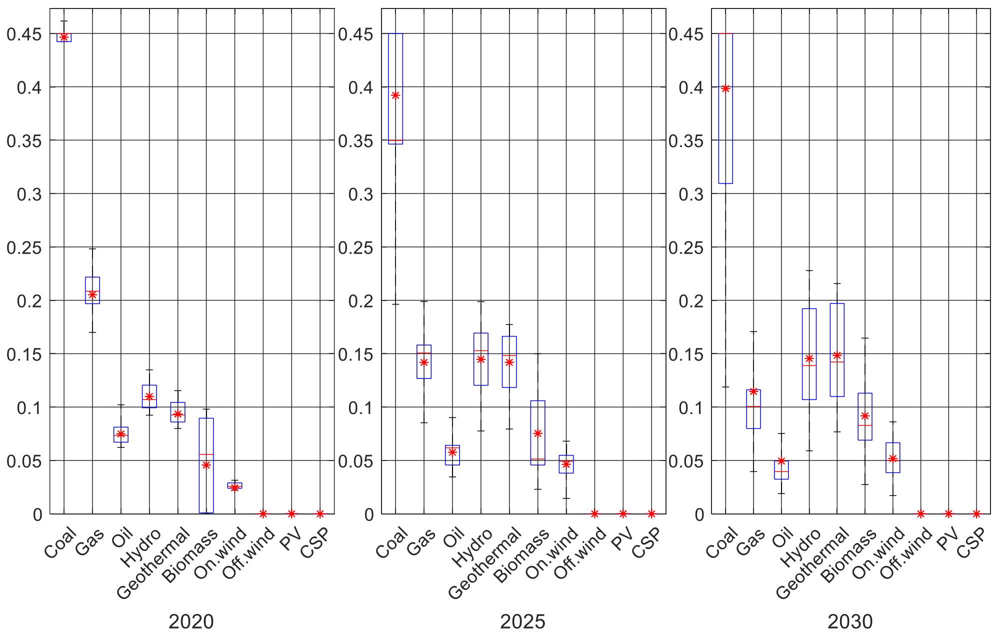


Figure 3-6 Optimised stochastic power generation mix throughout the simulation period under the Baseline Case

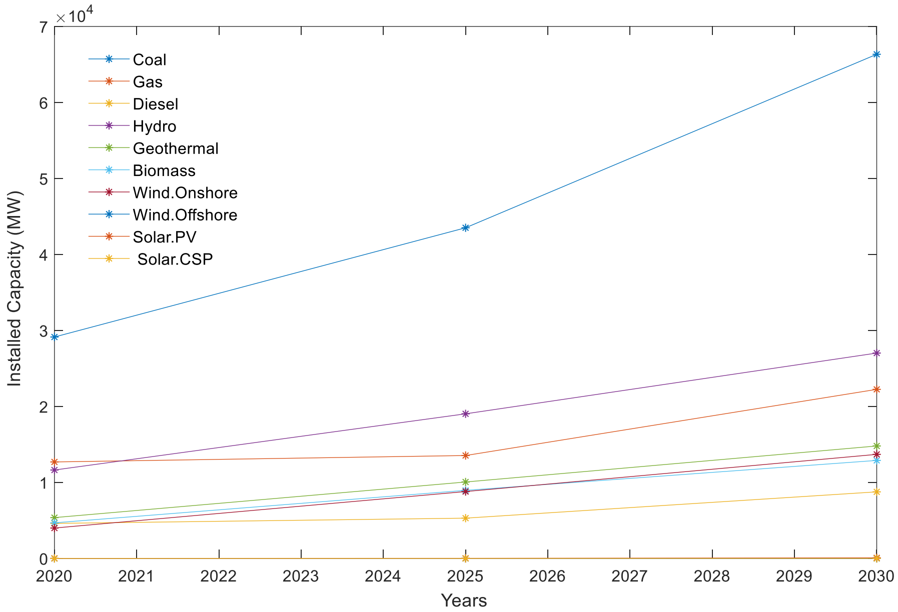


Figure 3-7 Weighted average installed capacity under the baseline case

The proposed model was, then, applied to determine the optimal power generation mix for three Planning Options (POs): Least cost, Policy compliance and Green Energy Policy option.

To illustrate the effect of the different bounds on the set of constraints, the Least Cost PO results are discussed here, while the rest of the results can be found in paper G. The Least Cost PO focuses on minimizing the cost of the power generation system, while no carbon emissions limit, renewable contribution and fuel diversity targets are in place. The power generation mix is dominated by coal power, since there is no imposed carbon emission restriction or renewable penetration target. Even though the renewable penetration of this option is not as high and varied as in other options, it can still fulfil the 25% renewable penetration target for 2030, because of the high contribution of the relatively low cost of hydropower, as well as the contribution of geothermal, biomass and onshore wind power plants. According to the results, overall power generation in 2030 will rely heavily on the three most cost-efficient technologies: coal (57.1%), geothermal (13.2%) and hydropower (13.1%). The rest of the power generation originates from gas (5.9%), onshore wind (4.6%), biomass (3.2%) and diesel power (2.9%). Cost-effectiveness accounts both for the total cost of the technology integrating the capital, fixed operational, variable operational and fuel cost, as well as for the total lifetime duration and the capacity factor of each technology. As can be seen from Figure 3-8, to satisfy the increasing demand at the least cost, coal installed capacity will keep growing rapidly throughout the planning horizon. On the other hand, natural gas and diesel consumption experience a decreasing trend as their contribution is slowly superseded by coal and hydropower.

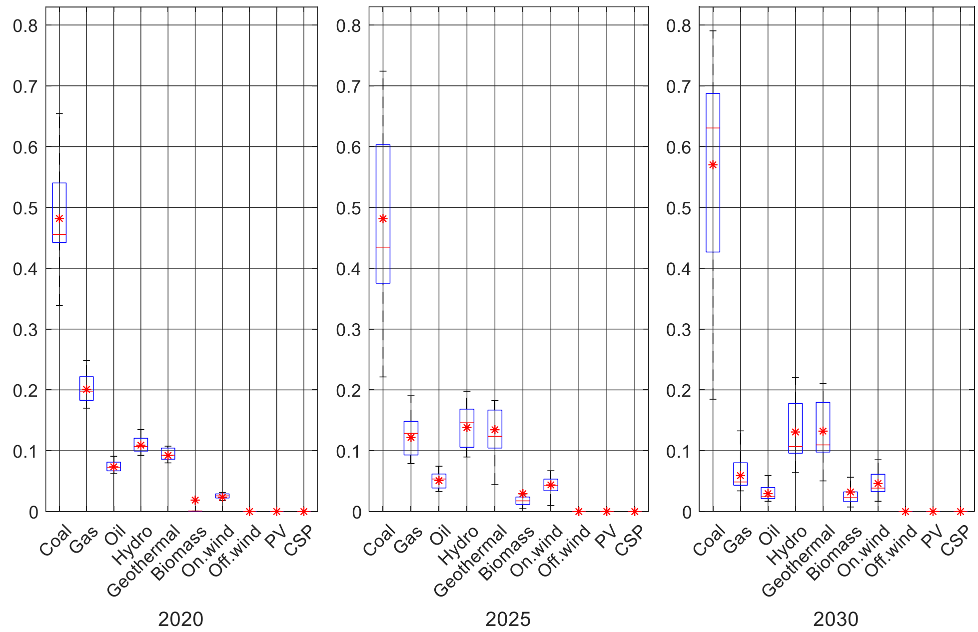


Figure 3-8 Power generation mix for Least cost option

3.2 Technology development level

3.2.1 Outcomes of the lifecycle techno-economic model of offshore wind energy assets

In paper C, the high-fidelity cost revenue model is developed taking into account the life cycle phases of the offshore wind energy investment. The model is particularly developed to account for the different entry and exit strategies of different investors. To demonstrate the model's applicability, a case study of a representative offshore wind farm located in European waters, was employed. Key assumptions of the wind farm site are included in Table 3-2. The 504MW capacity wind farm is located in the North Sea region, 36km away from the port. Weather data (3-hourly data over a 3-year period) were retrieved from BTM ARGOSS [37] for modelling the operational phase of the asset. A wind farm of approximately 500MW capacity was considered a reasonable selection, since there are a number of studies that have considered the same wind farm capacity in their baseline scenario, such as [40], [49], which can allow comparison of results.

Table 3-2 Case study wind farm specifications

Wind farm characteristics		Values
Wind farm	Total wind farm capacity, P_{WT}	504MW
	Projected operational life of the wind farm, n	25years
	Construction years, T_{constr}	5years
	Number of turbines, n_{WT}	140
General Site characteristics	Distance to port, D	36km
	Water depth, WD	26m
Wind turbine	Rotor diameter, d	107m
	Hub height, h	77.5m
	Pile diameter, D_{pile}	6m
	Rated power	3.60MW
	Cut-in speed	4m/s
	Cut-out speed	25m/s

The total undiscounted CAPEX encompassing costs during the Development and Consenting (D&C), Production and Acquisition (P&A), Installation and Commissioning (I&C) and Decommissioning and Disposal (D&D) phases amounts to £1.675 billion, while the undiscounted annual OPEX was estimated £56.6 million.

In Figure 3-9, the relative contribution of the 5 different phases of the life cycle to the total LCOE is presented. It is indicated that the costs incurred during the P&A phase have the largest share of the total costs (46%), followed by the O&M costs (30%). These results are consistent with a number of previous studies [40], [50].

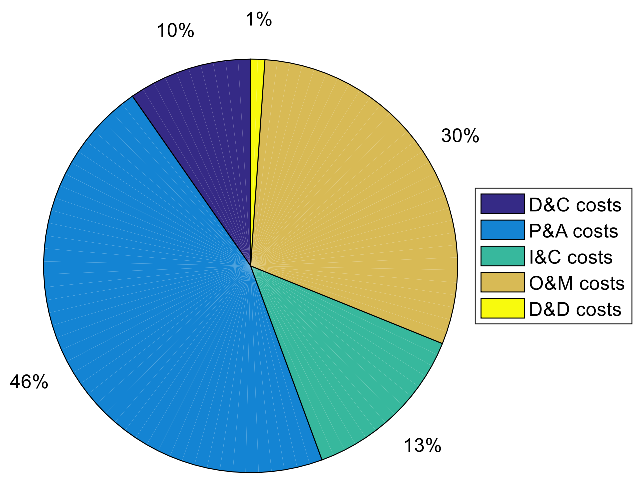


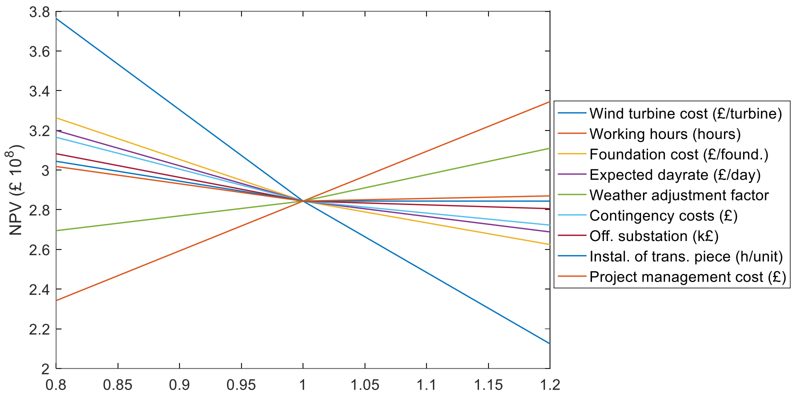
Figure 3-9 Life cycle cost breakdown of reference wind farm

For the sensitivity analysis of the model, the wind farm general specifications and site characteristics were considered as design parameters (parameters that remain unchanged) and the sensitivity of other variables were tested with respect to their influence on the NPV of the investment (as opposed to other works testing sensitivity of design parameters [40], [51]). This allows a targeted investigation of the impact of parameters that can be influenced during the lifecycle of a wind farm of a given location.

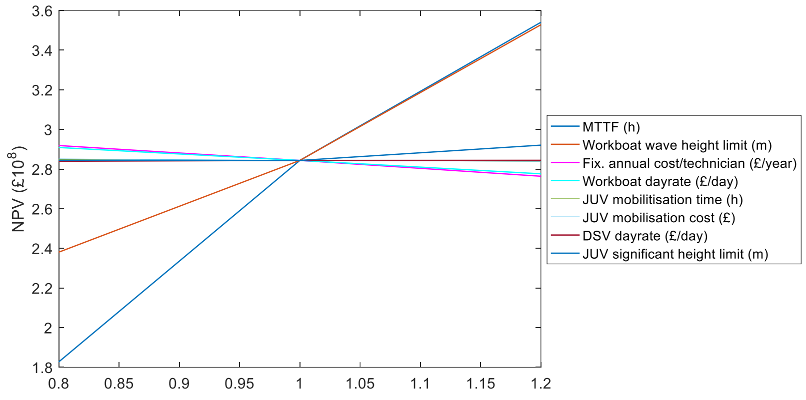
The results of the sensitivity analysis are illustrated in Figure 3-10 (a)-(d). The graphs include parameters which have an influence of at least ±2% (cut-off point) on the NPV upon a 20% increase/decrease in their values. For reference, under the baseline scenario, NPV of the investment was calculated £284.3 million at a real discount rate of 6.15% with an IRR= 10.3%. Further, LCOE was estimated £109/MWh.

The most influential CAPEX parameters appeared to be the wind turbine acquisition cost, the working hours of the personnel during the I&C phase and the foundation acquisition cost, followed by the day rate of the jack up vessels and the weather adjustment factor. As far as the OPEX parameters are concerned, the MTTF and the workboat wave height limit appeared to have the greatest influence on the NPV of the investment. Considering the significant effect of this factor on the feasibility of the project, the operator could consider measures to limit this risk. For example, by leasing workboats, which could provide safe access at higher wave heights or through hiring other modes of transportation. The NPV demonstrated high sensitivity to the WACC (with a 20% decrease in WACC more than doubling the NPV of the investment) and as a result, to its composing parameters (e.g. equity to debt ratio). In fact, a 20% decrease in these parameters, namely the return on equity, the interest rate on debt and the equity ratio increase NPV by 52%, 44% and 32%, respectively.

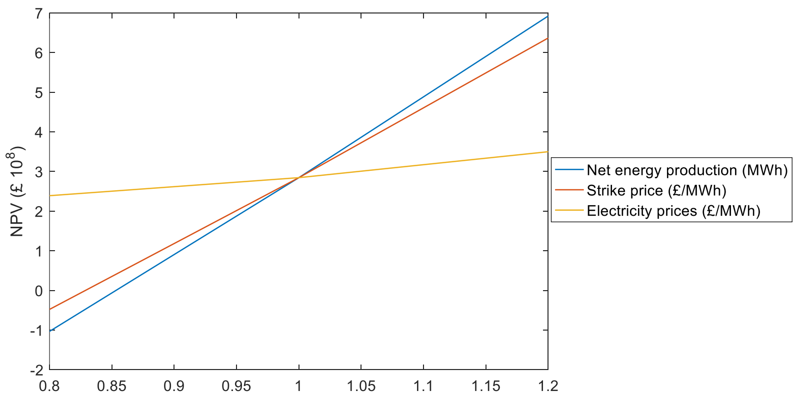
The last observation stresses the importance of financing costs on the feasibility of the investment. It is also noted that cost of equity is almost always expected to be higher than the cost of debt; thus, as the debt ratio increases, the WACC is expected to drop. Nevertheless, third party financing stakeholders would expect to see a reasonable equity being invested in the project to increase confidence in the investment. Hence, the final equity to debt ratio would be a balance of these opposite forces.



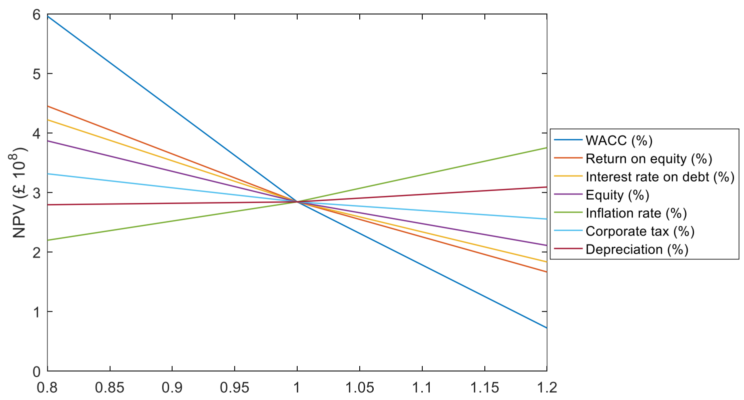
(a) CAPEX parameters



(b) OPEX parameters



(c) Revenue parameters



(d) FinEX parameters

Figure 3-10 Sensitivity analysis results

FinEX and revenues parameters appear to have the greatest impact on the NPV of the investment in comparison to the other two modules of the model, with WACC, net energy production and strike price having the greatest impact.

An objective of this thesis was to assess the expected financial returns from an OW farm asset for investors who are investing and divesting at different times across the service life. Implementation of the model for the respective investment strategies can provide, among other outputs, information regarding the financial return that different investor classes can expect from an investment in an OW farm.

Figure 3-11 (a)-(c) illustrate cumulative cash flow profiles for the three different investor classes (Late entry investors, Pre-commissioning investors, Build-Operate-Transfer investors) identified in paper B. The “Build-Operate-Transfer” (BOT) type of investor suggests that a single investor owns the asset from the consenting up to the decommissioning phase; hence, this is the typical case that financial appraisal studies usually consider. The temporal cost/revenue profile of the BOT investor is illustrated in Figure 3-11 (a). To account for the range of potential WACC values this investor cluster is likely to accommodate, results for WACCs equal to 8% and 10% (representing lower and upper expected levels of WACC respectively for the specific cluster of investors) are presented. The graph provides an estimate of the value of the asset across its life; the estimated break-even year can be found in the intersection of the cumulative cost and cumulative revenue curves (highlighted with the purple circle mark).

The model was, subsequently, applied to the other two investor profiles. “Pre-commissioning” (PC) investors undertake the development and construction of the wind farm, acting as turn-key developers, while they tend to sell the asset once the project is commissioned. Figure 3-11(c) illustrates cumulative costs (dashed red and blue lines) and revenues (solid red line) for an investor entering from year 1 of the asset lifecycle (P&C phase) and exiting at the end of year 5. As expected, since PC investors sell the asset following its commissioning (i.e.

before it starts to produce energy), revenues are expected to be zero before the sixth year of the project's life cycle.

The setting of the sale price of the asset needs to at least cover the construction cost and financing outlay to that point. This cluster of investors comprising OEMs and EPCI contractors have generally weaker balance sheets in comparison to big power producers (belonging to the BOT cluster of investors), and hence, have less financial strength to provide corporate finance to the project. Considering a WACC in the region of 12-15% [45], their cost/revenue profile for the construction period of the wind farm (from year 1 to year 5) is illustrated in Figure 3-11 (c) for the lower and upper bounds of potential WACC values. Assuming a 100% ownership, the PC investor is anticipated to balance the cost spent for the development of the asset and the financing cost (determined by the WACC values), to assess the minimum selling price of the asset. The application of the model indicated that the seller should ask for a minimum price of £1,078 million for a WACC=15% under the baseline scenario, while the minimum asking price when WACC=12% should be £1,170.5 million.

On the other hand, "Late entry" (LE) investors should consider future expected costs and revenues to evaluate the maximum price they can purchase the asset for. Taking into account the fact that this class of investors have more liquidity and stronger balance sheets, their WACC range is lower, approximately between 6% - 12% [45]. In Figure 3-11 (b), the cost/revenue profiles of the asset from year 6 (commissioning year) up to the D&D phase are outlined for WACC values 6% and 12%. Further, the cumulative costs (dotted lines) have been translated to intersect with the cumulative revenues (solid lines) at the end of the service life of the asset (i.e. year 31st). This means that the break-even point is found at the extreme end of the service life and, hence, the NPV=0. The blue dotted line corresponds to the translated cumulative costs for WACC=6%, while the red dotted line for WACC=12%. Correspondingly, the blue and red solid lines reflect the cumulative revenues for the lower and upper WACC limit, respectively. Cumulative costs are discounted to the year of acquisition (i.e., beginning of year 6). The translation of the cumulative costs enables the identification of the extreme purchase price of the asset at the commissioning point, which will allow the late entry investor to make marginal profit. The translation of the cumulative cost is realised by the following expression:

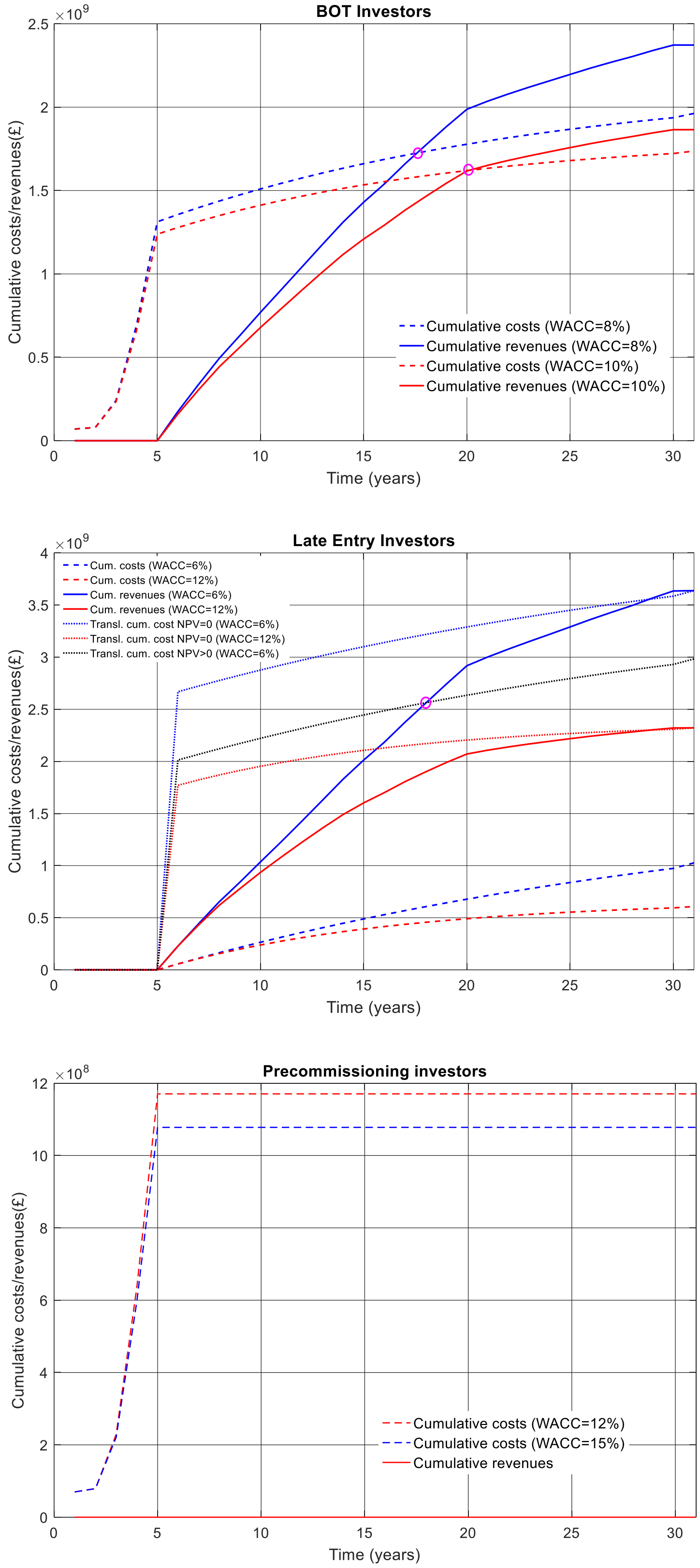
$$DCC_{translated,t} = DCC_t + (DCR_{t=31} - DCC_{t=31}), \forall t = 6, 7, 8, \dots, 31 \quad (3\text{-}2)$$

where, $DCC_{translated,t}$ is the discounted translated cumulative cost at year t, DCC_t is the discounted cumulative cost and DCR is the discounted cumulative revenues at time t.

If the acquisition price, at the point of the purchase, is less than this extreme, the two curves will be intersecting at a time earlier than the service life of the asset (i.e. the 31st year) and the profit margin will increase. For example, as illustrated in Figure 3-11 (b), if the acquisition price of the asset at year 6 (or else the discounted translated cumulative cost at year 6) amounts to £2 billion, the breakeven point will be reached during the 18th year, which is the intersection of the cumulative cost (black dotted line) with the cumulative revenues denoted by the blue solid line, assuming that WACC=6%.

Considering the upper and lower WACC bounds considered for this type of investor, the maximum price of purchase is, thus, £1,770 million for WACC=12% and £ 2,668 million for WACC=6%, as indicated by the red and blue dotted lines at the beginning of year 6, respectively. Therefore, it is deemed that the final price of the asset would, most probably, lie in the region between the minimum selling and the maximum purchase price, estimated by the PC and the LE investors, respectively. For the above-mentioned example, the price of the wind farm is, thus, expected to lie in the region £1,078 million-£2,668 million, depending on the cost of capital of both investors.

However, it must be highlighted that the "price" and the "value" of the asset represent different concepts, with the price of the asset being determined by supply and demand, while the value is estimated by accounting for the cost and the return of an investment [45].



(a)

(b)

(c)

Figure 3-11 Cumulative cost return profiles of the asset from the different investor perspectives

3.2.2 Outcomes of parametric expressions for CAPEX, OPEX and LCOE values

Paper C formed the basis for papers D and E, with the former comprising the development of a set of parametric expressions linking global deployment parameters with key financial performance indicators and the later performing the stochastic expansion of the lifecycle techno-economic model by the employment of advanced numerical methods.

As such, in paper D, the integrated cost model was applied to a number of scenarios aiming to map the cost performance across the multi-dimensional domain of the four independent variables. Subsequently, a set of nonlinear relationships was assumed based on the observation of the relationship between the input global parameters and the output variables (CAPEX, OPEX and LCOE), ensuring a realistic approximation and avoiding cases of overfitting which may reduce accuracy in the results. Once the most appropriate regression expressions were determined, a set of overall relationships were developed for each of the dependent variables and the nonlinear coefficients were estimated through application of the maximum likelihood method for a pre-determined shape of the target equation. The analysis also returned the overall value for the regression coefficients providing an indication on the overall quality of fit of the quantities considered. Based on the above, the following three expressions are proposed, considering the most up to date information and high-fidelity cost modelling structure in order to link the macro-variables, namely P_{WT} (MW), WD (m), D (km) and P_{WF} (MW) to the OPEX, CAPEX and LCOE figures.

$$\mathrm{dOPEX} = -6.349 \cdot 10^{8} \cdot \mathrm{P_{WT}}^{0.187} + 2.595 \cdot 10^{-19} \cdot \exp(0.830 \cdot \mathrm{D}) + 8.413 \cdot 10^{5} \cdot \mathrm{P_{WF}} + 9.506 \cdot 10^{8}, \text{ in £} \tag{3-3}$$

$$\mathrm{dCAPEX} = -1.485 \cdot 10^{11} \cdot \mathrm{P_{WT}}^{0.001} + 2.353 \cdot 10^{6} \cdot \mathrm{WD} + 2.530 \cdot 10^{6} \cdot \mathrm{D} + 2.451 \cdot 10^{6} \cdot \mathrm{P_{WF}} + 1.487 \cdot 10^{11}, \text{ in £} \tag{3-4}$$

$$\mathrm{LCOE} = 110.370 \cdot \mathrm{P_{WT}}^{-2.260} + 0.167 \cdot \mathrm{WD} + 0.004 \cdot \mathrm{D}^{2} + 0.001 \cdot \mathrm{D} + 2.889 \cdot 10^{9} \cdot \mathrm{P_{WF}}^{-3.399} + 95.045, \text{ in £/MWh} \tag{3-5}$$

The R^2 for each of the expressions are 0.986, 0.999 and 0.983 respectively, denoting a satisfactory fit to the original data. Furthermore, the data for the independent variables for the different scenarios were used as predictors using the regression coefficients and the average value of the absolute errors that were measured in each case were 1.62%, 0.83% and 0.82%. Finally, a series of separate test scenarios were run in order to test the performance of the model while interpolating and the results are summarised in Table 3-3.

Table 3-3 Testing scenarios and results produced by model and parametric expressions

Testing scenario		#t1	#t2	#t3	#t4
P_{WT}		**6**	3.6	3.6	3.6
WD		26	**15.6**	26	**15.6**
D		36	36	**21.6**	**21.6**
P_{WF}		504	504	504	**302.4**
$dOPEX$ (£)	**Par. expression**	4.872E+08	5.680E+08	5.680E+08	3.984E+08
	Cost model	5.036E+08	5.590E+08	5.569E+08	3.909E+08
	Error (%)	-3.3%	1.6%	2.0%	1.9%
$dCAPEX$ (£)	**Par. expression**	1.269E+09	1.336E+09	1.324E+09	8.055E+08
	Cost model	1.293E+09	1.325E+09	1.313E+09	8.108E+08
	Error (%)	-1.8%	0.8%	0.8%	-0.7%
$LCOE$ **(£/MWh)**	**Par. expression**	108.4	110.9	109.3	116.3
	Cost model	107.6	111.1	107.2	115.7
	Error (%)	0.8%	-0.2%	1.9%	0.5%

3.2.3 Outcomes of stochastic expansion of the techno-economic model

Moving forward, in paper E the stochastic expansion of the parametric model was carried out. To this end, advanced numerical methods, namely Artificial Neural Network (ANN) approximation model and an Auto-Regressive Integrated Moving Average (ARIMA) time series model were combined with Monte Carlo simulations in order to assess the impact of the system uncertainties on the performance of the asset. Joint probability distributions of the output variables, namely the NPV, capital cost, annual operating cost and LCOE are presented, providing insights regarding the profitability of the asset within defined confidence intervals.

The joint probability distributions of the NPV, LCOE, CAPEX and annual OPEX are plotted in Figure 3-12,Figure 3-13, Figure 3-14 and Figure 3-15. Because of the significant impact of the strike price on the NPV of the investment, probability plots under three different scenarios of strike prices, namely 100, 120, 140 £/MWh, are presented. The resulting NPVs demonstrated an approximate normal distribution. As expected, increasing the guaranteed tariff (strike price) on the wind farm energy output shifts the NPV probability distribution to the right, towards higher NPVs, thus, increasing the total value of the asset. As such, while for a strike price of £140/MWh, there is only 1% chance for the investment to yield a negative NPV, it is deemed that a strike price of £100/MWh would render the investment no longer profitable for the investor, since the chance of a positive NPV would fall below 1% under the specifications of the baseline scenario.

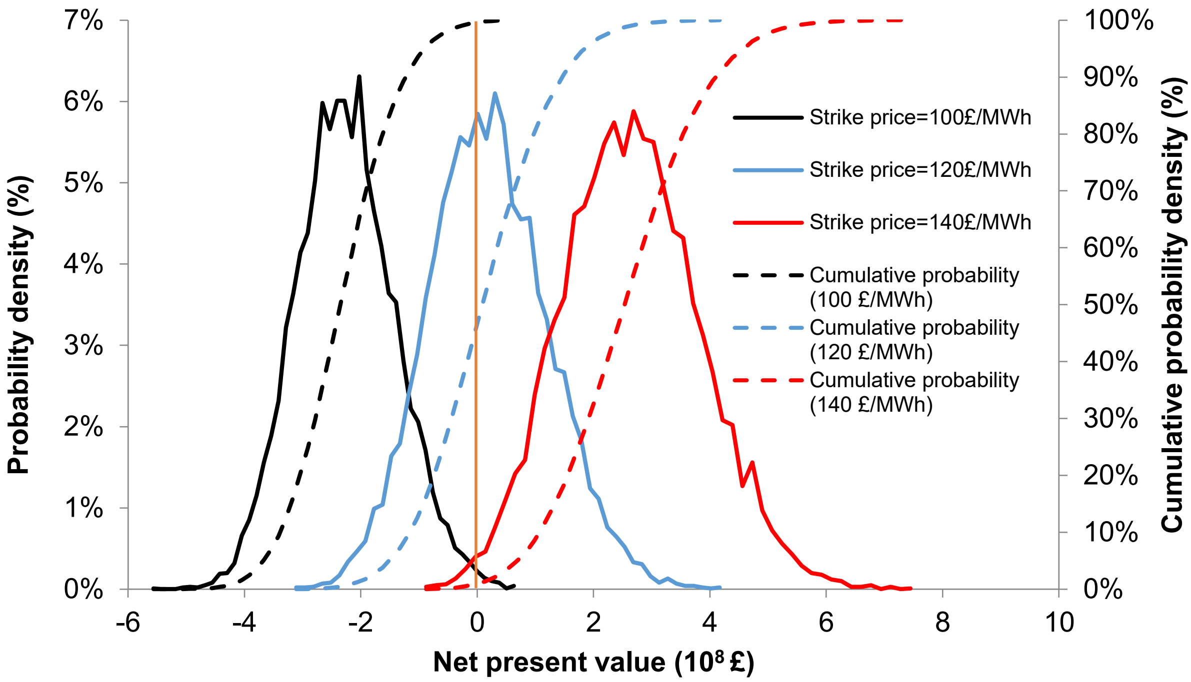


Figure 3-12 Probabilistic results of NPV under three different strike prices (£100, 120 and 140/MWh).

Furthermore, the probability plot of LCOE is illustrated in Figure 3-13 and it demonstrates there is a high probability at a 90% confidence interval the cost of energy lies within £93.6-115.5/MWh. The deterministic analysis of the LCOE has indicated a value of £108.9/MWh; nevertheless, according to the probabilistic analysis, it is deemed that there is an approximately 20% probability that the NPV can achieve higher values. Accordingly, the probability plot of investment cost approximates a normal distribution shape as depicted in Figure 3-14. The CAPEX output lies in the range of £1.60-1.77 billion at a 90% confidence interval (CI). The outcome of the deterministic model (£1.67 billion) was concluded to lie in approximately the median value of the distribution derived from the stochastic analysis. The probabilistic results of annual OPEX (Figure 3-15) indicated a range of £55.0-58.4 million per year for a CI of 90%.

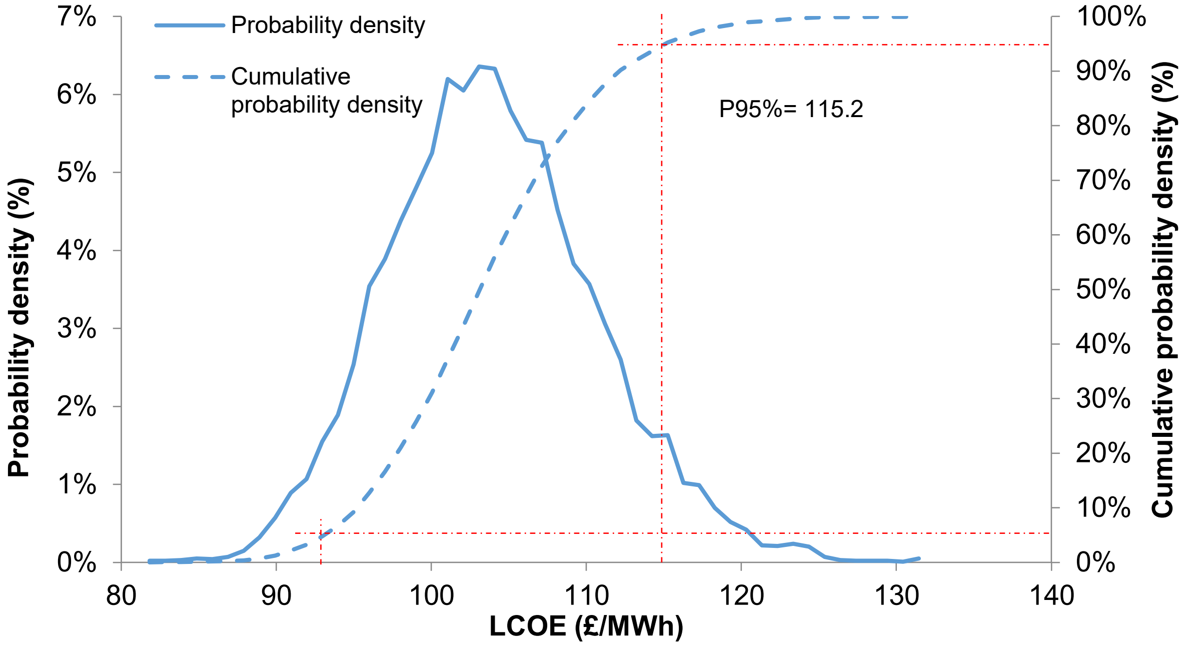


Figure 3-13 Probabilistic results of LCOE (£/MWh)

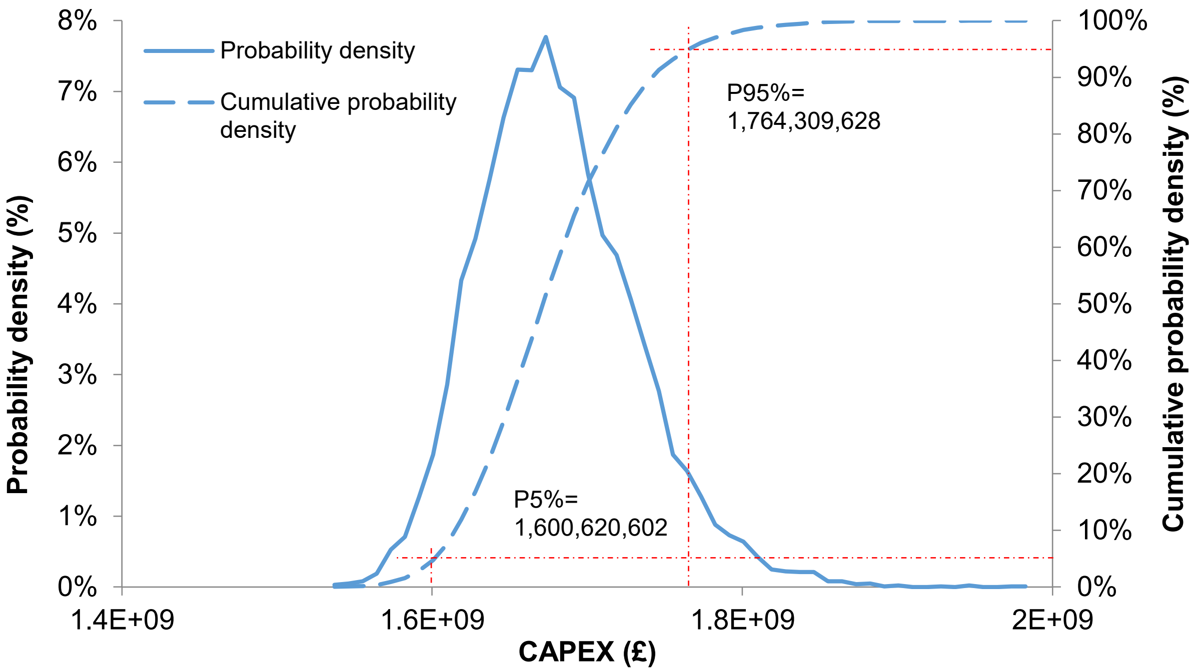


Figure 3-14 Probabilistic results of Capital costs

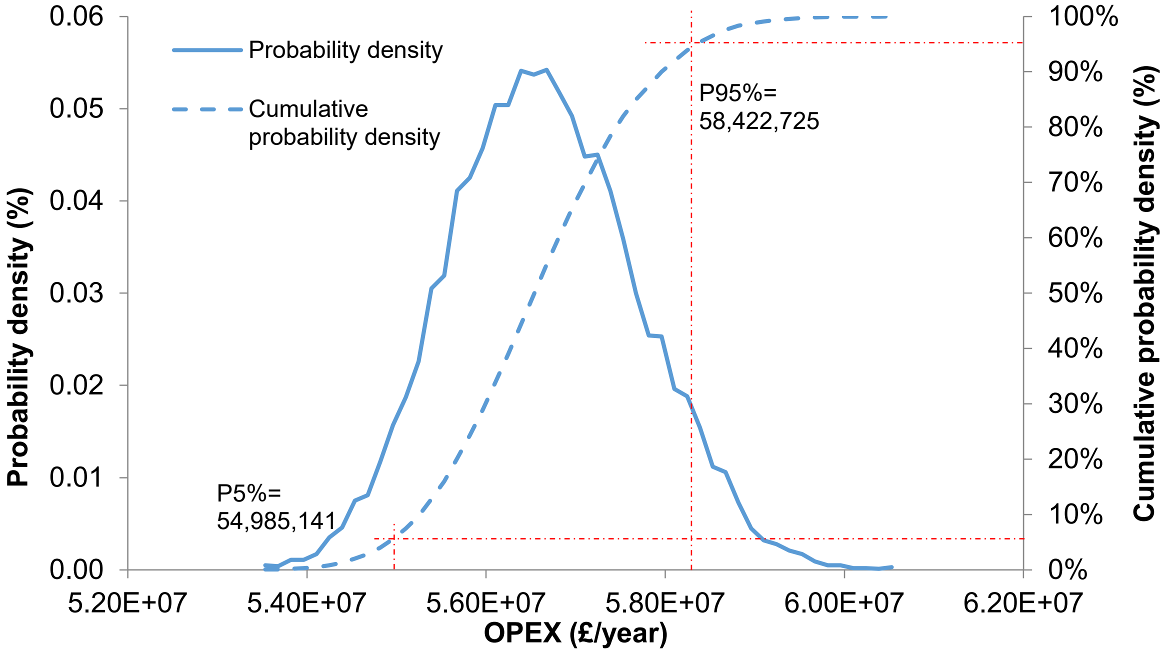


Figure 3-15 Probabilistic results of O&M costs

A sensitivity analysis of the variability of the stochastic variables was accordingly employed, based on the assessment of an increase/decrease of 20% of the standard deviations of the key statistic parameters on the NPV. Considering the mean NPV resulting from the probabilistic analysis under strike price=140£/MWh (reaching a value of £ 266.1 million) as the baseline case, the outcomes of the sensitivity analysis are presented in the Tornado plot in Figure 3-16. It should be noted that since strike prices were modelled by means of scenarios and electricity prices by means of time series the sensitivity of NPV on their variability has not been included in this analysis.

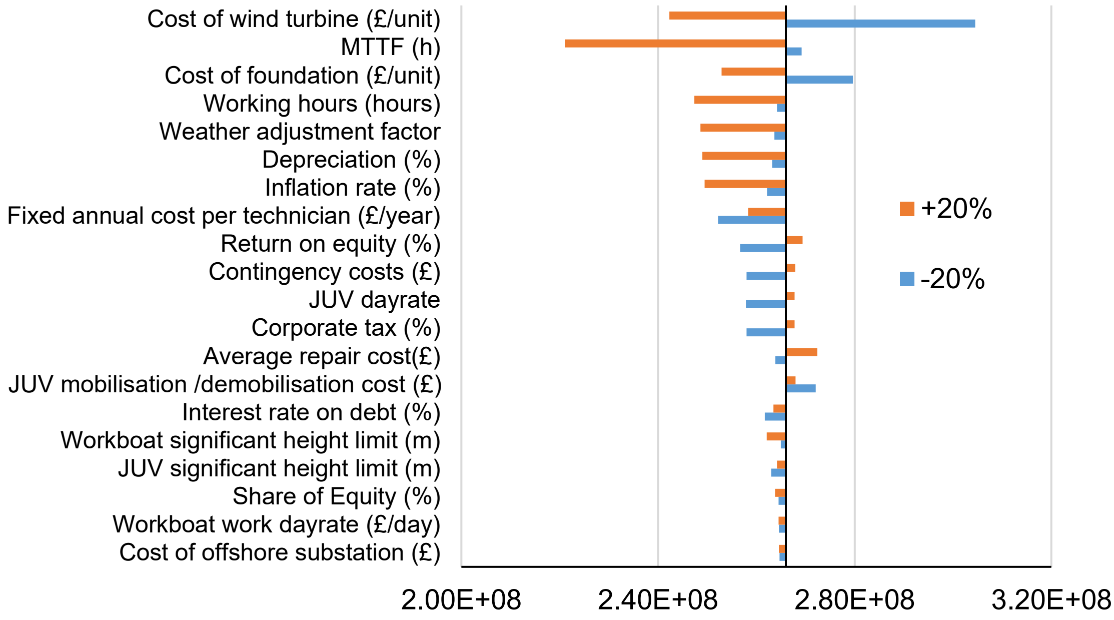


Figure 3-16 Tornado Chart - Sensitivity Analysis of standard deviations on NPV (£)

Variables whose variance appeared to have notable impact on the NPV were in descending order of impact: the cost of turbine component, the mean time to failure, the cost of foundation, the working hours and the weather adjustment factor. The general conclusion that can be drawn from this graph is that the increase in the standard deviation of key variables, results in increasing investment risk, hence reducing the confidence on the profitability of the investment. Nevertheless, increasing the variance of some parameters such as the return on equity and the contingency costs appears to result in slightly higher NPVs, which can be explained by the randomness of each Monte Carlo simulation. As shown above, considerable differences compared to the standard deterministic sensitivity analysis were observed, where the return rates of equity and debt, the MTTF, the share of equity, the cost of turbine, the inflation rate, and the working hours per shift were among the most significant variables.

3.2.4 Outcomes of the development of risk control policies for operational uncertainties of offshore wind energy assets

Finally, paper F uses the same wind farm characteristics summarised in Table 3-2 to apply the model developed for the calculation of operational KPIs (presented in section 2.2.7) across a number of different locations in a region by the south east coast of the UK.

Weather data were obtained from the BTM ARGOS database for a set of 204 different locations with latitude and longitude coordinates ranging between [0.000°, 2.667°] and [50.000°, 53.667°], respectively as shown in Figure 3-17. This region was selected due to its high concentration of currently operating and under construction Round 1, 2 and 3 wind farms [52].

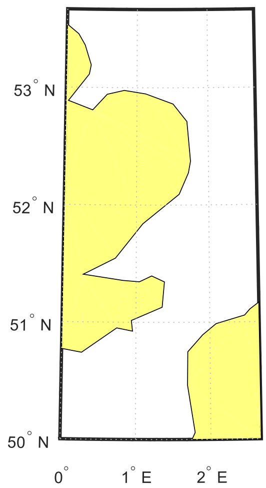


Figure 3-17 Focus region located in the south east coast of the UK

Existing ports near the locations of the focus region were identified from 4C offshore [53] and their coordinates are summarised in Table 3-4. It was assumed that each wind farm (located to each of the 204 locations) is served by its closest port. The cost of main and support vessels, crew and materials were adopted from [54].

Table 3-4 Coordinates of nearby ports

Port	Longitude	Latitude
Wells	52.954	0.853
Great Yarmouth	52.583	1.735
Lowestoft	52.473	1.755
Harwich Navyard	51.948	1.288
Sheerness	51.443	0.748
Ramsgate	51.327	1.412
Newhaven	50.7903	0.0546
Shoreham	50.8311	0.2381

3.2.4.1 Operational KPIs for a specific location

The model was initially applied for the prediction of the operational KPIs of the reference wind farm installed in the location with coordinates [0^o, 50.334^o]. The power output of each of the 140 turbines as well as the breakdown of downtimes are illustrated in Figure 3-18 and Figure 3-19, respectively.

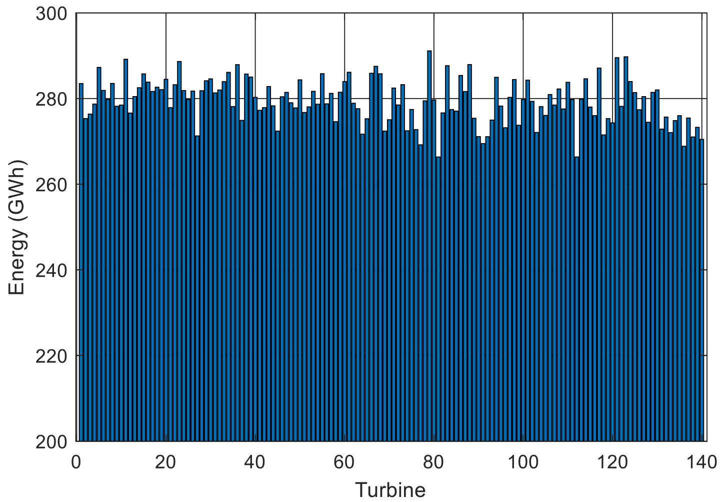


Figure 3-18 Power output per each turbine

Total power output was calculated 38,823 GWh and the total downtime $3.6658 \cdot 10^6$ hours with a power-based availability of 90.3% and a time-based availability of 89.1%. The downtime due to weather unsuitability had the highest share of the total downtime (21%) followed by the repair time (18.3%) and the spare availability downtime (12.6%).

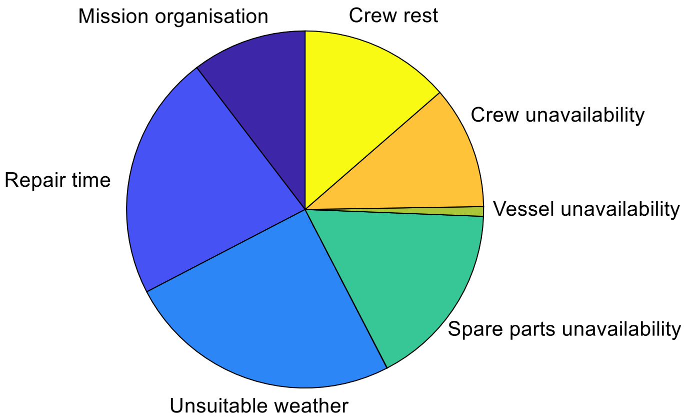


Figure 3-19 Breakdown of downtimes

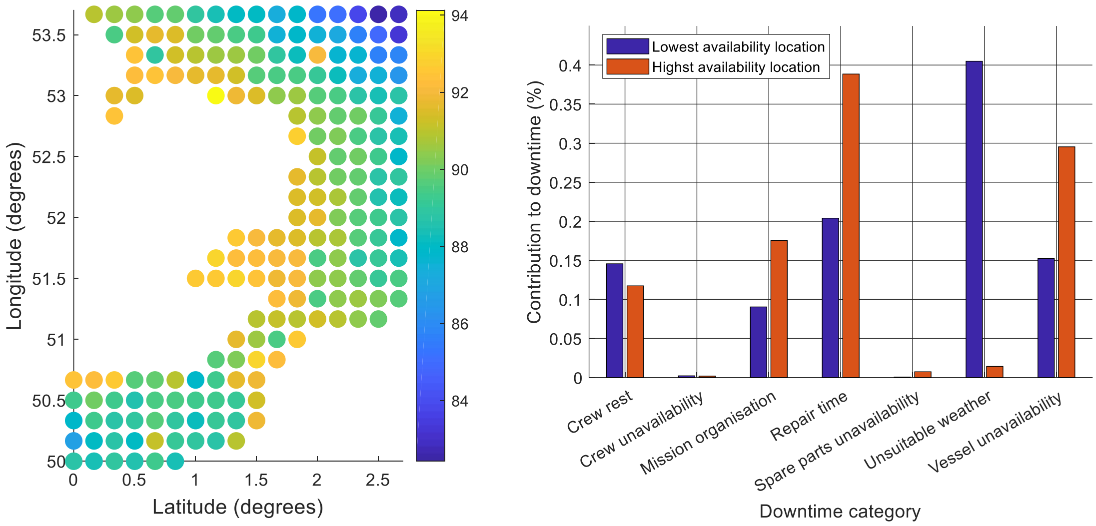
Total wind farm O&M cost during the entire service life was estimated at £686.5 million. Above results on the availability and O&M total costs show good agreement with a benchmarking study estimating O&M costs of an offshore wind farm located also in the south coast of the UK [55].

3.2.4.2 Parametric estimation of operational KPIs

Accordingly, the results from the application of the model for the 204 locations in the south east coast of the UK (corresponding to a respective historic weather dataset) were used to derive a number of location-specific colour-coded plots, illustrating resulting operational KPIs across the whole region.

The production-based wind farm availability results are plotted in Figure 3-20(a) for each of the 204 sets of coordinates under investigation. Higher availability levels can be observed in areas closer to the coast of the specified region (noting that half a degree is equivalent to 56 km). This can be attributed to the smaller distances between the port and the wind farm site, as well as the lower magnitudes of significant wave height and wind speed limits, improving the accessibility of the maintenance vessels for the performance of unplanned maintenance, hence reducing the total downtime of the asset. In general, results demonstrate a smooth transition from high availability values in locations positioned closer to the coast to gradually decreasing further from shore. Nevertheless, a number of outliers can be observed, for example the location point [2.000º 53.334º], where an availability peak is noted; this could be the result of measurement uncertainty of the historic met ocean data.

Figure 3-20 (b) illustrates the breakdown of downtimes for the location with the lowest and highest availability. Weather downtime appears to have the greatest contribution to the total downtime for the lowest availability location, while repair time is the main contributor for the highest availability location.



(a) (b)

Figure 3-20 Production-based availability (%) around the focus area of the study and (b) contribution of downtime categories to the highest and lowest availability locations

Figure 3-21 illustrates the total O&M cost per MWh, revealing a more uniform distribution of unit cost in relation to the availability values across the different locations. This is due to a trade-off of higher power generation due to better wind speed profiles and higher O&M costs due to decreasing accessibility of vessels for maintenance operations. Nevertheless, exceptions of this observation can be found, for example, in the areas positioned in the southern part of the specified region, where high availability together with relatively low unit costs can be observed.

Finally, the expected total power production loss due to the wind farm downtime is plotted in Figure 3-22. Production loss reflects the total revenue loss due to downtime, as it is calculated by subtracting the power produced during uptime from the potential power produced both during uptime and downtime (wind speed profile of the location is also taken into consideration); it is therefore a parameter with a great impact on the financial performance of the investment. The power production loss plot was found to follow a similar to the availability plot pattern, with locations closer to shore indicating lower revenue potential losses due to the reduced downtime of the wind farm.

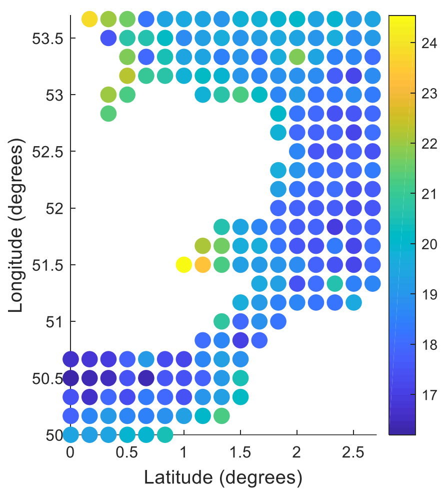


Figure 3-21 O&M cost per MWh scatter plot around the focus area (£/MWh)

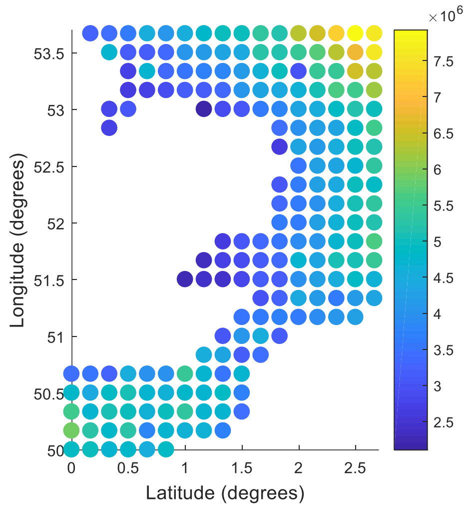


Figure 3-22 Production loss scatter plot around the focus area (MWh)

3.2.4.3 Weather risk control policy options

Traditional insurance products available for renewable energy projects typically protect against natural disasters [56] and physical losses during construction/operating phases [57]. Furthermore, academic literature on the effects of weather risks on offshore wind energy projects also focuses on analysing the effect of extreme weather events [58]–[60].

Risk management against the effect of seasonal fluctuations in climatic conditions, such as variation in wind speeds, temperature and wave height is becoming more relevant as investors are inclined to reduce their risk exposure.

Weather risk hedging products are usually financial contracts which can be executed in the form of insurance or weather derivatives structured as swaps, futures and options that are based on a weather related index [61]; in the case of offshore wind, significant wave height and wind speed could be relevant weather related indices. The seller of the weather derivative bears the risk of potential financial losses as a result of the weather conditions in exchange of an upfront premium. If the pre-determined limit of the index is surpassed, over a specified period, the project owner is compensated the downtime financial losses.

The index-based policy structure has the advantage of simplicity, although there may exist some ambiguity in terms of the actual financial impact caused by the exceedance of the specified threshold. In the case of offshore wind, for example, exceedance of the threshold of the significant wave height limit over a specified period of time may not necessarily lead to financial losses. On the contrary, power production loss due to downtime could be a risk index easier-to-translate into resulting revenue losses over a period of time, while relevant data can be retrieved by SCADA (Supervisory Control and Data Acquisition) systems installed in the wind farm.

Figure 3-23 illustrates the resulting power production losses due to the downtime on a monthly basis for the reference wind farm installed in the location [0.000^o, 50.334^o]. A threshold of 45,000 MWh over the period of a month was assumed, above which the buyer of the risk transfer product is compensated for the revenue loss corresponding to this threshold. The estimation of the premium should be based on the probability of exceedance of the specific limit. With a 5.9% monthly probability of exceedance, the risk of the investor is estimated (in terms of production losses) $45{,}000 \cdot 5.9\% = 2655$MWh. Assuming a strike price of 100 £/MWh, the maximum premium that the buyer would be willing to pay is therefore £265,500 per month.

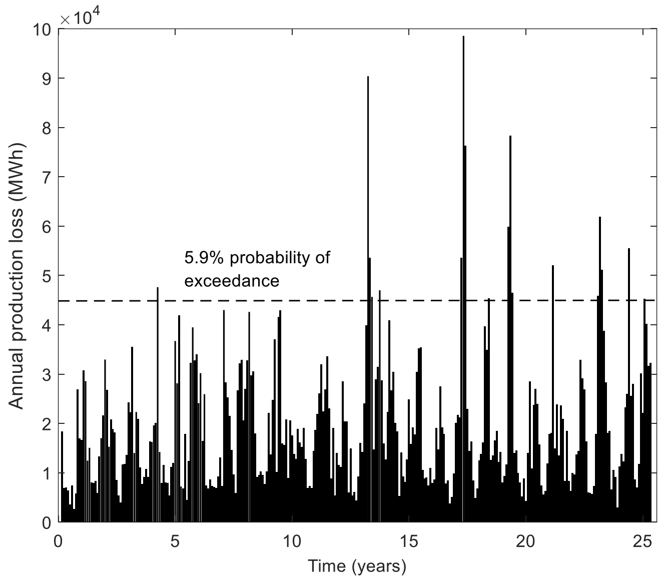


Figure 3-23 Monthly power production losses as a function of time for the location with coordinates [0.000º, 50.334º]

The exceedance probability (EP) curve is used by insurers to estimate the probable maximum loss (PML) for a portfolio of investments in a given period of time. The PML is a bespoke risk metric and is associated with a probability of exceedance reflecting the insurer's acceptable level of risk. As such, the insurer can use the EP curve to determine the magnitude of loss at the desired probability of exceedance level. In Figure 3-24, the monthly EP curve of the reference wind farm is demonstrated. The EP curve can also assist the distribution of losses between stakeholders. As such, the project owner would retain the first part of the loss (i.e. the deductibles), for example losses up to 45,000MWh, while the insurer covers monthly production losses occurring in excess of this amount.

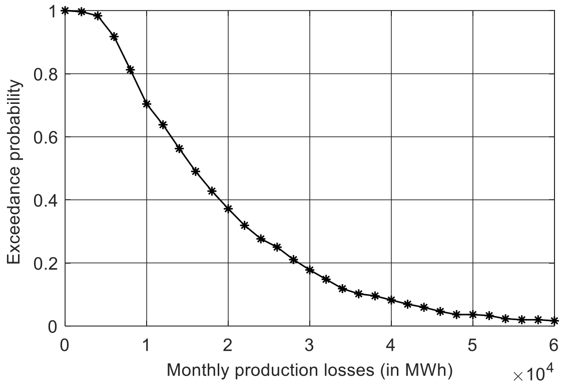


Figure 3-24 Exceedance probability curve

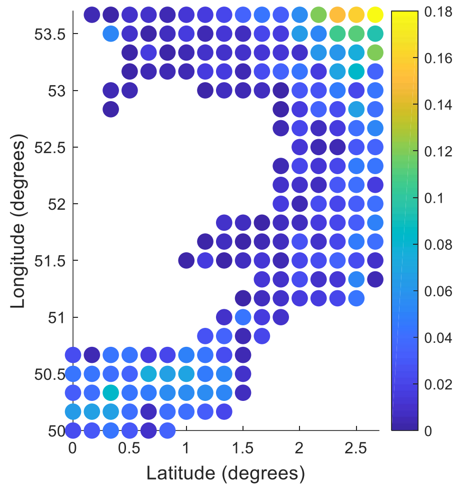


Figure 3-25 Probability of exceedance of monthly power production loss threshold

Setting the above threshold of monthly power production losses (i.e. 45,000 MWh) across all sets of coordinates of the designated region, the distribution of the exceedance probabilities is illustrated in Figure 3-25. For areas closer to the coast, the probability of exceedance does not surpass the level of 6%, while in areas further from shore probability reaches 18%. Comparing the scatter plot of probability of the production loss exceedance threshold with the production losses one (in Figure 3-22), it becomes evident that the amount of power production losses throughout the service life of the asset is not necessarily proportional to the entailed risk of surpassing a threshold set on a monthly or even annual basis. This map can provide a basis for screening which locations are likely to incur higher insurance premiums for weather related parametric risk control products.

4 CONTRIBUTION OF THE RESEARCH

This section aims to consolidate the findings and substantiate the contribution of the EngD thesis and the approach followed to fulfil the objectives. The overall contribution of this work is organised into three pillars: novelty, scientific soundness and value to different stakeholders.

Table 4-1 summarises the objectives of the research project, how these are addressed through the various research activities, along with the contribution of each objective in terms of novelty, scientific soundness and value to different stakeholders.

The first objective was addressed through a systematic literature review responding to a novel research question: which methods have been employed to address/model/incorporate risk and uncertainty attributes (related to energy security, generating costs, market risks, climate change risks, etc.) in sustainable power generation planning and feasibility studies? Furthermore, the assignment of the most appropriate methods to the particular types of risks was an additional outcome of this study. The systematic literature review approach was adopted, through the determination of keywords that would allow access to all relevant key references in a systematic, transparent, and reproducible manner, while also restricting the researcher’s bias [15]. This review will benefit researchers and academics in decision support systems for sustainable energy planning and feasibility studies, but also investors and policy makers who seek to identify the methods that can be most suitable to capture specific risks.

Table 4-1 Contribution of research analysed by means of novelty, scientific soundness and value per each set objective

Set Objective	Novelty	Scientific Soundness	Value to different stakeholders
	What is new?	*What methods have been used and how have they been validated?*	*Who will benefit from this part of the work?*
Assemble a state-of-the-art literature review of risk-based methods for sustainable energy systems planning and technology feasibility studies	The produced review paper responds to a unique research question: Which methods can be adopted for decision making under uncertainty for energy investments. Furthermore, it aims to find which methods are more suitable to address each type of risk.	The systematic literature review methods that was adopted allows to distinguish the relevant papers based on a set of predefined words, alleviating the bias of the reviewer and ensuring that all key references are included in the analysis.	This review can be valuable primarily to researchers and academics in decision support systems in energy related problems, listing latest applications of different methods and highlighting benefits and limitations of each method.
Distinguish different investment strategies followed by investors in the offshore wind energy industry through a multi-attribute cluster analysis	This analysis has collected real data from all existing wind farms in the UK and based on this data distinguished three distinct clusters of investors with common investment/divestment behaviour.	The systematic multi-attribute cluster analysis method that has been adopted in combination with the high quality of data that have been gathered ensure validity of the derived clusters.	This work can be relevant to researchers and policy makers which target policies and financial products which can be targeted to each of the clusters identified.
Develop an integrated, high-fidelity lifecycle techno economic model which allows for the temporal evaluation of a renewable energy investment, integrating (and developing) most relevant cost expressions	The life cycle costing approach that has been followed stands for the most analytical financial analysis presented to-date combining the detailed costing of all phases in the service life of an asset with modelling of revenues and temporal effect of cash in-flows and out-flows. Application of the appraisal model for different types of investors is also an achievement of this work.	This work has investigated detailed cost expressions qualifying the most relevant ones to the latest generation wind farms and derived new ones, where necessary, based on reliable data retrieved from existing wind farms. The cost of financing has been analytically modelled and a baseline application of the framework has been validated with parallel studies and published data.	This financial appraisal framework will be of value to investors aiming to appraise wind energy investments as well as consultants and researchers aiming to benchmark the effect of different technological options to the overall profitability of an investment. The framework developed can be transferred to other technological options, i.e. marine and onshore energy applications.
Formulate relevant parametric equations through appropriate selection of approximation models for the conceptual design and analysis of offshore energy assets	A set of new, convenient to use parametric equations have been developed, linking global input variables (i.e. distance from port, capacity of wind turbine) to output KPIs such as CAPEX, OPEX and LCOE. These expressions have applicability relevant to the current and next generation wind energy investments.	The expressions have been derived based on the validated high-fidelity financial appraisal method that was developed earlier. Nonlinearity of expressions has allowed for a good fit of the resulting curves as indicated by relevant statistical metrics and a series of testing cases that have run for validation of the resulting model.	These expressions can be of value to practitioners (investors, policy makers, researchers and academics) who aim for a high-level assessment of the cost of an offshore wind farm investment at the conceptual stage, once limited information is available.

Set Objective	Novelty	Scientific Soundness	Value to different stakeholders
	What is new?	*What methods have been used and how have they been validated?*	*Who will benefit from this part of the work?*
Expand the financial appraisal model to consider uncertainties of key input parameters through selection and implementation of appropriate methods	A stochastic expansion of the high-fidelity financial appraisal model has allowed to assign confidence levels to the expression of the resulting financial KPIs, as a result of uncertainties present in the analysis. This approach can be expanded to other deterministic models as it follows a staged approach to link the different stage of the expansion approach.	The Monte Carlo simulation method that has been adopted is a versatile method allowing the convenient expansion of deterministic models, once high numbers of probability are expected to be calculated. Forecasting of whole sale electricity price has been modelled through ARIMA, a suitable method for long term forecasting, using real historical data. The ANN method has been applied for generalisation of the O&M costs as a suitable approximation method for complex and nonlinear systems. The individual methods have been validated for specified test cases.	The stochastic expansion approach can be of value to investors, policy makers and researchers investigating systems with high uncertainties. The method can be applicable to a wide variety of engineering applications where different tools can be adopted for each stage of the analysis, alleviating the need for a fully integrated code to account for stochasticity of inputs.
Evaluate weather uncertainty during O&M and visualise cost performance and production losses through scatter plots	The developed module allows for the parametric calculation of operational key performance indicators (KPIs) and allows for recurring simulations for different locations, enabling the visualisation of the KPIs in scatter plots. Furthermore, the model can estimate the probability of exceedance of a set production loss threshold, evaluating the risk for deployment in different locations.	The development of the module includes a weather module for the forecasting of environmental conditions using Markov Chains and a structured approach for O&M planning to allow calculations of MTTR, MTTF and availability. The module was verified through comparison of availability and operating cost results for a baseline case against a benchmarking study.	The model that is developed is of value to researchers and practitioners who work on the planning and evaluation of O&M activities related to the operation of offshore wind energy assets. It can be particularly relevant to the insurance industry as new parametric risk control products can be qualified relevant to revenue cost modelling and risk transfer strategies offered to investors.
Develop and apply a stochastic optimisation framework for deriving optimal national energy technology mixes taking into account uncertainties of the system	An optimisation approach has been developed to allow for the derivation of the optimum energy mix under the presence of uncertainty. The approach can consider multiple constraints to reflect energy policy strategies, and contextual factors and can be applied to different locations. The novelty of this work lies in the extension of the possibilistic uncertainty modelling approach to a stochastic one allowing for certain random variables to be represented through continuous probability density functions, leading to a more realistic representation of uncertainty.	The multi-stage probabilistic approach that has been adopted and expanded to also account for a set of stochastic variables through Monte Carlo simulations can systematically account for uncertainty in the analysis. Particularly for the application presented, high quality data have been used for appropriate contacts that were consulted.	This work can be relevant primarily to policy makers who aim to translate energy policy strategies into a mix of technologies that should be added to/removed from the existing technological mix. The expansion of the method to account for stochastic variables (rather than only probabilistic expression) can more accurately represent potential future scenarios and can be applied in multiple relevant problems.

Paper B produced a cluster analysis, which classified 83 cases of investors investing or divesting part (or entirety) of their stake from a total of 27 operating wind farms located in the United Kingdom, disclosing the existence of distinct entry and exit investor strategies. The cluster analysis preceded the development of the lifecycle techno-economic model is the first attempt in the literature to clearly distinguish distinct investor profiles. Existing literature on the financial returns from renewable energy projects assumes that there is a single investor who owns the asset (e.g. the wind farm) throughout its entire service life [62]–[65]. However, as indicated from the cluster analysis, it is often the case that equity investors buy and sell their stakes at different phases of the OW farm service life, depending on their investment strategy [4], [66]. This output can help those wishing to develop customised commercial products and optimisation of financial schemes and financing parameters, which can later influence investor's and policy makers' future decisions and strategies.

The risk appetite of each cluster of investors can be quantified and then reflected to the return on investment expectation. It should be noted that similar profiles can be distinguished in similar industries involving high value assets such as the offshore oil and gas industry from which we can infer/anticipate further clusters of interest to be developed as offshore wind energy assets approach their end of lives and with a view to service life extension.

Following on from the cluster analysis, the third objective of this research was the development of a model that predicts temporal returns and can be applied for different entry and exit instances to simulate equity investors' strategies. This model is useful for investors and policy makers wishing to estimate the viability of an investment and to predict its temporal return profile. The high-fidelity financial appraisal model that was developed follows a systematic and transferable approach distinguishing key cost components to higher granularity, integrating in parallel the time relevance of financial cash in and out flows, revenue modelling and cost of finance allowing for different appraisal models to be derived for different investor profiles.

This unique approach can provide initial estimates for the value of a defined asset from a buyer's and a seller's perspective in the case of an asset acquisition, setting logical thresholds which can drive investment negotiations, setting as benchmark the NPV=0. The high-fidelity financial valuation model together with the purpose developed O&M tool can formulate an integrated fully parametric financial valuation model, which allows further advanced studies to be completed, including optimisation of CAPEX to OPEX ratio and supports decisions towards selection of end of life scenarios for return on investment maximisation.

Next, the financial appraisal model was used to produce a number of parametric expressions linking key financial performance indicators with global deployment parameters, with the view to provide initial estimates of the profitability of the investment requiring a limited number of inputs. The derived generalised expressions will be of value to investors, researchers and other stakeholders to undertake an initial estimate of CAPEX, OPEX and LCOE values for offshore wind farm projects with varying design parameters, as well as use them as reference for estimating the effect of the change in one of the selected design parameters**.** The framework developed can be directly transferred to other technological options, i.e. marine and onshore energy applications.

With the deterministic high-fidelity financial appraisal model as a starting point, an extension to a stochastic model, systematically accounting for stochasticity of inputs in the cost revenue model resulted to more meaningful expressions of the financial KPIs of interest. More specifically, it allows for a transition in terminology from a conventional deterministic assessment which results in a single deterministic output value (for a set of constant input values), to a stochastic evaluation with a confidence level according to which the set KPIs lie within predetermined thresholds (in the presence of uncertain inputs expressed as appropriate statistical distributions). For example, the transition from expressing an LCOE value of £108.9/MWh for a set of fixed input variables to a 90% confidence level that LCOE lies within £93.6-115.5/MWh, allows an investor/decision maker to better appreciate the expected performance of the asset/investment in an uncertain environment.

Furthermore, the parametric O&M model that was derived has allowed the evaluation of the sensitivity of the deployment selection and associated revenue loss risk exposure for investors, qualifying potential risk transfer financial instruments that would safeguard the balance sheet of energy investors. In parallel, this evaluation can stand as the basis from an underwriter's perspective for the development of better-informed risk control policies, through parametrically estimating the probability of exceedance of a specified revenue loss threshold, qualifying for the underwriting portfolio related to business interruption due to adverse weather conditions.

Uncertainties involved at an energy system development level are important as they include future trends for key decision factors and can influence determined policies and strategies. The final objective of this thesis was achieved through the development of an optimisation approach which allows for the derivation of the optimum power generation mix in the presence of uncertainty. The probabilistic approach that was adopted and expanded to a stochastic approach through integration of Monte Carlo simulations has allowed the incorporation of uncertainty in inputs as potential outcomes with assigned probabilities or fully stochastic variables as statistical distributions resulting to an evaluation of the energy mix taking into account the joint probability values. Through appropriately selecting the constraints, different policy targets and strategies can be translated into a specific mix of technological decisions. This approach could assist policy makers derive useful insights regarding optimal planning pathways towards sustainable energy systems, taking into account uncertain inputs changing over the planning horizon.

The scientific soundness of the selected methods has been discussed in sections 2.2 and 2.3. Selection of the most appropriate methods followed a systematic literature review which permitted the author to evaluate different applications, advantages and limitations, and variations of each method. Where possible, methods and/or their applications as they have been applied and documented in this thesis have been validated and verified against real data to additional testing simulations. One of the factors on the selection of the methods has also been their versatility ensuring that the different applications can be transferred to different technologies and contexts.

Figure 4-1 distils the thesis' customised outcomes from the different stakeholders' perspectives. Industrial actors comprise project developers, manufacturers, insurers, and other financial actors. The high-fidelity financial appraisal model can be of benefit to both investors and industrial actors, allowing for the fairer valuation of the offshore wind energy asset, as well as the valuation of cost impact of various technological variations/innovations to the total LCC of investments. Incorporating uncertainty in the financial appraisal analysis can increase the confidence of investors and the value of the outputs of the analysis, by assigning confidence levels to the predictions towards better informed decisions. Results of the cluster analysis could potentially be of great importance to policy makers and financing actors towards delivering customised policies and financing products, respectively, throughout the different phases of the lifecycle of the asset. The high-level parametric expressions can be used by investors and policy makers for an initial estimation of the expected cost of an investment as a function of global deployment parameters needing a small number of input variables. The proposed parametric framework linking deployment conditions (wind and wave profile) to the actual potential revenue losses that an operator might have due to the disruption of their activity can assist insurers in delivering better-informed parametric risk control policies towards hedging the financial impact of unforeseen weather conditions on a business. The development and application of methods systematically accounting for uncertainties, along with the systematic literature review on methods relevant to decision support in energy applications, can be of value to researchers and academics working on relevant fields of research. Finally, the stochastic multi-stage optimisation framework developed can stand as a useful tool for policy makers in order to derive the power generation optimum mix under a set of constraints and policy priorities.

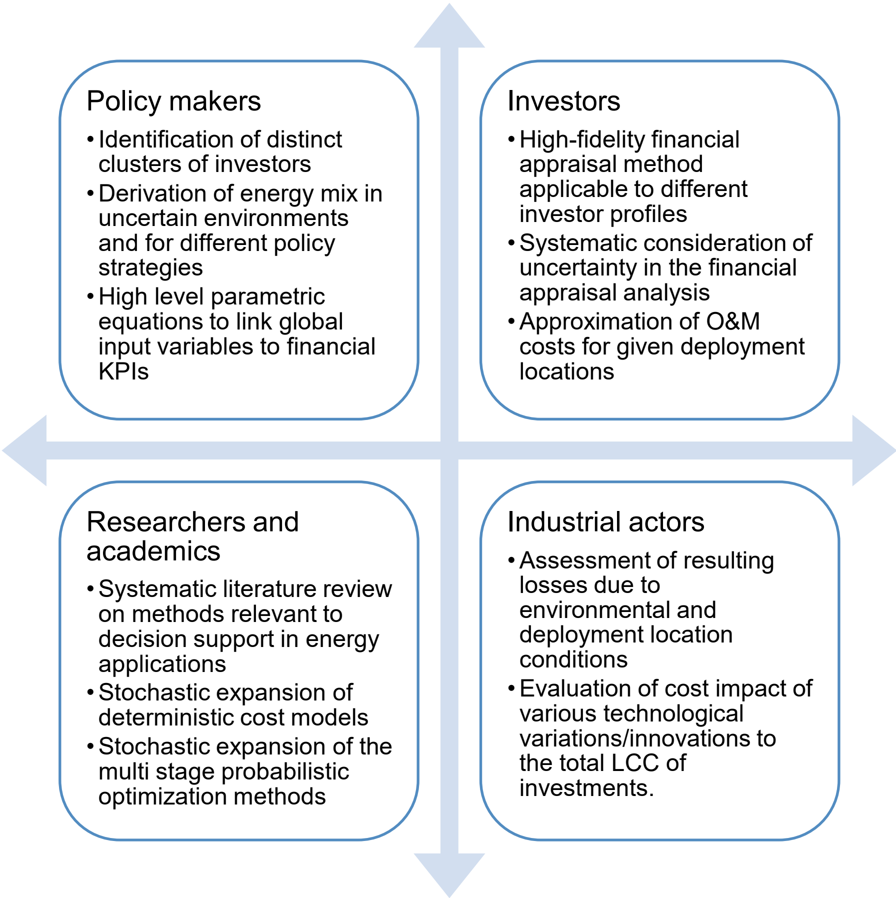


Figure 4-1 Customised benefits for target groups

5 CONCLUSIONS AND OUTLOOK

5.1 Main Conclusions

The research carried out within this thesis has sought to address the question of how appropriate methods dealing with uncertainty can provide decision support at a technology and energy system level to different stakeholders. The thesis comprises a portfolio of research activities, which contributed towards the fulfilment of the set research objectives. Outcomes of this research portfolio have been either published, are under the peer review process or will be submitted for publication imminently.

In papers B, C, D, E and F offshore wind was used as the technology of reference. This is because offshore wind has been recognised as one of the leading technology options to decarbonise the UK's energy system, as well as the relatively mature market that has been established, comprised by numerous, large investors where risk implications are seriously considered in investment decisions.

The main conclusions of each study undertaken to address the research question are summarised as follows:

- Methods that have been widely employed to address/model/incorporate risk and uncertainty attributes (related to energy security, generating costs, market risks, climate change risks, etc.) in sustainable power generation planning and feasibility studies were initially investigated. It was concluded that MVP, ROA, MCS and (stochastic) optimisation methods are usually employed to address/model statistical risk factors, while semi-quantitative methods such as scenario analysis and MCDA may also be employed to address non-statistical parameters such as social factors and the emergence of competitive technologies. Financial risks (e.g. variations in the investment return [67] or energy sale prices) have been widely accounted for in MVP and MCS methods; while the emergence of competing energy technologies (i.e. nuclear power) has been principally captured through scenario analysis [68]. Technology/innovation risk parameters are usually encountered in studies employing ROA, MCS, optimisation and scenario analysis by means of variation in future technology costs (learning curve effects). Stochastic optimisation models are frequently applied to assist policy makers in the definition of optimum energy mixes, taking into consideration uncertainties in the energy demand (i.e. macroeconomic factors), variation in electricity prices, generating costs, fuel risks, technological risks and carbon emission reduction targets. Finally, technical risks, such as reliability of components and access to the grid have been found to be frequently modelled by goal programming (i.e. MCDA methods) and optimisation methods. It was concluded that most recent literature tends to adopt more advanced methods that incorporate uncertainty.

- The cluster analysis of investor strategies in offshore wind market, employed in this doctoral thesis, indicated the existence of three distinct clusters: the late-entry investors, the Precommissioning investors and the Build-operate-transfer investors. It was found that late-entry investors represent corporate investors, infrastructure funds and institutional investors who tend to invest equity capital a few years following the commissioning of the plant or, less often, during the late construction. Being, on the most part, a risk adverse group of stakeholders, they tend to avoid construction risks. Long term returns of offshore wind energy assets match with the long-term liabilities of institutional investors (such as pension funds), while the high costs of due diligence reports urge third party financing stakeholders to prefer investing in fewer capital intensive assets rather than numerous less expensive ones. Furthermore, pre-commissioning investors include independent energy companies and OEMs/EPCI contractors, who enter the venture at the beginning of the project's lifecycle, in order to contribute their technical expertise and knowledge deriving from long term experience in the development of energy projects. An additional incentive for OEMs to invest in the early stage of the development of the wind farm is to ensure the sales of their equipment as well as the O&M contracts of the wind farm. This group usually lacks the balance sheet strength (except for large oil and gas IPPs) to provide large amounts of equity and rely on third party financing for the funding of the project. Finally, "Own-build-transfer investors" represent principally Utilities; however, IPPs and Sovereign wealth funds were also found to follow a similar trend in terms of the examined criteria. In general, Utilities hold a very strong position in offshore wind energy market operating across the value chain of the wind energy asset. Their strategy focuses on developing the offshore wind farm from the initial stage, and operate it following its commission, divesting mostly minority stakes to institutional and infrastructure investors after a few years of operation.

- This thesis developed a life cycle cost/revenue model, which is decomposed further into CAPEX, OPEX and FinEX components and applied it for the different investor clusters identified in the offshore wind energy market. The sensitivity analysis of the model has revealed that financial and revenue parameters have greater influence on the NPV of the investment in comparison to CAPEX and OPEX parameters. More in specific, the WACC along with the strike price and the energy production were found to cause the highest deviation, while the mean time to failure and the workboat wave height limit were the OPEX parameters with the highest impact. As far as CAPEX is concerned, reduction in the acquisition cost of wind turbines and foundations can yield the highest increase in the NPV of the investment. Implementation of the lifecycle cost/revenue model from the perspective of different investors can contribute towards the fairer temporal valuation of the wind energy asset.
- The expansion of the high-fidelity deterministic lifecycle techno-economic model to account for numerous time independent and dependent uncertain inputs by applying advanced numerical methods was then carried out. To this end, following a global sensitivity analysis of the deterministic model, the most influential parameters were indicated and further modelled as either time-dependent or independent stochastic variables. The probabilistic analysis highlighted the strike price impact over the total value of the asset, indicating that a strike price of 140 £/MWh can give 99% probability for a profitable investment, while when this value decreases by 14%, the respective probability falls to 53%. Furthermore, a significant deviation between the deterministic NPV of the project (estimated £284.36 million) and the probabilistic mean value (£ 266.1 million) was observed under the specifications of the baseline case. A sensitivity analysis of the variability of the stochastic variables was accordingly applied, based on an assessment of an increase or decrease of 20% of the standard deviations. Result of the indicated that variables whose variance

appeared to have notable impact on the NPV were in descending order of impact: the cost of turbine component, the mean time to failure, the cost of foundation, the working hours and the weather adjustment factor. Stochastic analysis has proven to be more insightful than a deterministic approach since instead of returning a deterministic value with limited context, it can respond with an evaluation of performance for an associated confidence interval.

- A set of parametric equations linking wind turbine capacity, water depth, distance from port and wind farm capacity with the discounted total OPEX, CAPEX and LCOE figures were developed, based on a number of high-fidelity cost simulations and regressions of the results. These high-level expressions are expected to assist investors, researchers and other stakeholders to derive initial estimates for wind farm projects based on global variables within the applicability range as defined above. Furthermore, it characterises the effect of these variables to CAPEX, OPEX and LCOE.
- This thesis also investigated uncertainties present during the operation phase of offshore wind energy assets with a view to inform risk control policies for hedging of the incurring losses. To this end, a parametric framework was developed for the calculation of operational KPIs, such as downtime, uptime, availability, operation costs and production losses across a number of different locations in the south east coast of the UK, so as to demonstrate the effect of deployment conditions. Higher availability levels were observed in areas closer to shore of the specified region, while the distribution of O&M cost per MWh demonstrated a general trade-off of higher power generation in locations further from shore due to better wind speed profiles and higher O&M costs, as a result of the decreasing vessels accessibility. The probability of exceedance of a specified power production loss threshold was also estimated across all locations of the south east coast, deriving insights regarding the distribution of the risk level of financial losses due to weather condition uncertainties and maintenance downtime across the designated region. It was highlighted that the amount of power production losses throughout the service life of the asset is not necessarily proportional to the entailed risk of surpassing a set threshold. This work aims at informing risk control products which can potentially transfer

operators' loss of revenue risks, through hedging the financial impact of adverse weather, during the operational phase of the asset.

- Finally, a multi-stage stochastic optimisation model was developed to derive optimum power generation mixes at a national level, accounting for uncertain energy demand, fuel prices (coal, natural gas and oil) and, capital cost of renewable energy technologies. The novelty of this work lies in the extension of the possibilistic (scenario-based) uncertainty modelling approach to a stochastic one allowing for certain random variables to be represented through continuous probability density functions, leading to a more realistic representation of uncertainty. The model was, then, applied in the Indonesian context incorporating detailed existing power capacity data to determine the optimal power generation mix under three planning options: Least Cost, Policy Compliance and Green Energy Policy option. Across all cases simulated, coal appeared to play a dominant role within the next 13 years as a result of its relatively low construction and operation cost. The results indicated that to achieve the sustainability target set by the policy, Indonesia needs a major expansion in renewable-based power generation capacity to meet the future demand as the conventional fossil-based power generation is capped up to a certain level to meet the $CO_{2,eq}$ reduction target. Enhancing the renewable energy and environmental impact mitigation targets can increase the RES share in the energy mix but it might jeopardise the security of the energy system. A more secure power generation system can be achieved by diversifying the generation capacities and accommodating fast start and flexible gas-fired power plants.

5.2 Future work

This thesis constitutes a step forward in the research on risk implications on valuation and decision support for sustainable energy investments. The objectives that have been achieved in this thesis can form the basis of future studies. Untapped issues that could be further explored are summarised below:

- Cluster analysis can be further applied for other geographic regions to identify market trends in different counties and potentially different clusters as we approach the end of the service life of these assets.
- Having derived the financial appraisal and customised O&M tool developed, a fully integrated appraisal model can be derived allowing for optimisation of CAPEX to OPEX ratio for offshore wind energy assets.
- The integrated cost/revenue model developed can be expanded to floating structures. The developed model can be adjusted to benchmark and valuate floating support structures such as spar and semi-sub configurations. Customised limits for maintenance missions as well as the appropriate installation processes should be considered.
- Investigation of the performance of other stochastic forecasting models for time dependent stochastic variables could be carried out. Furthermore, other variables can also be considered as stochastic time dependent, such as the cost of labour and the vessel cost, once historic data of these variables become available.
- Furthermore, more complex and context appropriate parametric expressions can be developed.
- The proposed model developed for the calculation of operational KPIs could be coupled with the lifecycle techno-economic model to derive the parametric profitability of wind turbine assets.
- Future work to stochastic optimisation could apply the methodology to different locations and investigate the effect of alternative constraints to the resulting mix such as technological factors (responsiveness of technologies) and socio-political factors (job creation, land footprint, health indicators).

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Part II: Journal papers A to G

A. Risk-based methods for sustainable energy system planning: A review

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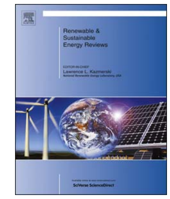

Risk-based methods for sustainable energy system planning: A review

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ABSTRACT

The value of investments in renewable energy (RE) technologies has increased rapidly over the last decade as a result of political pressures to reduce carbon dioxide emissions and the policy incentives to increase the share of RE in the energy mix. As the number of RE investments increases, so does the need to measure the associated risks throughout planning, constructing and operating these technologies. This paper provides a state-of-the-art literature review of the quantitative and semi-quantitative methods that have been used to model risks and uncertainties in sustainable energy system planning and feasibility studies, including the derivation of optimal energy technology portfolios. The review finds that in quantitative methods, risks are mainly measured by means of the variance or probability density distributions of technical and economical parameters; while semi-quantitative methods such as scenario analysis and multi-criteria decision analysis (MCDA) can also address non-statistical parameters such as socio-economic factors (e.g. macro-economic trends, lack of public acceptance). Finally, untapped issues recognised in recent research approaches are discussed along with suggestions for future research.

1. Introduction

Global investment in renewable energy (RE) in 2015 increased by 5% to $285.9 billion in relation to 2014, surpassing the last record of $278.5 billion in 2011 [1]. The annual increase in power capacity has also reached its highest level across all regions in 2015. Wind and solar photovoltaics (PV) account for an approximately 77% of new capacity, with hydropower accounting for most of the rest [2].

As the number of RE investments increases, so does the need to measure the associated risk and uncertainty from the perspective of different stakeholders throughout planning, construction and operational phases [3]. Energy developers, investors and policy makers face a future that implicitly involves technological, financial and political risks and uncertainties. Although, RE technologies potentially have a lower risk profile than conventional energy sources because they are disconnected from fossil fuel prices, they still entail considerable technological, financial and regulatory risk exposure, depending on the technology, country and regulatory regime. Fluctuation of cost components of power generation units, volatile crude oil prices,[1] electricity price and carbon costing in the context of the global climate change mitigation strategy, are examples of uncertainty components encountered by energy developers, investors and policy makers investors in the energy sector [4]. Often these risks are mitigated by governments in the form of price protection, but this can have a large budgetary burden, which often passes on to consumers through taxes and electricity bills [5].

Another stream of studies has focused on the identification and assessment of risks and uncertainty, as well as risk management solutions for sustainable energy projects [3,7,8,17–19]. In general, risk in the power generation investment sector is considered to be multi-dimensional and depends on the perspective of different stakeholders [9]. An array of analytical methods has been used to analyse various aspects of risk from the perspectives of different stakeholders. This results in a bewildering mix of studies that look at different sides of the same problem. However, there has been no systematic review of which techniques are most appropriate for reviewing individual, or groups of risks and how useful the outputs are to various stakeholders.

The aim of this paper is to provide an extensive, systematic literature review (SLR) of how risk and uncertainty has been analysed with respect to sustainable energy system planning. This will focus on identifying the attributes of risks (or modelled uncertainties) that each analytical method is most suited to address, as well as a critical comparison of the main outputs of such studies. The outputs of this review will map appropriate analytical techniques to specific risks, as

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[1] For example, international crude oil prices demonstrated dramatic changes from 2008 to 2009 (decreased by over 46%) as well as from 2009 to 2010 (increased by 25.6%, namely $60.4/barrel in 2009, $78.1/barrel in 2010) [161].

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well as comment on their application from the perspective of different stakeholders. The outputs are intended to provide a guide to researchers as to common practice in the assessment of risk and uncertainty for sustainable energy developments as well as indicating any possible gaps or new avenues for research.

The rest of this paper is set out as follows: Section 2 presents an overview of risk/uncertainty factors affecting investment decision-making in sustainable power generation planning and feasibility studies, along with an overview of the different perspectives among stakeholders. The risk-based evaluation methods are introduced in Section 3, and the cross-method comparison is conducted in Section 4. Finally, Section 5 summarises the findings of this work and suggests some focal points for future research.

2. Overview of risks and stakeholders' perspectives in sustainable energy generation systems

Risk in the power generation investment sector is generally considered to be multi-dimensional and depends on the perspective of different stakeholders. The "Comprehensive Actuarial Risk Evaluation – CARE" paper produced by the International Actuarial Association (IAA) provides a comprehensive taxonomy of risks faced by enterprises [9]. Among other classification schemes, the paper suggests a new perspective for risk categorisation into statistical and non-statistical risks. The former are the risks that can be measured or modelled with mathematical or statistical methods, such as stochastic modelling, while the latter are those that are difficult to model with existing knowledge.[2]

Risks associated with sustainable energy projects depend largely on a number of factors that are technology-, country- and regulatory-specific, while they also vary according to different stakeholders' perspectives. Authors working on risk identification, analysis and management in the sustainable energy investment sector have developed different risk categorisation schemes according to their intended focus. Table 1 summarises the most cited risks by employing a political, economic, social, technology, legal and environmental (PESTLE) approach.

Stakeholders involved in the field of RE investments comprise: project developers, project investors, insurers, manufacturers, consumers, affected local communities and policy makers. Each stakeholder tends to have different concerns and objectives from renewable energy investments. This means that risks will vary in importance across these different groups.

From a project developer's perspective, the objective is to make a sufficient return on investment (capital and other resources) through the sale of an RE project to an investor [12]. Investors are mostly interested in minimising risks of technical reliability, costs and risks of revenue disruption [14], while policy makers are concerned with designing efficient and effective policy schemes, which would provide the appropriate level of incentives to potential investors of RE projects that allow government targets to be met [15]. As such, risk analysis in RE projects has been performed in a generalised style covering numerous RES technologies and stakeholders' perceptions by some authors [6,16–19], while others distinguish risks through the related stakeholders' perspective (e.g. from the investor's and developer's view) [20] or by technology-specific risk factors [3,21].

3. Results of the literature review

Studies in this area tend to focus on the analysis of specific risk(s) from the perspective of a stakeholder or stakeholders. Therefore, the results section will map this research area in terms of which risks have been analysed by which methods and which stakeholders have been included.

3.1. Overview of the methods

The literature review was conducted on the basis of a SLR approach, which provides the synthesis of the research in a systematic, transparent, and reproducible manner, while also restricting the researcher's bias [22]. A description of the main steps followed to conduct the SLR approach is summarised in Appendix A. Analysis of the SLR results finds several methods used in the analysis of risk involved with sustainable energy generation systems. Table 2 provides a tally of how many times a paper using a particular method was identified by the systematic review process. This paper takes these methods forward for further analysis. As indicated in Appendix A, the total number of references considered for the review was 161 out of which, 113 originated from the SLR process, while the rest 48 references were identified through additional checks (e.g. via citation tracking or journal websites searching) in order to complement information on a particular topic which was not fully covered by the systematic review.

The review focuses on critically assessing which risks have been analysed by which methods, what are the common outputs of these methods and which stakeholders have been included in a number of widely cited representative risk-based methodologies applied in sustainable power generation planning and feasibility studies. These methods have been classified, for reasons of simplicity, into quantitative and semi-quantitative methodologies (see Fig. 1).

Quantitative risk-based evaluation methods deal with (statistical) risk factors that can be described by probability distributions. Widely cited methods falling into this category are: Mean-variance portfolio (MVP) theory, Real options analysis (ROA), stochastic optimisation methods, and Monte Carlo simulation (MCS). Semi-quantitative methods have the flexibility to take into consideration statistical and non-statistical risks. Semi-quantitative methods that were identified through the SLR are: MCDA and scenario analysis.

Table 3 matches the risk-based methods with risks/uncertainties as identified by the systematic review. The table can potentially provide guidance as to what methods are most suitable to address/model the specific risk and uncertainty factors listed.

3.2. Quantitative methods

3.2.1. Mean-variance portfolio analysis (MVP)

MVP is an established method of economic theory, based on the pioneering work of Harry Markowitz, who focused on the diversification of securities towards the construction of efficient portfolios, which would correspond to high expected return and low variance [97,98]. Later, Awerbuch [51] applied MVP for deriving optimal (or efficient) energy generation portfolios yielding maximum expected return in combination with minimised risk.

An energy generation portfolio constitutes a mix of generating assets put together to reduce total investment risks; as such, an efficient portfolio of energy generation technologies (with higher RE shares) reduces the threat of abrupt supply disruptions, hence reinforcing energy security through the mitigation of volatile fossil fuel price dependence.

Diversifying the power generation portfolio has been highlighted by a number of authors [18,20,99–102] as an effective strategy of risk hedging due to the creation of portfolio effects resulting in efficient power generating portfolios (i.e. optimum shares of different energy technologies in the portfolio resulting in a minimum level of risk towards attaining a given generating-cost objective). Diversification dimensions may be geographical, technological or value chain related. Numerous reports by international agencies, organisations, as well as

[2] Statistical risks include: market, credit, insurance, asset liability and liquidity risks, while examples of non-statistical risks are: reputational, opportunity, strategic, paradigm shift and black swan risks.

Table 1
Risks in renewable energy investment sector.
(Sources:[3,10–13]).

Risk category	Sub-category	Risk factors/Events
Political	Country	Changes in the national economy
		Political stability
	Regulatory	Changes in policy support schemes (for example changes in levels of tax credit or RPS targets)
		Liability to third parties
		Contracting risk
	Bureaucracy	Complex approval processes/Delay of permits
Economic	Market	Variability of revenue due to electricity price
		Demand fluctuations
	Financial/Fiscal	Generating costs (CAPEX, fixed and variable OPEX, pre-development costs)
		Interest rate swings
		Financing risks (insufficient access to investment and operating capital)
		Taxation regime
		Transaction costs
	Strategic/business	Damage to reputation
Social	Lack of public acceptance	Delays in the licence acquisition
	Health risks	Accidents, acute diseases
Technological	Project development	Revenue loss due to project delay for the commercial operation date (COD)
		Failure to obtain all required licences
		Failure to obtain grid access
	Construction	Damage during transport or construction
		Damages due to natural hazards
		Unreliability of components (e.g. damage to turbines)
		Unavailability of skilled labour
	Operation/maintenance	Damages due to natural hazards
		Technological/innovation risk
		Higher OPEX (due to critical failures of components)
		Unscheduled plant closure due to the lack of resources
		Risk of components generating less electricity over time than expected
		Sabotage, terrorism and theft risk
	Resource risk	Revenue loss due to intermittency
	Infrastructure	Variability of revenue due to grid availability
	Decommission	Decommission costs
Legal	Energy and climate change policy	Changes in the national energy and climate change policy
Environmental		Risk of environmental damage
		Carbon footprint and life cycle assessment

Table 2
Frequency of each method appearing in the SLR (representing the number of studies that were assessed as more relevant).

Methods	Frequency of papers reviewed using a particular method
Mean variance portfolio	16%
Optimisation methods	31%
Real options analysis	13%
Monte Carlo simulation	9%
Scenario analysis	11%
Multi-criteria decision analysis	21%

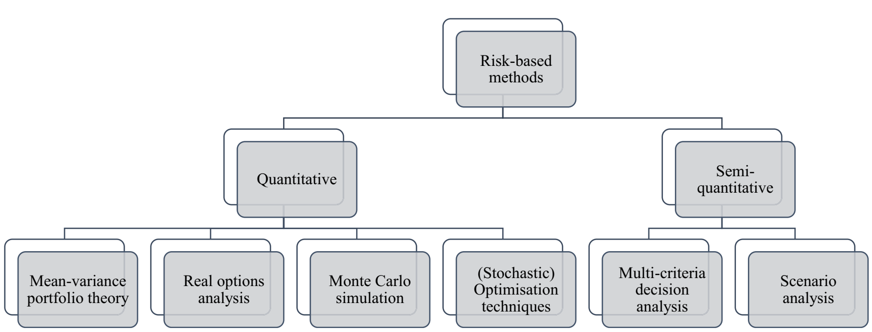

Fig. 1. Classification of the risk-based methodological approaches implemented in the field of sustainable energy planning and feasibility.

scientific papers [23,24,49,51,55,103–105] have stressed the importance of de-emphasising stand-alone energy generating costs and levelized cost assessments in generation planning, since these approaches do not capture the contribution of renewable and non-fossil fuel technologies to the electricity portfolio, in terms of reducing the variability of electricity costs and hence their impact on economic activity. At any point, some assets in the energy generation mix may have higher costs than others; yet, in another instance, the combination of alternatives serves to minimise overall expected generating cost relative to the expected risk.

Portfolio risk is usually measured as the standard deviation of historic annual outlays for fuel, operation and maintenance (O & M) and construction period costs examined on the basis of historical data [50]. Numerous papers have attempted to generate models that consider risks as the cost variance of a technology portfolio [23,49–52,103,105–107]. Huang and Wu [52] introduced portfolio risk by means of volatile fuel prices and uncertainty of technological change and capital cost reduction, while another MVP paper deemed market electricity prices and wind

Table 3
Risk and uncertainty parameters [1] addressed by risk-based methods.

	Risk-based methods →		Mean variance portfolio	Optimisation methods	Real options analysis	Monte Carlo simulation	Scenario analysis	Multi-criteria decision analysis
Risk categories	Political risks	Climate change policy risks	[6,23–25]	[26–32]	[33–40]	[41]	[24,42–45]	[46–48]
	Economic risks	Power generating costs	[5,6,23,49–52]	[26,53,54]	[33,55]	[41,56–59]	[43]	[47,60,61]
		Financial risks	[62]			[56,57,63,64]		[46,48]
		Market risks	[25,50]	[32,65–72]	[33,55,73–75]	[41,58,59,63,64]	[26,44,76–80]	[47]
		Fuel risks	[5,6,23,43,49,50,52,81]	[26,29,31,53,67,82,83]	[34,35,37,38,84]	[41,56,63]	[26,44,80]	[14,47,85,86]
		Uncertain macroeconomic parameters		[26,28,32,53,54,87,88]		[58,63,64,89]	[45]	[47]
	Social risks	Social risks						[47,48,61,90]
	Technological risks	Technical risks	[6,25]	[67,70,83,91]	[55]	[56–58,64,89,92]	[43]	[14,46,48,61,93]
		Emergence of competing technologies					[24,26,44]	
		Technological/innovation risk	[43,52]	[28–30,32]		[41,58,63,89]	[24,26,42,44,45,94,95]	[14]
		Resource/power output risk	[6,25]	[32,66,67,70,71]	[55,74]	[56–58,64,89,92]	[43,79,80,96]	[14,46,93]
	Environmental risks	Environmental risks	[6]	[26,31]			[42,43,94]	[14,47,48,61,85,86,90,93]

[1]Risk and uncertainty factors addressed by the outlined methods may be summarised as:

- Climate change policy risks mainly include fluctuations in CO_2 prices and reduction targets, changes in the climate change policy schemes (e.g. (retrospective) changes in RES subsidy/promoting policies).
- Variation in power generating costs may include variation in pre-development costs, fixed and variable operational and capital costs of the power generation technology.
- Financing/fiscal risks reflect the uncertainty in the financing of the power generation investment, variation in taxes and interest rates, sales and revenues as well as variation in the investment profitability (e.g. variations in IRR).
- Market risks are referred to in the literature usually by means of variability of revenue due to uncertain electricity market prices and fluctuations of electricity demand.
- Fuel risks usually capture variations in fuel prices, in fuel production, in the fuel/output ratio, disruptions in fuel delivery/supply, as well as fuel transportation risks in power-plant operation.
- Macroeconomic parameters mostly seek to reflect uncertainty in macroeconomic metrics, such as inflation rate and GDP.
- Social risks can potentially involve risks associated with the lack of public acceptance, as well as health risks (e.g. occurrence of accidents).
- Technical risks involve lack of access to the grid, construction risks, reliability of components (e.g. damage to turbines), variation in capacity factors, and unavailability of power plants and skilled labour.
- Technological/Innovation risks relate to cost uncertainties due to learning curve effects.
- Resource/power output risks can be associated with revenue loss due to intermittency, availability of natural resources, physical supply disruptions, curtailment of power generation sources and/or electric power produced (including intermittency of RES).
- Environmental risks may entail global warming (GHG emissions) effects, environmental damages (e.g. CO_2 emissions) and natural hazards.

resource availability as uncertain inputs represented by probability distributions with approximately normally distributed probability functions to compare the relative attractiveness of investing in a wind park under two RE policy support instruments, namely, feed-in tariffs (FiT) and feed-in premiums (FiP) [25].

Adopting a private investor's perspective, some authors have used cash flow models to calculate risk in terms of earnings, costs of O & M, credits, depreciation of facilities, and benefits [49,62,108]. Muñoz et al. [62] used the Internal Rate of Return (IRR) to represent the returns on investments, while the associated portfolio risk was reflected by the standard deviation of IRR. IRR proved to be a useful measure of the return from the real project, capable also of considering the uncertainty in electricity prices and future subsidies (introduced as stochastic inputs in the cash flow model). Roques et al. [109] concluded that in the absence of long-term power purchase agreements, optimal portfolios for a private investor are significantly different from socially optimal portfolios; since, from a private investor's viewpoint, there is little diversification value in a portfolio of mixed technologies, due to the high empirical correlation between electricity, gas and carbon prices. Bearing the above in mind, MVP theory is a method well suited to the problem of electricity generation portfolio planning and evaluation at a national and regional level (hence from a policy maker's viewpoint), since it can be used to derive efficient power generating portfolios, which reduce generating costs and enhance energy security, while the method has also been used to assess the maximum losses (or returns) of a private investor's (portfolio) investment within a specified confidence level.

3.2.2. Real-options analysis (ROA)

ROA is particularly applied to the analysis of the impact of uncertainty on investment decisions when management actions can be timed flexibly. This enables the investor to evaluate available options and take capital budgeting decisions (such as deferring, abandoning, expanding, staging, or contracting) as new information arises and uncertainty about market conditions and future cash flows is reduced [110]. ROA supplements the information provided by static discounted cash flow analysis and is based on the concept that it may be preferable to postpone irreversible decisions (e.g. in capital intensive investments) and wait to make a better informed decision at a future point in time [109]; hence, adding the ability of an investor to respond dynamically to changing market conditions. Common applications of ROA in low carbon energy projects include investigating the impact of climate policy uncertainty on private investors' decision-making in the power sector [33–36,111], such as the diffusion of various emerging RE technologies [73] or the investment timing and capacity choice for RE projects [33].

In more detail, [33] adopts ROA to analyse the flexibility of the investment timing (based on the investor's right to postpone investment once the licence is granted if the economic environment is not as favourable as desired) and capacity selection for RE projects under two different subsidy schemes (feed-in tariffs and RE certificate trading), by examining investment behaviour under these conditions. The option of investment timing and capacity choice is assessed taking into account the special characteristics of RE sources (wind power, solar power, and run-of-river hydropower), namely the intermittency of these power sources, as well as the uncertainties in capital costs, subsidy payments and electricity prices. Kumbaroğlou et al. [73] presented a policy planning model based on the ROA method featured through a dynamic programming process for recursively evaluating a set of investment alternatives on a year-by-year basis under uncertainty. They used the operational and cost data for existing power plants, electricity price data and capacity expansion structure, in order to derive annually added capacities and technologies from 2006 up to 2025 under different scenarios. The dynamic programming model allowed them to check the impact of uncertainty and technical change on the diffusion of various emerging RE technologies, concluding that market actors need, in the short-term, financial incentives to achieve a more widespread adoption of RES technologies in the longer run.

Other applications of the method focus on the impact of market uncertainty on investment electricity industry decision-making. Market uncertainty is expressed into stochastic CO_2 prices and policy uncertainty [36,55,111]. Authors in [36,111] emphasise the distinction between uncertainty coming from fluctuations in CO_2 prices around a known trend, which would arise in a market with emissions permits, and uncertainty emanating from the absence of clear policy signals. It has been shown that some market uncertainty may induce earlier investments in carbon capture and storage (CCS) equipment than in the case of perfect information. However, policy uncertainty may also lead to prolonged accumulation of CO_2 emissions in the atmosphere, since investors prefer to wait for the final decision of government before investing in climate change mitigation technologies. Hence, a clearer, long-term policy plan would leverage emission abatement actions. In both [34] and [35] the uncertainty is represented by carbon price uncertainty, which is modelled through stochastic variations in the carbon price. Results from Blyth et al.'s work [34] demonstrated that such uncertainty creates a risk premium for electricity investments which needs to be offset with extra incentives in order to overcome the effects of uncertainty on the timing of the investment decision. An important conclusion of their work suggests: the shorter the time before a future climate policy event, the higher the impact of climate change policy risks on the investment decision (a conclusion also reported in [35]). It is thus concluded that the method can derive useful outputs for both investors and policy makers. On the one hand, investors can evaluate available options and take capital budgeting decisions on the best timing; on the other hand, policy makers could be assisted to better understand the impact of market uncertainty (e.g. costs induced by an environmental policy) on the investment decisions of investors.

3.2.3. Stochastic optimisation techniques

Stochastic optimisation has been extensively used in a number of energy planning and feasibility problems, such as the determination of optimal energy mix planning at a national level (i.e. Indonesia [26], China [112], Korea [29], and Croatia [113]), expansion planning of sustainable energy systems [65,69,82,114–119], design of hybrid systems [120,121], and numerous others energy systems-related problems like unit commitment, energy storage management, bidding energy resources, pricing electricity contracts [122], introducing uncertainty in one or more of the input parameters subject to stochasticity. In this review, we focused on problems that are associated principally with the deployment of stochastic optimisation methods in investment planning decisions. Usually, the constraints considered in these problems depend on the perspective of the stakeholder. As such, studies looking at the problem from a policy maker's perspective, seek to develop least-cost optimisation models to allocate energy sources for sustainable development, under constraints such as energy security (demand), renewable penetration, satisfaction of greenhouse gas (GHG) emission reduction targets, budget constraints and maximum technology capacity [26,30,112]. An investor would aim at minimising both the cost (or alternatively maximising the revenues) and investment risk (e.g. by minimising CVaR measure), while the potential constraints would further include risk-aversion constraints [70,83,123,124]. Uncertainties that are usually represented include market electricity prices, fuel prices, production costs of existing and future power plants, CO_2 emission policy, energy demand, technological efficiency, and utilisation factors [26,30,112]. Stochastic optimisation problems are characterised by an array of fragmented modelling approaches, such as fuzzy, (dynamic) stochastic and interval mathematical programming [125], often leading to inconsistent and inaccurate results [122].

3.2.4. Monte Carlo Simulation (MCS)

MCS involves the random sampling of probability distributions of the model input parameters with the purpose of producing numerous scenarios. The sampling from each parameter's probability distribution is realised in a way that reproduces the shape of the output distribution; hence, the distribution of the values deriving from the application of the method reflect the joint probability distribution of the outcomes [126]. MCS offers many advantages but it also requires a considerable range of data as input variables, such as the probability density functions of uncertain or fuzzy values or forecasted variables. There are numerous studies performing risk analysis of sustainable energy systems with MCS in the literature [56,57,59,63,89,92,127,128]. Existing works disclose a number of advantages of the method, such as the ability to obtain fast results when modifying the variables of the problem, the ability to calculate the risk undertaken because of uncertain or stochastic input variables, as well as the ability to model the correlations and other interdependencies of the system. Input variables need to be statistically independent; otherwise the simulations will lead to inaccuracies and shortcomings in the interpretation of the results. In studies employing MCS, the best fitting probability density function (PDF) assigned to the input variables is determined either by using historical data of the variable (statistical or experimental methods) [5], or by using subjective judgements (e.g. performing interviews with experts) on the empirical worst, base and best case estimates (confidence intervals) usually interpreted as quantiles of a probability density function [57]; most often, both methods are used in order to derive the PDF of numerous variable inputs [56,89,128].

Studies performing stochastic financial risk analyses of sustainable energy systems by means of the MCS method tend to derive joint probability distributions of annual energy production and investment profitability metrics (i.e. net present value (NPV), IRR) at a plant level [92]. For the selection of input variables, a sensitivity analysis method can initially be carried out for checking the effect of a number of potential input variables on the NPV. Risks/Uncertainty factors that have been taken into consideration include fluctuations in wind resource potential, wind curtailment, access to the grid and macro-economic parameters [89]. MCS integrated in a typical financial model can assist investors to perform a first exploratory analysis to decide whether and where to invest and policy makers to assess policy parameters and explore possible scenarios of investing in an RE technology. For example, Pereira et al. [57] evaluated the risk in project implementation, under stochastic equipment costs, market financial conditions, O & M costs, and policy implications. They considered as independent variables the total initial costs, the interest rate and the value of energy produced and sold to the grid or utility; matching them with exponential, triangular and Bradford probability distribution functions, respectively, while NPV and the produced energy cost have been defined as the dependent variables.

3.3. Semi-quantitative methods

Along with the quantitative risk-based methods dealing with statistical risk and uncertainty in decisions associated with sustainable energy planning and feasibility problems, scenario analysis and MCDA have been identified by the SLR as methods that can consider non-statistical risks.

3.3.1. Scenario analysis

The potential impact of risks on the profitability of RE investments can be evaluated by the discounted cash flows under various scenarios, reflecting different potential future developments. A scenario incorporates the dynamics and the drivers resulting in a specific conceptual future [129]. Usually, these scenarios represent either the most probable situations (situations that are most likely to occur) or extreme cases (worst-case, and best-case scenarios). Each scenario usually assumes values of elements, such as the future price of electricity, CO_2 costs, and produced electricity among others. The elements used for the construction of the scenario depend on the area on which the researcher seeks to focus [129].

Scenario analysis can potentially assist the planning of robust energy technology portfolios that will achieve set objectives under a range of future scenarios [42,76,130]. For example, [42] considered three scenarios, reflecting strong, mediocre and poor technological breakthrough and policy support for the development of the RE industry. This allowed the encompassing of uncertainties with regard to the relationships among the technology alternatives and the decision values of elements. The latter were divided into two dimensions: the importance of each technology (assessed through the market value, and the compound market growth) and the technology risk (indicators considered were the position of the technology and the manufacture capability). Conclusively, technology portfolio planning implications were derived for each of the three scenarios generated. On the other hand, Kannan [130] investigated the uncertainties in the future UK power generation mix via a range of power sector-specific parametric sensitivities under a 'what if?' scenario analysis framework, to provide a systematic exploration of least-cost energy system configurations, while [76] investigated the impact of energy price uncertainties on the supply structures of four EU countries using a stochastic risk function incorporated into a partial equilibrium energy systems model. Scenario analysis has also been used for the quantification of policy risks in the wind power industry [131].

3.3.2. Multi-criteria decision analysis (MCDA)

MCDA is a family of decision support methods which has been widely used in the energy sector and specifically in the evaluation of alternative energy sources as well as the consideration of risk perceptions, due to their ability to incorporate multiple actors' opinions, bringing along multiple different criteria, stemming from the political, economic, social, technological and environmental context [13,132–135]. MCDA methods rely on relationships such as priority, outranking and distance among the alternatives and factors (i.e. criteria) that influence the decision. These methods are categorised as semi-quantitative since they can also accommodate criteria or attributes whose numerical values are hard to obtain or even cannot be quantified (intangible criteria) through the deployment of qualitative scales (i.e. a Likert scale) [136]. An example of a work using both quantitative and qualitative attributes can be found in [137]. Several authors have carried out reviews on MCDA methods with applications in the field of sustainable energy systems [132,138,139].

A few common outputs of these applications associated with sustainable energy generation technologies when risk and uncertainty is embedded in the investment decision, include: evaluation/ranking of the different RE technologies according to a number of risks/criteria [90,136,140,141], prioritisation of feasible projects through a risk analysis process [46] and risk prioritisation of RE technologies [13].

Types of uncertainty encountered in such problems stem from either the inherent valuation uncertainties (i.e. problem-specific technical parameters determined by the decision maker) or from the technical empirical uncertainties related to the data (such as the carbon emissions and technology costs) which are outside the decision maker's control [86].

Apart from the basic MCDA methods which are usually set to assess the strengths and weaknesses of the pre-determined energy options without re-defining them, another group is the continuous MCDA models seeking to identify the optimal design of the option. These methods are usually employed to deal with problems comprising multiple (usually conflicting) objectives, where decision variables are infinite variables, subject to constraints and are known as multi-objective optimisation methods. These methods have also received considerable attention in sustainable energy applications [14,47,85,86,93,142]. Goal programming is a category of multi-objective optimisation methods assimilating LP to handle problems with multiple, potentially conflicting objectives. For example, goal programming can be used to address the compromise between the cost per kWh of an electricity generation portfolio and the total risk for an investor-owned utility [14]. A common application of the method in the field of sustainable energy system planning is to forecast optimum RE supply percentages under different conditions of portfolio risk and cost [14,83,143]. For example, in [14] the authors presented a multi-objective model for determining the share of different energy generation assets in an investor-owned utility portfolio that reduces risk while providing the lowest cost per kWh of electricity generation possible. The failure mode and effects analysis (FMEA) was employed to assign risk priority numbers (RPNs) to each risk. Subsequently, the share of each type of energy (i.e. solar, coal, and natural gas) in the mix was determined through a multi-objective model for the minimisation of levelized cost of electricity (LCOE) and minimisation of the aggregated RPN of each technology.

It is often encountered that the numerical values of the criteria or attributes are not easy to obtain and there is therefore a need to express them in linguistic terms. In this case, fuzzy logic is employed to address the uncertainty in human judgement by applying membership functions to vague information. There are numerous studies in the literature using fuzzy analysis in energy planning [61,144–149].

As mentioned above, we recognise that there are also other methods dealing with risks and uncertainties in investment decision making; for example, parametric sensitivity analysis can be employed to identify sensitive input parameters (focusing on uncertainty in technical empirical parameters) by analysing their effects on the model output [86]. However, here we focus our review on methods – exported through an SLR – widely implemented to solve planning and feasibility problems seeking to investigate: the risks/uncertainties each method is best suited to cover, the stakeholder perspective each method addresses; while also critically assess their most common outputs and reveal advantages/disadvantages regarding content and methodology.

3.4. Combinations of quantitative and semi-quantitative methods

Methods described above are frequently combined with each other or with other methods in order to produce different kinds of results, e.g. in ways that the output of the one method works as the input for the other method. Subsequently, we present indicative papers combining different risk-based methods in the field of energy system planning and feasibility.

A number of studies have combined ROA with portfolio theory in order to derive optimal portfolio strategies towards meeting specific climate change stabilization targets under different socio-economic scenarios [37,38]. Fuss et al. [37] employed the real options model, in order to analyse the impact of uncertainty on investment decisions at the plant level. The Greenhouse Gas Initiative (GGI) Scenario Database was considered as a starting point for obtaining optimal technology portfolios which are robust across a number of socio-economic scenarios and across climate change targets. In [38], a multidimensional table indicating the best option (regarding the retrofit of a fossil fuel-fired plant and a biomass plant with CCS units) for each time period, possible state and possible carbon price realised during that period was produced. The implementation of the ROA resulted in the distribution of coal, gas, and biomass technology costs (for given parameters on fuel and CO_2 prices), which subsequently entered a portfolio optimisation model to provide the optimal strategy across all possible scenarios.

Methods employing portfolio theory are usually combined with optimisation methods, such as linear programming (LP) to determine optimum RE technology percentages under different conditions of portfolio risk and cost. Bhattacharya and Kojima [5] used the method of MVP risk analysis to create experimental electricity supply portfolios with high diversity (more fuel choices) and conducted a special type of optimisation method, namely simulation optimisation, in order to incorporate the various stochastic variables in their model so as to minimise the risk of the supply portfolio. The major sources of risk that were identified during the development and operation of power projects in Japan were the variation in capital costs, fuel costs, O & M costs, along with the price of CO_2 traded in the world market. Kumar et al. [105] determined optimum portfolios through the minimisation of portfolio fuel cost, portfolio fuel risk and CO_2 emission by employing a multi-objective genetic algorithm. They concluded that the limitation of the MVP theory from the perspective of a developing nation such as India lies in the fact that the method only considers risks associated with cost components while neglecting barriers associated with the implementation of projects; thus, a comprehensive risk barrier index is needed to indicate the combined impact of risks and implementation barriers associated with each portfolio.

A number of studies have combined scenario analysis with other methods as a way to incorporate uncertain situations emerging from political, economic, environmental, technological and environmental futures. Such methods include: portfolio theory [23,24,43,52,103], ROA [33,37,38,73], energy system modelling [76,130] and MCDA [148,150]. The latter study concerns the application of multiple criteria decision analysis to prioritise investment portfolios (with the overall objective of the generation mix corresponding to the anticipated electricity demand while fulfilling specified constraints), while at the same time testing the robustness of the prioritisation against several scenarios. Each portfolio reflects the distribution of the alternatives' power generation capacity denoted as $X_i=[p_{1i},\ldots,\quad p_{ni}]$ where p_{ki} is the proportion of each energy asset capacity of portfolio X_i to be gained by alternative a_k belonging to a set $A=[a_1,\ldots,\quad a_n]$ of n technologies. Performance criteria alternatives are assessed against economic, technical (e.g. availability and energy security risks) and environmental dimensions, with the goal to rank technologies and portfolios and then apply scenarios to validate the sensitivity of the results.[3] Emerging conditions considered for the construction of scenarios (elements) concern, among others, different projections on electricity consumption annual growth and high price volatility for natural gas and oil, as well as combinations of these. A similar approach is followed by Heinrich et al. [86] ranking power expansion alternatives for given multiple objectives and uncertainties, using a value function multi-criteria approach, across different scenarios yielding information regarding the power expansion alternatives' relative performance and credibility. Energy system models are also often used in combination with scenario analysis in relevant studies [76].

4. A cross-method comparison

4.1. Risk measures and common outputs of the methods

Having laid out widely cited and applied risk-based evaluation approaches from the literature (Section 3), this section discusses and summarises the key findings of the literature review by providing a comparative overview of the most significant outputs of each method as well as by highlighting the weaknesses and strengths of each approach as identified by authors that employed them in sustainable energy technology planning and feasibility problems. Fig. 2 illustrates the main outputs of the bulk of the studies that have employed these methods.

MVP method measures risk in several ways [151]. Usually, the standard deviation of historic periodic returns calculated through the Sharpe ratio, which is defined as the ratio of expected excess return to standard deviation of the return [152], is used; this definition assumes that financial returns follow a normal distribution, hence the prob-

[3] Alternatives (power generation portfolios) are assessed against the performance criteria by means of a Likert scale rating measuring the degree the alternative meets each criterion (1-High, 0.5-Low, 0-Blank).

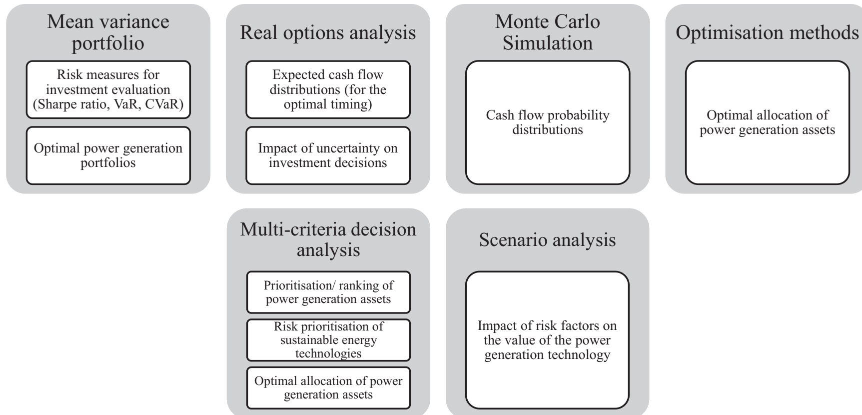

Fig. 2. Common outputs of risk-based methodologies in energy planning and feasibility studies.

ability dimension of the portfolio risk cannot be accurately reflected through this measure. However, Value-at-risk (VaR) is another traditional risk measure utilised by MVP theory approximating the probability that the value of an asset or portfolio will drop below a particular value over a specified confidence level and in the context of a planning horizon. The method can be applied to a power generation asset portfolio with available periodic market parameter values not necessarily following a normal distribution. Given the probability distributions of all portfolio assets, VaR values can be used to approximate the maximum loss for the whole portfolio. Being a widely used risk measure embraced not only by risk managers and actuaries but also by researchers and in investment banking, VaR (also known as percentile risk measure) is always specified with a given confidence level α (usually with values 90%, 95% or 99%) and can be used for portfolio optimisation when the cost/return distributions of the different technologies are not necessarily normal (in contrast to the Sharpe ratio metric). In the majority of MVP studies, risk is approached by the variability of the generation cost components originating from the market (deviations in demand for power, electricity price, fuel price), economic and financial (CAPEX, OPEX, project delay, capacity factor, energy generation) and political (such as retroactive/prospective regulatory changes, uncertain CO_2 prices) contexts. The method's applicability is subject to the availability of historic data of cost components and other statistical parameters of the RE project, as well as the availability of correlation values of risks among assets [109].

ROA supplements the information provided by static evaluation approaches, by recognising that in an uncertain future one needs to have the flexibility to adjust the timing of the investment decision [109,153]. Real options methods help to evaluate the value of waiting as part of the decision-making problem. The method commonly uses dynamic programming which allows the sequence of investment decisions to break down into options and systematically derive and compare the expected NPVs from immediate investment, waiting and all subsequent remaining decisions. In most studies in the domain of energy technology evaluation, uncertainty is introduced by means of forecasted input fuel prices, average wholesale price of electricity, uncertainties in policy support schemes (e.g. subsidy payments) and capital costs. The output of ROA can subsequently inform portfolio optimisation, while the importance of different energy technology options under specific political, technological and socio-economic circumstances can be captured by scenario analysis, providing valuable insight for policymakers about the incentive mechanisms needed to promote robust long-term climate risk mitigation.

Optimisation methods with stochastic inputs have been widely implemented to the problem of allocating optimal power generation assets. This may apply to long-term optimal energy mix planning in a national level, minimising total discounted (annualized) cost against a number of constraints ensuring the energy security, attainment of environmental targets, maximum capacity of different technologies, etc. This is thus a method that can be potentially derive policy recommendations for more efficient energy technology roadmaps [26]. The method can, however, be useful from an investor's (energy producer) viewpoint, e.g. for the determination of the optimal expansion planning of the power generation capacity over a long term horizon [65].

Scenario analysis recognises that altering individual variables whilst holding the remainder constant is not realistic. Depending on whether scenario analysis is embedded in a qualitative or quantitative methodological framework, risks considered may vary. Empirical scenario analysis techniques can provide a first-step in understanding inherent risks and uncertainties of future energy systems under different socio-political scenarios [154]. Outcomes of scenario analysis in empirical studies could also be the rating of electricity generation technologies and their mixes across different scenarios. Scenarios simulate the development trajectory of RES technologies between a *status quo* (current projection) and alternative scenarios which deviate from the *status quo* because of considering a different development in a number of driving forces, e.g. technology progress, climate change policy and situation of global warming. Although scenario analysis, when used on its own (potentially in an empirical framework) lacks the scientific rigour for assessing the frequency and quantified impact of risk and uncertainty on the RE technology value; when combined with other methods, such as portfolio theory and ROA, it can be a valuable tool to simulate various interconnected conditions. In this case, scenarios can derive optimal technology portfolios across different socio-economic scenarios resulting in different stabilization targets [37].

Monte Carlo is a method that allows accounting for numerous stochastic or uncertain input parameters and can be employed to produce probabilistic valuation models which incorporate risk assessment in the evaluation of RE technologies. Thus, it is a method that can capture statistical fluctuations of input variables and derive probability density distributions of cash flows.

MCDA establishes preferences between project options in accordance with a set of criteria and objectives, normally stemming from policy/project objectives as well as other financial, social, technological, and environmental factor considerations. MCDA is often applied as an alternative risk assessment technique because it is able to accommodate multiple criteria and is not constrained to use only monetary values; rather, subjective scales can be employed to rate each option (such as Likert scales). For example, when considering the problem of deciding on whether to invest in a power plant project and determine the order of priority of the projects in the company's portfolio, an investor has to consider a number of risk factors, such as the country risk (the political and economic instability as well as the level of corruption), risk of change in energy policy which may undermine the reliability of the project's economic feasibility, risk of changes in policy premiums, etc. [46], which may be hard to monetise and therefore the application of appropriate multi-criteria methods can prioritise the alternatives through pairwise comparisons in terms of each risk factor (e.g. Analytic Hierarchy Process).

4.2. Strengths and weaknesses

This section outlines briefly some of the strengths and weaknesses of the risk-based evaluation methods, which were not explicitly examined in the previous sections.

As such, the Sharpe ratio has been widely used as a metric for risk-adjusted return in power generation and feasibility studies employing MVP methods [25]. However, the metric has received much criticism since it assumes that financial returns follow a normal distribution, as well as the assumption that investors only focus on the mean and variance of costs of an investment. Nevertheless, several studies have shown that financial returns of assets very often have non-normal characteristics, such as (negative) skewness. This shortcoming of the method can be potentially overcome by using alternative risk measures such as the VaR reflecting the amount that losses will not exceed a specified confidence level over a predetermined time schedule, while another measure often used is the Conditional value-at-Risk (CVaR) (also known as Tail-VaR, mean excess loss and mean shortfall) which is considered a more consistent measure of risk than VaR [155]. From an applicability perspective, the method lacks managerial flexibility since the investors are not able to assess the dynamics of the investment environment and take decisions on the portfolio rebalancing – within the specified investment timeframe – accordingly. Additionally, conventional MVP theory disregards costs of moving from inefficient to efficient energy asset portfolios. Nevertheless, these costs are essential for electricity generation portfolios since there are usually significant salvage and decommissioning costs for existing technologies. The decommissioning cost might be included in the cost of energy, but the costs of shifting from one set of technologies to another are not explicitly addressed.

On the one hand, probabilistic approaches (such as MCS) provide the flexibility to assign probability density functions to input variables using historical data to foresee future developments of parameters; on the other hand, they cannot capture the extremities which might have a critical impact on the power generation system [108]. Each point on the output distribution represents the outcome of the joint probability function of the uncertain input variables. It should be noted that accuracy in the result depends on the appropriate statistical modelling of the stochastic input variables as well as the proper selection of the quantile value for the joint probability distribution function.

Investment planning decision making problems involving deterministic mathematical programming have been developed in standardised modelling frameworks, facilitating the validation and reproducibility of results. Nevertheless, the introduction of uncertainty in one or more of uncertain input parameters has generated a fragmented number of works following different approaches to modelling uncertainty leading to significant lack of precision and conflicting results [122].

Finally, scenario analysis does not provide the flexibility of probabilistic analyses while the uncertainties are not specifically integrated into the solutions explored [86]. Nevertheless, when combined with other risk-based methods, it can be a valuable tool to simulate various interconnected conditions. Further, the strengths and weaknesses of the methods cited above are outlined in Table 4.

5. Conclusions

The analysis of different risk factors (technological, political, social, environmental, etc.) assists stakeholders (developers, investors, utilities) in the RE sector to speak the same language in reference to what risks are associated with a sustainable power generation project and which of these can be transferred, mitigated, avoided or accepted.

The present paper brings together an array of methods that has been widely employed to address/model/incorporate risk and uncertainty attributes (related to energy security, generating costs, market risks, climate change risks, etc.) in sustainable power generation planning and feasibility studies. It was observed that MVP, ROA, MCS and (stochastic) optimisation methods are usually employed to address/model statistical risk factors, while semi-quantitative methods such as scenario analysis and MCDA may also be employed to address non-statistical parameters such as social factors and the emergence of competitive technologies.

Financial risks (e.g. variations in the investment return [62] or energy sale prices) have been widely accounted for in MVP and MCS methods; while the emergence of competing energy technologies (i.e. nuclear power) has been principally captured through scenario analysis [26]. Technology/innovation risk parameters are usually encountered in studies employing ROA, MCS, optimisation and scenario analysis by means of variation in future technology costs (learning curve effects). Stochastic optimisation models are frequently applied to assist policy makers in the definition of optimum energy mixes, taking into consideration uncertainties in the energy demand (i.e. macroeconomic factors), variation in electricity prices, generating costs, fuel risks, technological risks and carbon emission reduction targets. Finally, technical risks, such as reliability of components and access to the grid have been found to be frequently modelled by goal programming methods (i.e. MCDA methods) and optimisation methods.

A general conclusion of the review process is that no modelling approach can combine every element of the problem. Each approach requires different assumptions and views from different perspectives of the socio-techno-economic systems depending on what it attempts to investigate. As an example, microeconomic analysis models (such as ROA) cannot replace models with a wider view of national or regional markets (such as energy system models), rather these methods should complement each other [159]. Untapped issues recognised in the recent methodological approaches reviewed dealing with risk and uncertainty in sustainable power generation planning are summarised below:

- MVP theory is one of the key methods advocated to support that diversification of energy technologies can ensure long-term electricity generation under a balanced risk-return relationship [160]. Yet, an important issue neglected to date in the technique is the consideration of the load structure of the technology combination so that technologies can cover demand during peak hours [37]; hence results derived by the method may ultimately not be insightful for policy makers and practitioners. For providing recommendations on the optimal energy mix, the load structure of the technology mix needs to be incorporated in the model, for example by introducing minimum constraints on peak-load technologies.
- Scenario analysis is particularly useful for explicitly modelling trend uncertainties and plausible future technology developments, especially when conducted according to industry's perceptions, since their actions are grounded on their perceptions, while scenarios constructed by policy makers should be used to derive the expected behaviour of the agents that participate in the market.
- Long-term uncertainties (those that cannot be hedged in forward markets) are usually represented by stochastic input parameters (such as energy demand, electricity price, CO_2 costs) and modelled through probabilistic methods (such as MCS), assuming that they follow a probability distribution. However, the development of their values critically depends on future policies and/or macroeconomic developments, so one has to be sceptical regarding the stochastic process assumption.
- Diversification of technologies has been widely cited as an effective risk mitigation technique also for investor-owned utilities which usually distribute their investments among different power genera-

Table 4
Strengths and weaknesses of risk-based methods.

Methods	Strengths	Weaknesses
MVP theory	1. VaR and CVaR are widely recognised risk metrics allowing for assessing the maximum losses of the portfolio within a specified confidence level [38,156]	1. Focuses on monetary risk attributes [105] 2. Static approaches can understate, if not ignore, managerial flexibility [109] 3. The Sharpe ratio assumes that financial returns follow a normal distribution [25]
ROA	1. Investment timing consideration [110] 2. It can evaluate in depth risk factors likely to occur in the future [157]	1. Complicated numerical calculations 2. Reliance on quantitative data [158]
Stochastic optimisation	1. More suitable than deterministic optimisation approaches for a number of decision making problems in energy systems in presence of uncertain inputs [125]	1. Lack of a standardised way to model uncertainties often leading to significant lack of precision in the results [122]
MCDA	1. Incorporates important non-statistical risk attributes [136]	1. Criteria, weights and values are difficult to accurately estimate and greatly depend on subjective judgements
Scenario analysis	1. Provides information on the impact of potential risks which contribute most to the overall risk.	1. Cannot account for the probability of occurrence of a scenario [86]
Monte Carlo simulation	1. Allows accounting for numerous varying stochastic or uncertain input parameters simultaneously 2. Allows calculating probabilities of a parameter (such as NPV) being below or above a certain target value or within a desired confidence interval [126] 3. Commercial software available to automate the tasks involved in the simulation	1. Requires considerable data volume (definition of probability distribution functions) for random input variables or uncertain and predicted input parameters [57] 2. Difficult to capture extremities

tion technologies. Methods employed to address risk/uncertainty in investor-owned power generation utilities mostly emphasise the statistical risks. However, it is increasingly accepted that non-statistical risks are frequently the drivers of failures (such as policy instability, economic instability, lack of public acceptance, restrictions in terms of land availability) [105]. Translating non-statistical risks (e.g. aggregated through a risk priority number) into a cost per kWh for a number of sustainable energy technologies could contribute towards deriving more cost-effective solutions [14]. The quantification of such risks could be achieved with the support of expert opinions.

In the absence of data, risk factors identified in reference to a sustainable power generation project could be used to create specific scenarios (or else failure modes) that experts could possibly rate in terms of their probability of occurrence and impact [131]. Accordingly, quantitative risk impact evaluation methods could be employed to take advantage of the obtained values. The development of a structured risk-based evaluation framework, focusing on determining the risk-cost profile of sustainable energy generation technologies and mixes of technologies could, thus, constitute a focal point that future research in modelling risk and uncertainty in energy planning and feasibility studies should take into consideration.

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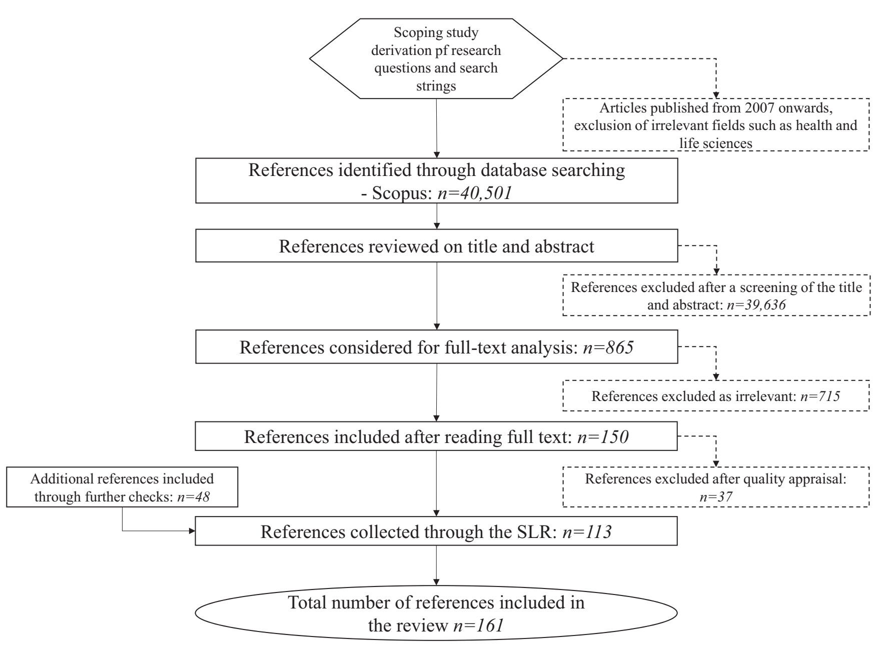

Fig. 3. Summary diagram of the systematic literature review process.

Appindx A. Description of systematic review approach

The literature review was conducted on the basis of a systematic literature review (SLR) approach, which provides the synthesis of the research in a systematic, transparent, and reproducible manner, while also restricting the researcher's bias [22]. To this end, a literature review protocol was produced to frame the research methodology. The literature review protocol outlines the aim and questions underlying the review, the search strategy, the inclusion and exclusion criteria and the plan for data extraction.

Important criterion when selecting the keywords of the research was to be as inclusive as possible in order to avoid missing important studies. Key words selected, were clustered into four (4) different thematic categories: 1. energy & power & electricity & renewable* & fuel (5 keywords), 2. Risk* & uncertain* & stochastic* & fuzzy (4 keywords), 3. Method* & model*(2 keywords) and 4. Feasibility & planning & portfolio & mix & expansion*(5 keywords). Terms belonging to the same category were inserted with a Boolean operator ‘OR’ in the search box, while accordingly terms of Categories 1,2,3 and 4 were combined via a Boolean operator ‘AND’, resulting in 5*4*2*5=200 search strings.

After the search strategy was defined, a number of inclusion/exclusion criteria as regards the papers retrieved was determined to eliminate papers that fall outside the scope of the research topic. The search was limited to scientific peer-reviewed papers to ensure a collection of robust and validated works. Papers were retrieved from Scopus, while the final inclusion of papers considered for full-text analysis was determined following a quality assessment process (Fig. 3).

The initial literature was supplemented with additional works through a bespoke process, when further information to cover a particular topic was needed, or a key text in the literature had been missed by the systematic review.

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B. A cluster analysis of investment strategies in the offshore wind energy market

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A cluster analysis of investment strategies in the offshore wind energy market

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***Abstract*—This paper maps different investor strategies in the offshore wind energy market based on data from existing wind farms in the UK. This is realized through the employment of cluster analysis, which classifies offshore wind energy investors – who have purchased equity stakes- in terms of the entry timing, exit timing, purchase timing and stake purchased. We, then, perform a SWOT analysis to identify the major strengths, weaknesses, opportunities and threats encountered by each cluster of stakeholders. Cluster analysis revealed the existence of three distinct investment strategy profiles: i) Late entry investors, ii) Pre-commissioning investors, and iii) Own-build-transfer investors. Corporate and institutional investors tend to be late entry investors, whose strategy is based on buying assets while they are fully operational avoiding construction risks, retaining a risk aversion profile. The exit timing of OEMs and EPCI contractors usually takes place before or right after the commissioning of the wind farm. Finally, major Utilities tend to keep the operating assets on their balance sheet and divest only part of them (mostly minority stakes) during the operating stage; Independent energy companies are found in both 2nd and 3rd cluster; however, exceptions may be observed.**

Keywords — equity capital investors, offshore wind, cluster analysis, entry and exit timings, investment strategies, SWOT

I. Nomenclature

CfD:	Contracts for Difference
OEM:	Original Equipment Manufacturer
EPCI:	Engineering, Procurement, Construction and Installation
WACC:	Weighted average cost of capital
PPA:	Power purchase Agreement
O&M:	Operation and Maintenance
LEI:	Late-entry investors
PCI:	Pre-commissioning investors
OBTI:	Own-build-transfer investors

II. Introduction

Wind energy has become a significant part of the energy mix within the UK and Europe. It is now established as a mainstream rather than a developing technology, with a mature supply chain. Offshore wind offers favorable conditions for high yield energy production with higher wind shear, abundant available space and limited social impact. Currently, offshore wind farms with capacities similar to those of conventional energy technologies are already built, with higher capacity projects in the pipeline.

Within the existing market, a variety of investors exists with different investment strategies and appetite for risk. Acknowledging the vast uncertainties within the offshore wind energy sector, it becomes pertinent to identify means to systematically assess uncertainty with respect to service life valuation, hence supporting decisions of investors. Each investor develops their bespoke assessment and valuation framework projecting revenues and costs, in order to decide effectively their potential entry and exit instances of the offshore wind farm life-cycle.

As far as revenues are concerned in the United Kingdom, there is currently a transition from the Renewables Obligation (RO) scheme (set to finish on the 31st of March 2017) to the Contracts for Difference (CfD) scheme. According to the CfD scheme, an electricity generation party with CfD is paid the difference between the constant “strike price” and the average UK market price for electricity - “reference price”. If the reference price is higher than the strike price, the generation party has to pay back the difference. Bottom line is that company always gets the strike price for electricity generated. The scheme lasts for 15 years (while the average lifetime of an offshore wind energy asset is 25 years), after which the electricity output is sold on the average UK electricity market price, hence imposing uncertainty to the revenues yielded by the investment after the 15th year of operation [1].

The present paper aims at mapping different investor strategies followed by stakeholders in the offshore wind industry in terms of a number of factors through a cluster analysis [2], by processing data obtained from industry for existing installations; we, then, distinguish the major strengths, weaknesses, opportunities and threats applied to each cluster of stakeholders. The study focuses on offshore wind farms installed in the UK sites, but the methodology can be applied in different regions.

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III. The existing landscape of the UK offshore wind energy investors

Offshore wind (OW) is one of the most rapidly growing markets of all RE technologies. By the end of 2016, there are 3,589 offshore wind turbines with a combined capacity of 12,631 MW fully grid connected in European waters in 82 wind farms across 11 countries, including demonstration sites [3]. The UK is the world's largest generator of electricity from offshore wind, meeting around 5% of annual demand, which is expected to reach 10% by 2020 [4]. Total installed capacity is 5,156MW, representing 40.8% of the total installed capacity worldwide.

Although offshore wind is a proven technology with an expanding supply chain, with the technology's levelised cost of electricity still being relatively high, in the region of 118£/MWh [5], the issue of financing is of major importance. To this end, debt and equity investors along with innovative financing structures are required to support the further deployment of offshore wind.

During the initial stages of the offshore wind market development, major Utilities have been the main investors, bearing all risks from the consenting up to the decommissioning stage of the investment. With the scaling up of the market, new entrants became active in different aspects of the business. Currently, market comprises of a diverse pool of equity investors: Utilities, OEMs (Original Equipment Manufacturers) and EPCI contractors (Engineering, Procurement, Construction and Installation), Independent Power Producers, Pension Funds, Infrastructure Funds, Institutional investors, and Sovereign wealth funds. Different classes of investors usually accept to uptake risks of higher or lower magnitude and of different nature; while, a considerable number of Banks have gained experience in lending to projects and taking construction risks as well [6], improving the financial landscape of the sector.

Corporate finance is dominant in the European offshore wind energy sector, according to which both debt and equity are raised at corporate level (owner's balance sheet), with the corporation's weighted average cost of capital being the weighted average of the required returns as determined by the market. On the other hand, in project finance, funding is raised at the level of each project, individually. Since, project finance investments apply only to the given project, the cost of capital considered provides a good insight for the effective cost of capital of the project and hence the discount rate [7]. Nevertheless, project finance has been underused by power producers since it was considered too expensive; further, the risk of damaging their credit rating is higher, while the due diligence processes are quite time consuming [6].

IV. Cluster analysis of investors in the offshore wind industry

Cluster analysis partitions data into groups so that everything within a group are similar, but different to everything outside that group [8]. A cluster analysis of investors in the offshore wind industry was employed to identify whether specific elements from specific groups of investors can be detected. The analysis gathers knowledge gained by the existing UK offshore wind installations based on data collected from desktop research (e.g. 4C Offshore online database [9] and market reports/online announcements such as: Centrica Company news).

A. Selection of variables and data collection

The 'objects' to be clustered in this analysis are the offshore wind energy investors who have acquired a stake in offshore wind energy projects and the 'observations' are: entry timing, exit timing, purchase timing and stake purchased. There are numerous additional variables that could be considered depending on the aim of the grouping task. Such variables include: the value of stake, the capacity of the wind farms, the O&M costs, the capital cost, the corporate WACC, the divestment stakes and timings, among others. We, nevertheless, focused on above-mentioned parameters since the focus of the study is to explore whether there are distinct trends of investment timings throughout the life of the offshore wind farm, along with the ownership share that different types of investors are willing to buy.

To normalize the data acquired from all currently operating UK offshore wind energy projects investigated (so as to eliminate specificities of each project with regards to the timing of the investment e.g. due to delays during the licensing process or other stages), a scaling of the timing was adopted which is illustrated in Table I. The scaling was considered appropriate, taking into account that offshore wind projects have often very different characteristics to each other. For instance, the construction of a project with high total power capacity (over 500MW) will probably last longer (since it would require more complex installation operations) than the construction of a lower capacity one, while a project whose location is more likely to cause public opposition or has higher environmental impacts may be subject to longer licensing processes. Since this study focuses on the stage each type of investor enters, exits and purchases stake, rather than the actual year before or after the commission of the project, the time scaling of Table I was assigned to the observations (exit, entry, purchase timing).

Table I
Time scaling of the different stages of an offshore wind farm

Offshore wind energy life stages	**Scaling**
Consenting period (from pre-consenting up to consent authorization)	-3
Production and acquisition	-2
Construction and installation	-1
Commissioning	0
Operation and maintenance (throughout the 5 year OEM warranty)	1
Operation and maintenance (following the 5 year OEM warranty)	2
Long Term Operation (towards Decommissioning)	3

B. Results

Cluster analysis starts with a data matrix, where objects are rows and observations are columns. Results of the cluster analysis method applied to operating installations, indicated the formation of distinct groups following similar strategies in terms of their entry, exit, purchase (of equity stake of the investment) timing, as well as the stake purchased.

The resulting scores in the afore-mentioned observations vary among the different stakeholders. A hierarchical cluster analysis was employed, using SPSS software, to maximize the variability between clusters and minimize distance between objects of the same cluster [2]. Following the calculation of the distances between the objects (using the "squared Euclidean distance"), next step in the clustering process is to determine the number of clusters. The dendrogram in Fig. 1 shows the sequence by which the observations and clusters were merged. As mentioned above, the objects of the analysis are the equity capital investors who have purchased stakes in the UK offshore wind sector, while the underscore number refers to the relevant offshore wind energy project. A list of the projects that were considered for the analysis is presented in Appendix A. Figure 2 indicates the composition of the different investor classes found in each cluster along with the mean values of the observations applying to each cluster.

Finding the suitable number of clusters can be determined through a variety of statistical methods. Yet, the clustering should ultimately fit the purpose of the analysis [2, 10] to conceptually support the relevance of the objects of the same cluster. A three-cluster solution was thus adopted and the distinct investor strategy scenarios are documented below:

i) Late entry investors

The first group of investors primarily comprises third party capital investors. Third party financing originates from investors seeking to contribute equity capital without having an involvement on the core activities of the asset. Corporate investors (Marubeni corporation, BlackRock Investment Management, TCW), infrastructure funds (Green Investment Bank) and institutional investors (Development Bank of Japan, AMF Pensionsförkäkring) tend to be late entry investors, buying equity stakes usually a few years after the plant is fully commissioned or, less often, during the late construction phase. The strategy of institutional investors is traditionally based on undertaking exclusively operational risks and avoiding construction risks, retaining a low risk profile with stable returns [6]. The purchased stakes are in general minority stakes (a mean value of 40.7% stake was calculated as shown in Fig.2) and the exit timing is usually long term, most frequently surpassing the 5 year-warranty period of the offshore wind farm. A representative case is the consortium consisted of Green Investment Bank and BlackRock Investment Management in the Lynn and Inner Dowsing offshore wind project, who purchased 61% and 39% equity stake respectively, from Centrica and EIG Global Energy Partners during the 7th year of operation of the above offshore wind project, while Centrica is committed to purchase 100% of the power produced and 50% of the Renewable Obligation Certificates until 2024 [11]. A 49.9% equity stake was sold to Marubeni Corporation on operation year 1 of the Gunfleet Sands wind farm, while 2 years later the Development Bank of Japan purchased the 25% of Marubeni's stake.

ii) Pre-commissioning investors

Independent energy companies (AMEC Offshore wind power, Statkraft, Warwick Energy & Partners, Shell WindEnergy, Eurus Energy, Ecoventures, SLP energy, Eclipse Energy, WIND Prospect Ltd, Enxco AS, Zilkha Renewable Energy), as well as EPCI (Engineering,

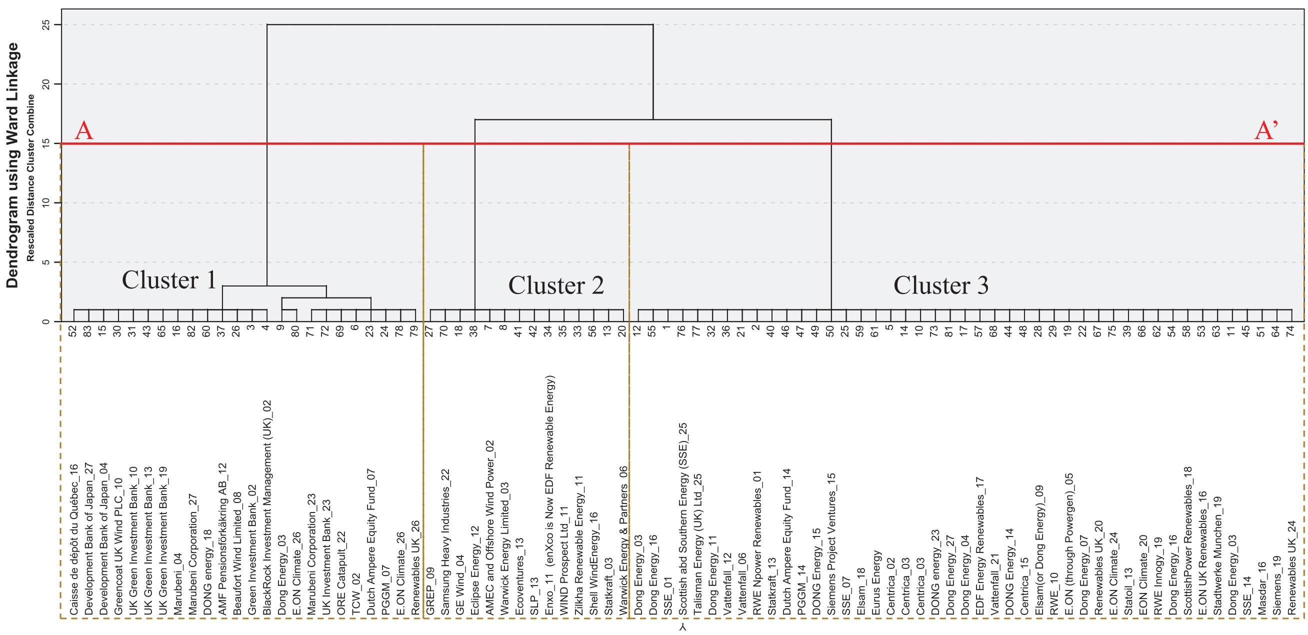

Fig. 1. Dendrogram of clusters of organizations divesting stakes of offshore wind energy assets

Procurement, Construction and Installation) contractors, and Original Equipment Manufacturers (OEMs) (GE Wind and Samsung Heavy Industries, GREP, SLP and Shell Wind Energy) are the majority of investors included in this cluster. Investors in this cluster enter the investment at the beginning of the project's lifecycle, usually from the tendering process of the offshore wind site; the exit timing also takes place prior the commissioning of the wind farm either during the pre-construction (Consent submission, consent authorization, pre-construction period) or during the construction period. The exit year often coincides with the year of disinvestment suggesting that the percentage of stakes disinvested usually amounts to 100%, with the exception of SLP energy and Ecoventures, who have initially disinvested half their stake from Sheringham Shoal project during the initiation of the project (preconstruction phase) and the rest of their stake during the construction stage. On the other hand, the SeaScape Energy joint venture formed to develop the later called Burbo Bank was a venture among: Zilkha Renewable Energy, Enxo AS and WIND Prospect Ltd. Nevertheless, the full ownership and development rights were sold to DONG Energy during the preconstruction stage of the asset.

iii) Own-build-transfer investors

The third group represents investors/project developers who tend not to divest their assets once fully permitted or constructed; rather, they prefer to keep the operating assets in their balance sheet and divest part of their stake (minority stakes) during the operating stage of the asset. The majority of this group consists of Major Utilities like DONG Energy, RWE, Vattenfall, SSE Renewables and E.ON and Independent power producers. As such, this cluster tends to invest equity from the licensing period, work on the development and operation of the wind farm, and divest minority stakes usually during the construction period; holding, however, their remaining share of equity capital for longer periods. Nevertheless, this cluster also includes investors who act as turnkey developers entering the venture at an early stage of its lifecycle, in order to get involved in the construction and installation stage, and following a few years after the project is fully commissioned, they tend to sell the majority (if not the entire) stake they own exiting during the operating stage of the asset. A representative example of such an investor type is Centrica acting as a turnkey developer, assuming the project development risks, running the wind farm for the first years of its operation and exit usually before the end of the 5-year warranty period provided from the wind turbine manufacturer (OEM) [12].

V. SWOT ANALYSIS OF DIFFERENT PROFILES OF INVESTORS' STRATEGIES

A SWOT (Strengths, Weaknesses, Opportunities, and Threats) analysis was further developed in order to map the characteristics of the different investor strategies.

A. SWOT analysis of "late-entry investors"

As shown in Fig. 2 Corporate investors, infrastructure funds and institutional investors account for approximately 70% of the "late entry investors" cluster. Institutional investors consist of pension and life insurance funds. Infrastructure funds' motivation to join the sector is driven by a requirement to promote green energy; hence, they typically invest during the late construction or early operation of the wind farm contributing corporate financing and using their corporate WACC to evaluate the investment.

Strengths: Institutional investors and infrastructure funds typically manage very large amounts of money (mostly in the scale of billions). Institutional investors are interested in owning projects during their operating life and the cost of capital for this class of investors lies in the region of 6%-12% [6, 13]. This group benefit from the lack of construction risk and known factors that affect operational risks (thoroughly investigated through due

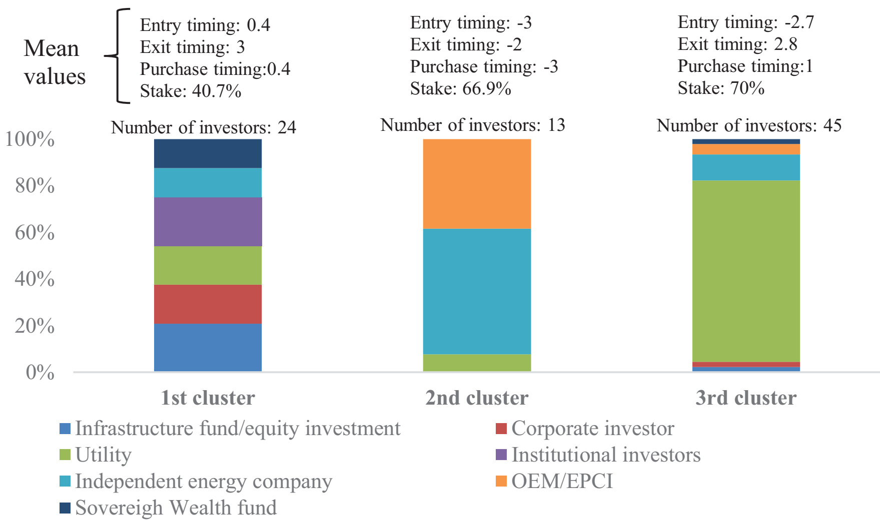

Fig. 2. Composition of Owner classes in each cluster

diligence reports). Institutional investors are interested in making long term investments so as to meet their commitments in terms of pension and insurance claims [6].

Weaknesses: Because of the nature of their business model, third party financing investors are low risk, low return investors. They require warranties (mostly from partners power producers) to cover risks such as power price, construction, variability of wind speeds and O&M costs; however, this results in relatively low returns (low profit margins) also due to unanticipated contingencies. Institutional investors are generally unexperienced in directly investing in infrastructure projects and hence need to employ high cost due diligence surveys in order to evaluate the investment and account for entailed risks when taking on stakes during the operating stage [6]. Nevertheless, recently under project finance deals, infrastructure and institutional funds have started taking construction risks while working together with major power producers who can evaluate in detail the entailed risks. A representative example is PGGM & Ampere Equity Fund refinancing of their 24.8% stake bought from Dong Energy in Walney offshore wind farm [14].

Opportunities: Offshore wind can be a suitable investment for corporate and institutional investors for a number of reasons. Considering the costs of due diligence and their business model orientation, managing fewer large-scale investments is more cost-effective than numerous cheaper ones. Additionally, pension and insurance funds are suitable for providing financing to investments yielding long term returns (until investees claim their life insurance or pension), constituting a good match with the offshore wind energy investments, whose revenues are paid out over the lifetime of the asset (namely 20-25 years), while the break-even of the investment has already taken place and the institutional funds can fulfill their liabilities [6].

Threats: The investment period usually exceeds the subsidy contract period, following which revenues are calculated based on undefined market electricity spot prices. Therefore, the period beyond which power sales are contracted, called merchant tail [15], is difficult to predict, impeding the accurate estimation of the internal rate of return of the project. There are still no reference projects to allow for a confident estimation of decommissioning costs and further for an accurate assessment of O&M costs of assets within the second half of their service life.

B. *SWOT analysis of "Pre-commissioning investors"*

The second cluster comprises mostly of independent power producers and OEMs/ECPI providers. Independent power producers (IPPs) develop, construct and operate offshore wind energy projects; accordingly, they usually sell the generated energy to the grid or to large scale power providers through Power Purchase Agreements (PPAs). Nevertheless, there is a considerable number of IPPs (found in the 3rd cluster), tending to keep the operating assets on their balance sheet or divest smaller stakes. OEMs/ECPI providers bring technical expertise not only during the construction and installation stage of the project but also during the maintenance operations of the wind farm. Nevertheless, above stakeholders contribute equity capital mainly up to the construction and early operation.

Strengths: IPPs with a background in the offshore oil & gas industry (such as Shell) can bring their long experience in the sector. OEMs/ECPI providers' investment strategy is aligned to their business model, gaining profit margins from the installation, manufacture and maintenance of the wind farm. The latter type of investor has the flexibility to consider building a higher-CAPEX asset (more conservative designs through higher material factors in accordance to Industrial Standards [16]) aiming at reducing the OPEX associated with inspections and maintenance (by increasing the intervals between consecutive inspections) and accordingly increase the value of the asset aiming at selling it to another investor at a higher price. OEMs dominate the offshore wind O&M activity and the main reason is the warranties that are sold alongside the procurement of the turbines. These warranties refer to minimum levels of availability and have a typical duration of five years [12].

Weaknesses: IPPs do not have as strong balance sheets as Utility companies and their cost of capital lies in the region of 10-20% (with the exception of IPPs with a background in the offshore oil & gas industry) [6]. They, therefore, seek for third party financing or sell their consent-authorized projects to other parties able to inject cash for the construction of the wind farm, keeping part of the ownership. OEMs and EPCI providers invest equity primarily to ensure the sales of their equipment and technical services for the project; nevertheless, projects they invest equity in, need to be reliable in order to fulfill certain return requirements [17]; indicative risk adjusted return of this class of investor lies between 12-14% [13]. OEMs and EPCI contractors with weak balance sheets typically do not intend to be long-term owners; they, rather, exit either during the construction, commission or a few years following the commission of the asset. However, they may be required by the debt covenants not to divest their stake at an early stage and therefore usually investment in offshore wind projects are taken by OEMs/EPCI providers with strong balance sheets.

Opportunities: EPCI providers and OEMs can mitigate risks by providing turnkey solutions and demonstrating successful track records in their balance sheets, which will contribute to attract new sources of equity and debt funding. Although multi-contracting might be an attractive solution to sponsors, lenders prefer to reduce contract interface risks (increasing counterparty risks) [6]. Following the 5-year warranty period, increasing opportunities for ECPI providers and OEMs are disclosed to increase their market share, diversifying their business and secure additional revenues [18]. Independent power producers' need for capital can also attract financing innovation. By bringing their experience in renewable energy projects, they can create partnerships with equity providers who lack the technical knowledge, such as institutional investors and infrastructure funds.

Threats: OEMs face barriers related to entry in the supply chain due to the significance of the reputation of the firm, keeping the supply of main equipment closed to large manufacturers such as Vestas and Siemens (~65% of total installed capacity) [6]. A study conducted by Deloitte [18] highlighted that one of the biggest challenges in the wind services sector is the lack of qualified technicians to undertake O&M activities.

Table II
SWOT analysis key points

Strengths	**"Late-entry investors"** - Large amounts of money available - Lower cost of capital - No construction risk - Known operational risks (due diligence reports) **"Pre-commissioning investors"** - IPPs from the offshore oil & gas experience in the sector - OEMs/EPCI providers have flexibility to decide on the specifications of the asset influencing its future value **"Own-build-transfer investors"** - Major utilities hold a strong position in offshore wind energy - Strong balance sheets - High competence through the whole value chain of the offshore wind asset - Vertical integration	*Weaknesses*	**"Late-entry investors"** - Risk adverse - No opportunity to influence specifications of the structure - High costs for conducting due diligence surveys **"Pre-commissioning investors"** - OEMs and EPCI providers lack the financial strength to finance the project **"Own-build-transfer investors"** - Financial crisis has impacted financial performance of Utilities
Opportunities	**"Late-entry investors"** - More efficient to manage a few large scale investments rather than many smaller ones (e.g. due to due diligence reports); - Matching of asset's long term returns with liabilities of institutional investors (such as pension funds) **"Pre-commissioning investors"** - OEMs/EPCI providers ensure sales of their equipment and O&M services; - OEMs/EPCI providers can provide turnkey solutions to attract financing from institutional and infrastructure funds **"Own-build-transfer investors"** - Political support for offshore wind; - Strategic agreements	*Threats*	**"Late-entry investors"** - No reference projects to estimate decommissioning costs and late O&M costs - Uncertainty during the merchant tail period **"Pre-commissioning investors"** - High competition to enter the supply chain **"Own-build-transfer investors"** - Competitive environment - Risk management of the project

C. *SWOT analysis of "Own-build-transfer investors"*

The Own-build-transfer group is dominated by major Utilities, Independent energy companies and Sovereign wealth funds.

Strengths: Utilities hold a very strong position in offshore wind energy market. Their strategy focuses on developing the offshore wind farm from the initial stage, and operate it following its commission, divesting mostly minority stakes to institutional and infrastructure investors after a few years of operation. Major Utilities follow a vertical integration business model, operating across the value chain from energy production to retail and trading (to end customers), which drives synergies and places a competitive advantage of the company, while also meeting the requirements under the Renewable Obligations scheme. They are able to finance the project from their own reserves or through corporate finance at a low cost of capital (~8-10%) [6]. Sovereign wealth funds are state funds and hence their cost is typically low, while they typically have large amount of capital to invest in their disposal.

Weaknesses: Although Utilities still dominate the offshore wind energy market, their financial performance has been impacted by the financial crisis, and they hence need to look for other sources of equity and debt financing. To this end, other financing schemes are gaining popularity such as project financing and joint ventures.

Opportunities: The political consensus on promoting clean energy technologies creates great opportunities for big energy companies to participate in the transformation of the energy system. Opportunities lie within the creation of strategic agreements and partnerships, as well as the reduction of the cost of energy.

Threats: Stakeholders within this group operate under a competitive environment, while since they get involved from the development to the operation stage, they need to manage all risks entailed: complex approval processes causing delays or higher payments, regulatory/policy risks related to the uncertainties in policy support schemes, counterparty risks either from equipment/O&M services suppliers or from PPAs not kept, revenue variability due to the intermittency issues or/and due to the grid availability, and electricity price risk, among others [19].

VI. Discussion

Results of the cluster analysis have highlighted the existence of three distinct clusters. Considering that the earlier developed wind farms are now reaching the middle of their service lives, i.e. approximately 10 years, we might expect to see another cluster forming concerning investors choosing to enter or exit the market as the assets approach the end of their service life with the view to repowering or proceeding to the service life extension of the assets. This paradigm has been observed in onshore wind energy assets where a secondary market has developed. Moving on to the next generation to offshore wind energy assets, their potential to allow multiple entry/exit points could be built in even from the planning and design stage.

Typical example comprises the potential decision to employ appropriate provisions of standards to initially over-design the assets or decide to install appropriate integrity monitoring systems with a view to reduce required inspection and unplanned maintenance, hence reducing expected CAPEX. Such an approach will also allow certification, which is a pertinent provision towards transferring risks during operation.

It becomes apparent that evaluating an offshore wind energy project needs to take into account the presence of risk, through appropriate analytical methods [20]. For instance, common industry practice in order to account for the uncertainty in electricity prices after the 15 years (during which revenues are determined by the strike price secured) is to apply forward curves to predict future electricity prices and sensitivity analysis in key input parameters, such as cost of capital, CAPEX and OPEX components, etc.

VI. Conclusion

As the offshore wind energy market expands and the number of operating wind farms increases, commercial aspects begin to receive a lot of attention. Currently, investors from different backgrounds and with different strategies seek for opportunity instances throughout the lifecycle of the asset to invest by purchasing stake of the ownership and contribute equity capital. To better understand whether specific trends can be observed by the different stakeholders, we performed a cluster analysis, where objects were assumed to be investors who have purchased stake in offshore wind energy projects and the observations were the entry timing, exit timing, purchase timing and stake purchased. This process indicated three distinct clusters: the late-entry investors, the pre-commissioning investors and the Own-build-transfer investors.

Late-entry investors represent corporate investors, infrastructure funds and institutional investors who tend to invest equity capital a few years following the commissioning of the plant or, less often, during the late construction. Being, on the most part, a risk adverse group of stakeholders, they tend to avoid construction risks. Long term returns of offshore wind energy assets match with the long term liabilities of institutional investors (such as pension funds), while the high costs of due diligence reports urge third party financing stakeholders to prefer investing in fewer capital intensive assets rather than numerous less expensive ones.

Pre-commissioning investors include independent energy companies and OEMs/EPCI contractors, who enter the venture at the beginning of the project's lifecycle, in order to contribute their technical expertise and knowledge deriving from long term experience in the development of energy projects. An additional incentive for OEMs to invest in the early stage of the development of the wind farm is to ensure the sales of their equipment as well as the O&M contracts of the wind farm. This group usually lacks the balance sheet strength (with the exception of large oil and gas IPPs) to provide large amounts of equity and rely on third party financing for the funding of the project.

Finally, "Own-build-transfer investors" represent principally Utilities; however, IPPs and Sovereign wealth funds were also found to follow a similar trend in terms of the examined criteria. In general, Utilities hold a very strong position in offshore wind energy market operating across the value chain of the wind energy asset. Their strategy focuses on developing the offshore wind farm from the initial stage, and operate it following its commission, divesting mostly minority stakes to institutional and infrastructure investors after a few years of operation.

Similar clusters can also be observed in the offshore oil and gas industry where assets have been operated significantly beyond the end of their service life and an additional cluster is present offering opportunity to invest or disinvest as the assets approach their nominal service life.

Appendix

A. Offshore wind energy projects

1.Greater Gabbard	15. Lincs
2. Lynn and Inner Dowsing	16. London Array Phase One
3. Barrow	17. Teesside
4. Gunfleet Sands 1 & 2	18. West of Duddon Sands
5.Robin Rigg	19. Gwynt Y Mor
6. Thanet	20. Humber Gateway
7. Walney 1	21. Kentish Flats Extension
8. North Hoyle	22. Levenmouth Demonstration Turbine (Energy Park Fife)
9. Kentish Flats	23. Westermost Rough
10. Rhyl Flats	24. Scroby Sands
11. Burbo Bank	25. Beatrice Demonstrator
12. Ormonde	26. Blyth Offshore
13. Sheringham Shoal	27. Gunfleet Sands Demonstration Project
14. Walney 2	

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C. A lifecycle techno-economic model of offshore wind energy for different entry and exit instances

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A lifecycle techno-economic model of offshore wind energy for different entry and exit instances

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HIGHLIGHTS

- A lifecycle techno-economic model of an offshore wind farm is developed.
- Analytical consideration of OPEX linking latest reliability data to ECN O&M tool.
- Sensitivity analysis specified the most sensitive parameters on the investment NPV.
- The model was applied to different investor clusters in the wind energy market.
- Insights regarding potential minimum asking and maximum offered price are derived.

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ABSTRACT

The offshore wind (OW) industry has reached reasonable maturity over the past decade and the European market currently consists of a diverse pool of investors. Often equity investors buy and sell stakes at different phases of the asset service life with a view to maximize their return on investment. A detailed assessment of the investment returns taking into account the technical parameters of the problem, is pertinent towards understanding the value of new and operational wind farms. This paper develops a high fidelity lifecycle techno-economic model, bringing together the most up-to-date data and parametric equations from databases and literature. Subsequently, based on a realistic case study of an OW farm in the UK, a sensitivity analysis is performed to test how input parameters influence the model output. Sensitivity analysis results highlight that the NPV is considerably sensitive to FinEX and revenue parameters, as well as to some OPEX parameters, i.e. the mean time to failure of the wind turbine components and the workboat significant wave height limit. Application of the model from the perspective of investors with different entry and exit timings derives the temporal return profiles, revealing important insights regarding the potential minimum asking and maximum offered price.

1. Introduction

With 92 wind farms in operation across European countries (including sites with partial grid-connected offshore wind (OW) turbines [1]), the OW market and supply chain have been rapidly expanding, attracting a diverse pool of investors that include Utilities, Original Equipment Manufacturers (OEMs), Independent Power Producers, Japanese Trading Houses, Pension Funds and Banks [2]. Broadly speaking, these investors can be segmented based on their attitude to risk (technology readiness level, track record, portfolio diversity, country, and asset phase), return expectations (Internal Rate of Return (IRR) and yield), holding length, and level of engagement [2,3].

Numerous authors have conducted research in the technical and economic feasibility of OW farms [4–9] and related innovative concepts [10,11], and the development of cost models for OW farms [12–15]. In [4], a feasibility study was performed for the development of an OW farm installed in the Northern Adriatic Sea, in order to test the suitability of the region for the development of the technology, while [9] refers to a feasibility study off the Turkish coast. Another study determining the profitability of an OW energy investment across different areas of Chile was performed in [8]. Kaiser and Snyder have developed models for the installation and decommissioning costs of offshore wind farms, based on existing data in European wind farms [13,16]. Myhr et al. developed a lifecycle cost model with the aim to predict the LCOE of a number of offshore floating wind turbine concepts and compare them with their fixed monopile counterparts [5]. One of their

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conclusion was that LCOE is particularly sensitive to the distance from shore, load factor and availability. Authors in [7] develop a methodology for the life-cycle costing of a floating OW farm and apply it to analyse a location in the North-West of Spain and indicate the best platform option. Dicorato et al. formulated a general model to evaluate the costs in pre-investment and investment stages of OW farms and then employed this method to indicate the most suitable wind farm layout [12]. A review of offshore wind cost components was performed by [17], summarising parametric expressions and data available in literature including the acquisition and installation of wind turbines and foundations, the electrical system, the predevelopment costs, etc. Shaffie et al. have also developed a parametric whole life cost model of offshore wind farms, which requires less input data in relation to other tools available [14], aiming to provide a simple framework for estimating the LCOE of the investment. Data were also trained in order to provide expressions for the estimation of the cost of materials used in a wind turbine, as well as the cost of the offshore substation. Finally, sensitivity analysis was performed in order to indicate the most impactful parameters of the model on LCOE.

Existing literature on the financial returns from renewable energy projects assumes that there is a single investor who owns the asset (e.g. the wind farm) throughout its entire service life [7,9,18,19]. However, recent research [3], as well as market reports [2,20,21] show that equity investors buy and sell their stakes at different phases of the OW farm life, depending on their investment strategy. To this end, a model that predicts returns over time could be useful for investors and policy makers to check the viability of the investment and to predict the temporal return profile of the investment. Additionally, the analytical consideration of the capital expenditure (CAPEX), operational expenditure (OPEX) and financial expenditure (FinEX) variables could contribute to the identification of input parameters that have the highest impact on the feasibility of the project.

This paper aims at addressing this challenge through developing a lifecycle techno-economic assessment framework for the prediction of lifecycle costs of OW farms, which incorporates up-to-date models for the estimation of key cost components, taking into consideration technical aspects associated with the installation and maintenance of the asset. The model developed takes into account the time that expenses occur as well as the time value of money. The high-fidelity model predicts the different costs of a typical OW farm in a lifecycle-phase-sequence pattern, by:

- adopting the most up-to-date parametric equations found in the literature;
- developing new parametric equations where latest data are available;
- including the use of industry standard ECN O&M Tool [22] for the prediction of operation and maintenance costs in conjunction with latest reliability data from [23].

Compared to existing literature related to the life-cycle cost assessment of OW farms, the novelty of this paper lies on, firstly, the consideration of different equity investors with different investment strategies that buy and sell stakes at different time instances during the life of an OW farm project and the development of a relevant tool that enables such investors to assess the viability of their investment [3]; secondly, the prediction of the maintenance cost of the OW farm by linking the latest reliability data published in literature to the industry standard ECN O&M tool, which can account for site specific details (such as the wind profile of the location which affects the available weather window for maintenance interventions); and, finally the derivation of cumulative cost and revenue curves which can reflect the temporal value of the asset, providing a decision support framework to investors and, deriving insights on expected upper and lower bounds for the OW farm price setting.

Although the focus of this study is placed on Europe and especially the UK, a country with significant technical resource [24], as well as a mature market with significant secondary sales activity, the proposed methodology can be applied to other country contexts (such as Japan, Korea and China which are regarded as significant emerging players in the OW market), provided the corresponding policy regime and cost adjustments (personnel cost, material costs, etc.) are taken into consideration. It, thus, needs to be highlighted that results should be treated with caution as input data have been adopted from wind farms mainly installed in North Europe, while no data currently exist for the USA or Asian offshore wind farms. Furthermore, for regions of Asia and the USA (where the frequency of hurricanes and typhoons is much higher than in Europe), existing design standards should also be potentially adjusted to ensure that extreme weather phenomena are properly accounted for.

2. Methodological approach

2.1. Investor profiles in the European offshore wind market

Within the existing market, there is a variety of investors with different investment strategies and appetite for risk. OW power plants are subject to a number of uncertainties of both technical and financial nature [25], which can be encountered across the whole life of the asset by means of variability in the energy performance, capital costs, operational costs, and economics of the LCOE model [26]. As such, during the predevelopment phase, investor faces uncertainties associated with the legal, environmental survey and project management costs, among others. During the procurement phase, there is uncertainty in the prediction of the cost of materials of the different components of the wind farm, while during construction, variability in the cost of labour, availability and cost of installation vessels, weather conditions, along with the duration of the installation operations induce additional risk in the evaluation of the investment. Damages to the wind turbines during the operation and maintenance phase result in uncertain repair costs and loss of revenues due to downtime. Finally, variability in the cost of capital can have a significant effect on the LCOE. Acknowledging above uncertainties within the OW energy sector [27], it becomes pertinent to identify means to systematically assess uncertainty with respect to service life valuation, hence supporting decisions of investors [28]. Each investor develops their bespoke assessment and valuation framework projecting revenues and costs, in order to decide effectively their potential entry and exit strategies.

An analysis [3] of investor strategies, based on data from existing OW farms in the UK indicated the existence of three distinct profiles: (i) Pre-commissioning investors, (ii) Build-Operate-Transfer investors, and (iii) Late entry investors.

Late entry investors comprise third party capital investors, who are investors seeking to contribute equity capital without having an involvement on the core activities of the asset, such as corporate investors, infrastructure funds and institutional investors. They undertake exclusively operational risks, entering after the commissioning of the wind farm, thus avoiding construction risks. This strategy is generally consistent with a low risk profile with stable returns. They principally purchase minority stakes in wind farm assets (mean value of 40.7%).

Pre-commissioning investors principally comprise independent energy companies, EPCI (Engineering, Procurement, Construction and Installation) contractors, and Original Equipment Manufacturers (OEMs). They can be considered as turnkey developers entering the venture at an early phase of its lifecycle to get involved in the construction and installation phase. Further, they tend to sell the majority (if not the entirety) of their stake and exit few years after the project is fully commissioned.

Finally, Build-Operate-Transfer investors comprise major utilities and independent power producers, who build and then keep the operating assets in their balance sheet. Further, they tend to divest part of their stake (minority stakes) during the operating phase of the asset.

Accurate prediction of the temporal returns profile of the investment is useful for the different types of investor clusters to conduct the techno-economic assessment of the asset during the specific year of purchase or divestment. To this end, a parametric life cycle techno-economic model was developed to accommodate the different investor

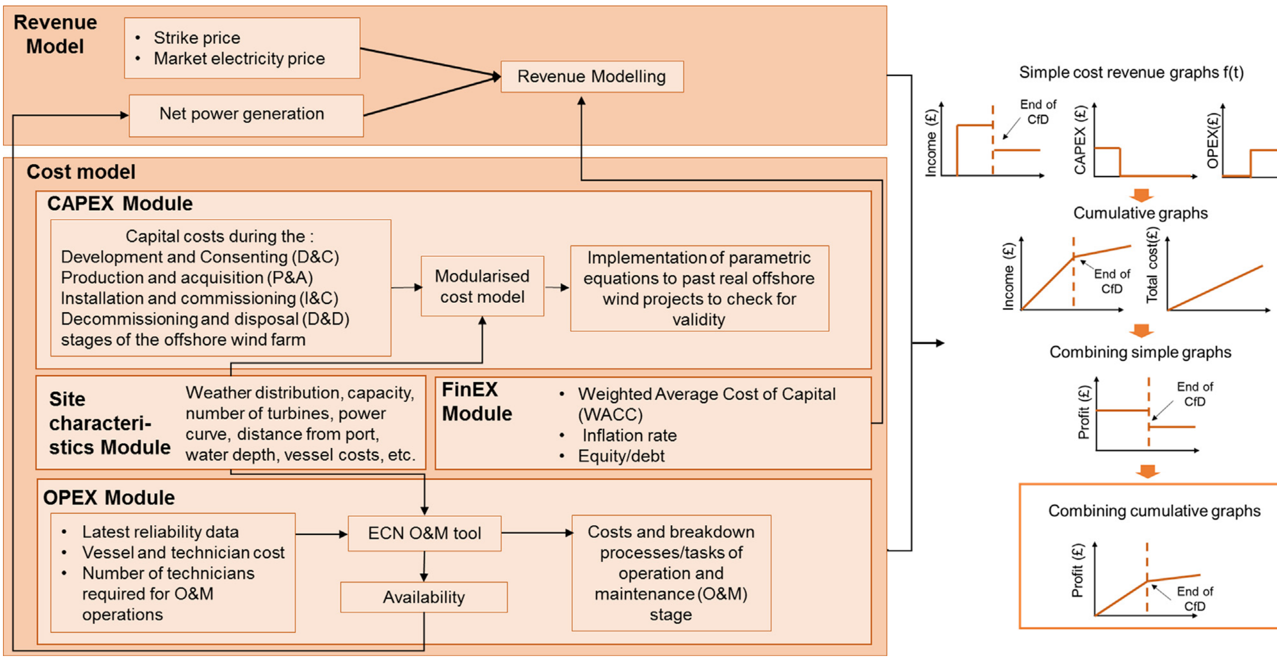

Fig. 1. Methodological framework.

strategies with the view to identify temporal return profiles of the asset.

2.2. Overview of the developed techno-economic model for the valuation of an offshore wind energy project

In this section, the different components or programming modules of the techno-economic model of the OW energy farm are presented. The 5 main phases of an OW farm project considered are: Development and Consenting (D&C), Production and Acquisition (P&A), Installation and Commissioning (I&C), Operation and Maintenance (O&M) and Decommissioning and Disposal (D&D).

The methodological approach followed in this paper consists of the modules illustrated in Fig. 1, namely: (i) the CAPEX module, which includes costs during the D&C, P&A, I&C and D&D phases of the OW farm, (ii) the general site characteristics module with details on the weather conditions, site water depth, distance from port, vessels, cost of personnel etc., (iii) the FinEx module with parameters related to the financing expenditures, namely the Weighted Average Cost of Capital (WACC), inflation rate, equity and debt ratio, etc., (iv) the OPEX module considering reliability data from literature, cost of personnel, materials, vessels and related maintenance processes, which will provide availability, and O&M cost estimates pertinent for the cost analysis and (v) the revenue module, which considers the net power generation, the energy policy scheme in place for supporting the technology, namely the Contracts for difference (CfD) scheme, and the market electricity price (the scheme mandates that revenues are calculated on the basis of the strike price during the first 15 years of operation of the asset and the market electricity price over the rest of its life) to derive the revenues yielded by the investment. Outputs of the model are temporal cumulative return profiles of the investment, which can support the appraisal of investment opportunities for different types of investors in various periods of a wind farm service life, taking into account the technical parameters of the problem.

3. Case study site characteristics, weather, vessel and personnel data

This section outlines the assumptions and characteristics of the reference wind farm, corresponding to a realistic OW farm in the UK. It also compiles data that apply to multiple phases of the lifespan of the asset, such as the specifications of vessels and the cost of personnel. Key assumptions of the wind farm site are included in Table 1. The 504 MW capacity wind farm is located in the North Sea region, 36 km away from shore. Weather data (3-hourly data over a 3-year period) were retrieved from BTM ARGOSS [29] for modelling the operational phase of the asset. Weather delays during the I&C and the D&D phases were modelled by the use of an adjustment factor (*ADJWEATHER*), which will be described in more detail in Section 4.1.3. A wind farm of approximately 500 MW capacity was considered a reasonable selection, since there is a number of studies that has considered the same wind farm capacity in their baseline scenario, such as [5,14], which could facilitate comparison of results.

3.1. Vessel data

Vessel data encompass the cost (and key characteristics) of vessels chartered for carrying out the I&C, O&M and D&D phases of the project. The specifications of the vessels (for instance, speed, day rates and mobilisation costs) employed for the completion of above phases are integrated in Table 2, while further data regarding the number and the type of vessels used per phase and task is clarified in the respective Sections of the paper. The wind speeds are referenced at 10 m above the mean water level, while the mobilisation and demobilisation activities comprise the

Table 1
Case study wind farm specifications.

Wind farm characteristics		Values
Wind farm	Total wind farm capacity, P_{WT}	504 MW
	Projected operational life of the wind farm, n	25 years
	Construction years, T_{constr}	5 years
	Number of turbines, n_{WT}	140
General Site characteristics	Distance to port, D	36 km
	Water depth, WD	26 m
Wind turbine	Rotor diameter, d	107 m
	Hub height, h	77.5 m
	Pile diameter, D_{pile}	6 m
	Rated power	3.60 MW
	Cut-in speed	4 m/s
	Cut-out speed	25 m/s

Table 2
General data for O&M vessels and transportation equipment.

Vessel type	Technician space	Vessel speed (knots)	Weather limits		Mob./demob. Cost (k£)	Mob./demob. Time (h)	Day rate (k£/day)
			Sign. wave height (m)	Wind speed (m/s)			
Crew transfer vessel[i]	12	26	1.8[iii]	16[iii]	–	–	3.25[ii]
Jack-up vessels[iii]	–	10[iv]	2	10	405	720/48	112.6
Heavy lift vessel[vi]	–	9	–	–	500[ix]	–	135
Helicopter[v]	6	–	99	20	4.7	8/4	4.7
Diving support vessel (DSV)[iii]	–	16	2	25	185	360[v]	60
Cable laying vessel [iii]	–	14	1	10	445[iii]	720[v]	80 (Array), 100 (Export)
Rock dumping vessel	–	13.5[vii]	–	–	10.6[viii]	–	13.8[viii]

[i] Source: [30].
[ii] Source: [31].
[iii] Source: [32].
[iv] Source: [33].
[v] Source: [22].
[vi] Source: [13].
[vii] Source: [34].
[viii] Source: [35].
[ix] Source: [36].

Table 3
Cost breakdown of P&C costs.

Cost components	Total cost (£ million)	Percentage over total P&C cost (%)
Legal costs, $C_{legal,pc}$	16.7	8.1%
Environmental survey costs, $C_{surveys,pc}$	19.2	9.3%
Engineering costs, $C_{eng,pc}$	1.14	0.6%
Contingency costs, $C_{cont,pc}$	126.4	61.4%
Project management cost, $C_{proj,pc}$	42.3	20.6%

cost and time allocated to the planning, preparing and modifying a vessel for a marine operation (mobilisation), and then to restoring it for release and reassignment to other operations (demobilisation).

3.2. Personnel cost

Apart from the vessel crew, additional personnel is hired to perform mechanical/electrical operations for the installation, erection and other services at a rate of £270/day [5,37]. Offshore personnel works on a shift pattern of 2 weeks "on" followed by 2 weeks "off" according to working time regulations for offshore workers [38]. Finally, a total of 12 working hours per day is assumed [5].

4. Integrated techno-economic model

4.1. CAPEX module

As previously mentioned, the CAPEX module includes costs during the D&C, P&A, I&C and D&D phases of the OW farm, which are further analysed in the following Sections.

4.1.1. Development and consenting phase (D&C)

Development and consenting costs include all costs prior to the point of financial close (i.e. the point when all financing agreements of the project have been signed and the conditions have been met) including project management, surveys (environmental, coastal process, Met station, sea bed, human impact), legal authorisation, front-end engineering and design and contingency costs [14,39]. Costs during D&C of the wind farm vary significantly across different sites; thus, different values of costs can be found in literature. Indicatively, in [39] a total of £60 million for a 500 MW wind farm is reported, while in [14] costs were estimated £202.8 million for a wind farm of the same capacity. Myhr et al. [5] assumed a cost of £89.9 million/500 MW, while in [40] a total cost of £156.5 million/500 MW was estimated, when adjusted to the respective currency and inflation rate. In the examined case study with the total windfarm capacity of 504 MW, the cost breakdown of [14] is adopted as shown in Table 3, as a more conservative scenario.

4.1.2. Production and acquisition phase (P&A)

4.1.2.1. Wind turbines. The acquisition of a fully equipped turbine is one of the most expensive cost components of the P&A phase of the wind farm. Cost is usually expressed as a function of the turbine capacity and different parametric models have been developed to predict the cost of different sizes of turbines [11,12,15,17]. Within the context of the reference case study, the following expression has been formulated for the estimation of the wind turbine cost [14]:

$$c_{T,pa} = 3\cdot10^6\ln(P_{WT})-662{,}400,\text{in£/turbine} \tag{1}$$

where, P_{WT} is the capacity of the wind turbine (MW). For a wind turbine of 3.6 MW, Eq. (1) results to £3.1804 million/turbine, while by adding the tower cost into the total turbine costs (which according to [39] is of the order of £1 million for a 5 MW turbine), total cost for the acquisition of the turbine and the tower accounts for approximately £3.90 million/turbine.

4.1.2.2. Foundations. A monopile configuration was assumed for the reference case study as it remains the most popular substructure up to date with a cumulative amount of 87% of all installed foundations in 2017 [1]. The cost of foundation depends largely on the type of foundation, the depth of the site, the seabed characteristics as well as, to a lesser extent, the turbine capacity, the wave and wind conditions [17]. The cost of foundation, $c_{F,pa}$, was estimated by means of a parametric expression linking the foundation cost to the turbine geometry (hub height, h and rotor diameter, d) and the water depth (WD) according to [41]:

$$c_{F,pa} = 320{,}000\cdot P_{WT}\cdot(1 + 0.02\cdot(WD-8))\cdot\left(1 + 8\cdot10^{-7}\cdot\left(h\cdot\left(\left(\frac{d}{2}\right)^2-100{,}000\right)\right)\right) \tag{2}$$

Application of the above expression to the reference case study resulted in £1.52 million/foundation. Other parametric expressions, found in the literature, link foundation cost with water depth, turbine capacity, as well as cost of material usage and fabrication [5,12,17]. For example, application of [17] to the baseline case study gives £1.14 million/foundation.

4.1.2.3. Transmission system. The transmission system of the wind farm consists of: the collection system of the generated power by means of array cables, the integration of the power through an offshore substation, the transmission of the electricity from the offshore substation to shore through the export cables. Two kinds of export cables are distinguished: the offshore export cables transmit the electricity from the offshore substation to the onshore substation, and the onshore export cable which transport the power to the grid connection point.

4.1.2.3.1. Cables. Array cables organise turbines in clusters adopting various different grid schemes, such as the radial design according to which, turbines of each cluster are interconnected in a 'string' ending at an offshore substation.

Mean Voltage (MV) submarine cables are most frequently used as array cables, while High Voltage (HV) export cables carry the stepped up voltage from the offshore substation to the grid connection point. MV cable unit costs, similarly to HV cable unit costs vary according to the cable section (i.e. data summarised in Table 4) and nominal voltage (as shown in [12]).

Export cables can be either high-voltage alternating current (HVAC) or high-voltage direct current (HVDC) depending on a number of factors and especially the distance from shore. Generally, if the distance from shore is less than 50 km, AC cables would be preferred while for longer distances and in more remote wind farms, DC cables are used since HVDC cabling has no reactive power requirements resulting in lower power losses [40,43].

In general, the total cost of the cables, $C_{cables,pa}$, is calculated by the product of the unit-length price of the cable, c_i (£/m), with the number of cables, N_i, and the average length of each cable, L_i (km). Protective equipment (such as J-tube seals, passive seals, bend restrictors etc.) is required to protect the cables [14].

$$C_{cables,pa} = \sum_{i=1}^{3} (c_i \cdot L_i \cdot N_i) + C_{protection}, \text{in } £ \tag{3}$$

where, i denotes the cable type of the wind farm, namely: the MV array cables ($i = 1$), the HV subsea export cables ($i = 2$) and the HV onshore export cables ($i = 3$).

Retrieving data from 4C Offshore [44], a linear equation with two predictors namely, the number of wind turbines, n_{WT} and the rotor diameter d (in m) was produced as follows:

$$L_1 = 1.125 \cdot n_{WT} + 1.055 \cdot d - 122.64 \; (R^2 = 0.959), \text{in km} \tag{4}$$

The length of the subsea export cable, L_2, is assumed equal to the distance between the centre of the OW farm (where the offshore substation is located) and the shore (where an onshore substation is located), an assumption also taken in [45], which for the baseline case study is 36 km. Finally, the length of the onshore export cable, L_3, is equal to the distance from the onshore substation to the grid connection point (assumed to be 10 km long each). The electrical system is comprised of 33 kV array cables and two offshore substations of 336 MW HVAC transmission system. Further, the transmission assets are connected to the onshore substation by three 800 mm^2 132 kV subsea export cables. The resulting costs of the electric system are summarised in Table 5.

Table 4
Unit costs of AC submarine cables from companies A and B.
Source: [42].

Conductor size (mm^2)	95	150	400	630	800
	Collection system unit cost (£/m)				
Company A	142	213	356	534	561
Company B	426	462	570	594	684
	Transmission system (£/m)				
Company A				706	
Company B				805	

Table 5
Electric system cost components.

Cost component	Total cost (k£)	Total length of cables (km)
Array cables	28,039	147.7
Offshore export cables	84,002	108
Onshore export cables	7,778	30
Offshore substation (x2), $C_{off,subst,pa}$	121,340	–
Onshore substation, $C_{on,subst,pa}$	30,334	–

4.1.2.3.2. Substations. The most cost efficient electric power transmission method to reduce cable losses is by means of an offshore substation, which is considered appropriate for projects located at a distance of > 20 km offshore [40]. The total offshore substation cost has been estimated by a number of authors [14,17] who derived parametric expressions linking the offshore substation cost to the total installed capacity of the wind farm. In the present study, the offshore substation cost, $C_{offSubst,pa}$, was estimated based on [12], which breaks down the cost of offshore substation to: (1) the MV/HV transformer cost, C_{TR}, (2) MV switchgear cost, $C_{SG,MV}$, (3) HV switchgear cost, $C_{SG,HV}$, (4) HV busbar cost, c_{BB}, (5) Diesel generator cost, C_{DG} to supply essential equipment when the OW farm is off, and (6) substation platform cost, $C_{offSubst,pa_f}$. The expressions of the individual cost components are the following:

$$C_{TR} = n_{TR} \cdot (42.688 \cdot A_{TR}^{0.7513}) \tag{5}$$

$$C_{SG,MV} = 40.543 + 0.76 \cdot V_n \tag{6}$$

$$C_{DG} = 21.242 + 2.069 \cdot P_{WF} \tag{7}$$

$$C_{offSubst,pa_f} = 2534 + 88.7 \cdot P_{WF} \tag{8}$$

$$C_{offSubst,pa} = C_{TR} + C_{SG,MV} + n_{TR} \cdot (2 \cdot c_{SG,HV} + c_{BB}) + (C_{DG} + C_{offSubst,pa_f}) \tag{9}$$

where, n_{TR} is the number of transformers, V_n is the nominal voltage and A_{TR} is the rated power of the transformers. Using Eq. (5)–(9) the total cost of offshore substation was calculated £60.67 million. In the context of the case study, 2 offshore substations are assumed to be placed in order to transmit the power at 132 kV. Platform 1 contains three transformers each rated 180 MVA, while Platform 3 has two 90 MVA transformers installed. Finally, the export cables connect the offshore substations with an onshore substation which further transforms power to grid voltage (e.g. 400 MW). Onshore substation cost was assumed to be half the cost of the offshore substation according to [14,39].

4.1.2.4. Control system. More recent wind farms have integrated supervisory control (including health monitoring) and data acquisition (SCADA) systems, with the view to optimise wind turbine life and revenue generation [39]. Health monitoring of wind turbines is performed by means of sensors and control devices, gathering data that can be used for optimising operation and maintenance operations. Cost of monitoring was estimated $C_{SCADA,pa} = 75$ k£/turbine [12].

4.1.3. Installation and commission phase (I&C)

This phase refers to all activities involving the transportation and installation of the wind farm components, as well as those related to the port, commissioning of the wind farm and insurance during construction.

Once a suitable number of components are in the staging area, the offshore construction starts with installation of the foundations, transition piece and scour protection, followed by the erection of the tower and the wind turbines. Accordingly, the installation of the offshore substation, the array cables and finally the export cables and onshore substation takes place.

4.1.3.1. Foundation and wind turbine installation. Installation costs are a function of the vessel day rates, the usage duration and the personnel costs required for carrying out the operations. Vital components of both the wind turbine and the foundation installation cost are the vessel day rates and the duration of the installation processes. The total time per trip of an installation vessel is broken down to: the travel time, the loading time, the installation time and the intra-field movement time.

For the installation of monopiles a jack-up vessel can be employed with an assumed deck capacity of $VC_{F,JU} = 4$ foundations. After foundations are secured, the transition pieces are lifted and placed on the top of the foundation pile and are then grouted. In the context of the present case study, it is assumed that the installation of monopiles and the placement of transition piece can be realised by the same vessel.

The total installation time of foundations was estimated by the following expression:

$$T_{F,Instal} = 2\cdot N_{F,voy}\cdot T_{j,port} + 2\cdot n_{WT}\cdot T_{j,site} + n_{WT}\cdot T_{F,Load} + T_{porttofarm} + T_{betwtrb,F} + n_{WT}\cdot T_{F,Lift} \tag{10}$$

where, $N_{F,voy}$ is the number of voyages, $T_{j,port}$ is the time of jacking at port (up/down), n_{WT} is the number of turbines, $T_{j,site}$ denotes the time of jacking at installation site, $T_{F,Load}$ denotes the monopile foundation loading time, $T_{porttofarm}$ is the travel time from port to farm, $T_{betwtrb,F}$ represents the time to travel between turbines, and $T_{F,Lift}$ is the offshore lift/installation time of the monopile. More details on the calculation steps for the estimation of the foundation installation cost are included in Appendix A.

Turbines are installed after foundations have been placed. The vessel used both transports turbines in the installation site and performs installation. Turbines typically consist of seven components, namely nacelle, hub, 3 blades, and 2 tower sections. Onshore assembly of some of the parts of the OWT is usually performed in order to reduce lifts offshore, which can be considered risky and prone to cause delays due to wind speeds. The installation process of OW turbines is composed by the following time steps: 1. Travel/transportation time, 2. Lifting operation time, 3. Assembly operation time (onshore and offshore), and 4. Jacking up operation time. The pre-assembly (i.e. onshore assembly) strategy followed determines the total time of turbine installation, along with the distance from the port, the number of turbines, the nameplate capacity, etc. Characteristics of different pre-assembly methods are summarised in Table 6.

For this reference case study, preassembly method 5 was used entailing 3 offshore lifts. Total installation time was estimated by the following expression [46]:

$$T_{T,Instal} = \frac{T_{T,Travel} + T_j + T_{T,Assemb} + T_{T,Lift}}{V_{N,JU}} \tag{11}$$

where, $T_{T,Travel}$ represents the travel/transportation time of turbines, T_j is the jacking up operation time, $T_{T,Assemb}$ is the assembly operation time, $T_{T,Lift}$ is the lifting operation time, and $V_{N,JU}$ symbolizes the number of identical jack up vessels. Considering 12 h of total working hours, effective installation time was estimated 264 days, equivalent to 1.89 days/turbine, which is in agreement with mean installation times found in literature [13]. The individual time components of the turbines installation time are presented in Appendix B.Finally, for the installation of the tower and the Rotor Nacelle Assembly (RNA), 30 additional offshore workers are employed, and another 30 for the installation of the foundations and transition pieces. An overview of the results produced by the model on the installation costs of OW turbines and foundations is given in Table 7. A weather adjustment factor of $ADJWEATHER = 0.85$ was assumed in the baseline scenario to account for delays due to unpredictable unfavourable weather conditions.

Table 7
Summary of results on foundations and turbines installation.

Parameter	Value
Total effective days of foundations installation, $T_{Effectdays,F}$	292 days
Total effective days of turbines installation, $T_{Effectdays,T}$	264 days
Total effective days per foundation + transition piece	$2.08\frac{\text{effective days}}{foundation}$
Total effective days per turbine	$1.89\frac{\text{effective days}}{turbine}$
Cost of personnel employed for the installation of foundations	£2.36 million
Cost of personnel employed for the installation of turbines	£2.14 million
Total installation cost of foundations, $C_{F,ic}$	£102.2 million
Total installation cost of turbines, $C_{T,ic}$	£62.6 million

4.1.3.2. Scour protection installation. The scour phenomenon takes place around structures undergoing steady current conditions, and is associated with the increase in the sediment transport capacity and erosion [47]. To ensure structural stability of the wind turbine foundation (as well as protection of cables), scour protection is usually applied. Available options to protect from scour are: placement of geotextile containers/sandbags, concrete armour units/block mattresses, grout bags/mattresses and rock armour (among others), which cover a particular area of the seabed [48]. The scour protection option employed is site-specific, i.e. at some locations the amount of protection varies with sediment and current conditions, while in others scour protection may not be needed. The input data used for the estimated mass of scour protection [49], the vessel leased for installation and the total installation time were adopted from [13,50,51].

The total effective duration for the installation of scour protection takes into account the lead time due to potential adverse weather conditions during the installation operations. As such, the total effective days were calculated by the following equation:

$$T_{Effectdays,Scour} = \frac{T_{Scour,Inst}\cdot N_{trips,scour}/24}{ADJWEATHER} \tag{12}$$

The total effective days correspond to the actual number of days that the rock-dumping vessel should be leased to perform the operations. As such, the installation cost of scour was estimated based on the vessel day rate and mobilisation cost (included in Table 2). Table 8 presents inputs and outputs related to the calculation of the total cost and installation time of the scour protection.

4.1.3.3. Cables installation. A dedicated Cable Laying Vessel (CLV) needs to be leased for the installation of the inner array and export cables. Average installation rates of inner-array and export cables were

Table 6
Pre-assembly methods characteristics.

Installation method	Sub-assemblies	No of onshore assemblies	No of lifts/assemblies during installation (N_{Lj})
1	(Nacelle + hub) + 3 blades + tower in 2 pieces	1	6
2	(Nacelle + hub) + 3 blades + tower in 1 piece	2	5
3	Nacelle + (hub + 3 blades) + tower in 2 pieces	3	4
4	(Hub + nacelle + 2 blades)+ tower in 2 pieces + 1 blade	4	4
5	(Nacelle + hub + 2 blades) + 1 blade + tower in 1 piece	4	3
6	(Nacelle + hub + 3 blades + tower in 1 piece)	6	1

Table 8
Input and output data for scour protection installation.
Sources: [16,34,50,51].

Parameter	Value
Inputs	
Tonnage of scour protection per unit, *SPU*	6,890 ton/turbine
Rock-dumping vessel capacity, VC_{scour}	24,000 ton
Number of trips required to the installation of scour protection, $N_{trips,scour}$	41
Total transportation time of scour protection by rock-dumping vessel, $T_{Scour,Tr}$	2.97 h/trip
Dumping time per trip, $T_{Scour,Dump}$	16 h/trip (4 h/turbine)
Loading time per trip, $T_{Scour,Load}$	12 h/trip
Mobilisation cost of rock-dumping vessel, $V_{scour,Mobil}$	£10,650
Outputs	
Total time for scour protection installation, $T_{Scour,Inst} = T_{Scour,Tr} + T_{Scour,Dump} + T_{Scour,Load}$	31 h/trip
Total effective days for scour protection installation, $T_{Effectdays,Scour}$	62 days
Installation cost of scour protection, $C_{Scour,ic}$	£872,600

calculated by taking into account historic data from past projects on the total length (in km) of the cables and total installation time (in days) [13]. Average installation rates were estimated approximately 1.6 and 0.6 km/day for export and inner array cables, respectively. For the installation of the subsea cables, a trenching ROV (Remotely Operated underwater Vehicle) was employed for the post–lay burial of the cables with a daily charter rate of 82.5 k£ [39]. The installation cost of export and array cables was, thus, estimated based on the total duration of the installation operation, and the day rates of the CLV and the trenching ROC. As such, the installation cost of array and export cables were calculated by the following expressions:

$$C_{C-array,ic} = T_{C-array,Inst}\cdot(V_{DR,CLV-array} + V_{DR,Trench}) + V_{Mobil,CLV} \quad (13)$$

$$C_{C-export,ic} = T_{C-export,Inst}\cdot(V_{DR,CLV-export} + V_{DR,Trench}) + V_{Mobil,CLV} \quad (14)$$

Input and output data for the cable installation are summarised in Table 9.

4.1.3.4. Substation installation. Substation is assumed to be barged on site and get installed by a Heavy-Lift vessel (HL). The installation time is comprised of the jacket foundation installation time, the grout application (if applicable) and, the installation of the substation topside. The voyage time from the port to the installation site and vice versa is estimated by:

$$T_{HL,voy} = 2\cdot\frac{D}{V_{S,HL}} \quad (15)$$

where, $V_{S,HL}$ is the speed of the heavy lift vessel used for the installation of the substation units. The total installation time of the substation is calculated as:

$$T_{Subst,Inst} = (n_{Subst,pile}\cdot R_{Subst,pile}\cdot D_{pile}) + T_{reposit} + T_{Substjacket,Inst} \quad (16)$$

The symbols of Eq. (16), the input data used in the context of the case study, along with the derived results concerning the transportation and installation time of the substation foundation/topside are demonstrated in Table 10. To estimate the weight of a typical substation topside, a dataset from existing OW farms was established consisting of the substation topside weights for various wind farms whose capacities range from 60 to 630 MW (data retrieved from [52] from deployed wind farms) and a linear regression model was trained based on this dataset. As a result, the mass of the topside substation can be approximated by the following linear equation (shown in Fig. 2):

$$W_{Subst,top} = 3.5129\cdot P_{WF} + 388.85 (R^2 = 0.9011) \quad (17)$$

Table 9
Input and output data for cables installation.

Parameter	Description	Value
Cables installation – inputs		
Installation rate of export cable		1.6 km/day
Installation rate of array cables		0.6 km/day
Cables installation – outputs		
Effective days required for the installation of export cables, $T_{C-export,Inst}$		147 days
Effective days required for the installation of array cables, $T_{C-array,Inst}$		537 days
Installation cost of export cables, $C_{C-export,ic}$		£27.3 million
Installation cost of array cables, $C_{C-array,ic}$		£87.7 million

Table 10
Input and output data for offshore substation installation.

Parameter	Value
Offshore substation installation – input	
Number of piles per substation foundation, $n_{Subst,pile}$	4
Rate of piling the piles of the substructure, $R_{Subst,pile}$	0.115 h/m
Depth of pile under the soil, D_{pile}	36 m
Reposition time of the vessel, $T_{reposit}$	8 h
Installation time of the substation's jacket, $T_{Substjacket,Inst}$	20 h
Offshore substation installation – output	
Total effective installation days for one substation, $T_{Subst,Inst}$	13 days
Total installation cost (for the 2 substations), $C_{OffSubst,ic}$	£3.99 million

The weight of the topside substation will determine the vessel that will be required with the appropriate crane capacity as shown in Table 10. Instead of assuming one topside substation of 2160 ton, two identical substations of 1080 ton were assumed. The estimation of the installation cost of the substation was based on the total effective duration of the installation operation, $T_{Subst,Inst}$, and the HL vessel day rate, $V_{DR,HLV}$, and mobilisation cost, $V_{Mobil,HLV}$, as expressed below:

$$C_{OffSubst,ic} = T_{Subst,Inst}\cdot V_{DR,HLV} + V_{Mobil,HLV} \quad (18)$$

Input and output data for the substation installation are summarised in Table 10.

4.2. OPEX module

4.2.1. Failure modes and latest reliability databases utilised

For the prediction of O&M total cost, an updated database of failure rates, number of technicians required for repairs and cost of repairs was used as input. A number of onshore wind reliability analysis exists in literature, covering the whole onshore turbine as well as its subassemblies

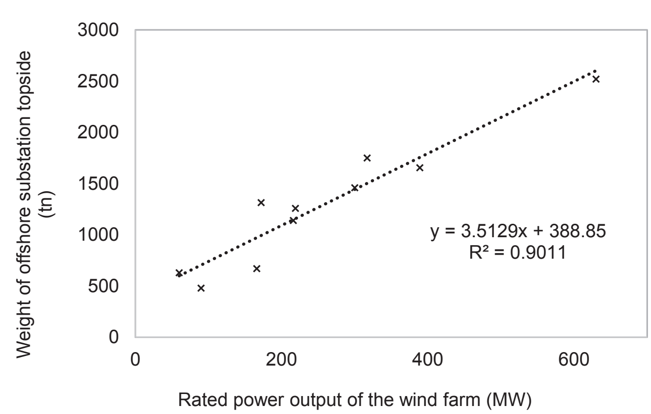

Fig. 2. A linear model for offshore substructure topside mass used in a wind farm (data retrieved from [52]).

[53–56]. As far as the reliability analysis of OW turbines is concerned, in [23] authors have gathered information from around 350 OW turbines with nameplate capacities ranging from 2 to 4 MW and ages between 3 and 10 years old. The failure rates used in the present analysis are provided in a per turbine per year format, defined as:

$$\lambda = \frac{\sum_{e=1}^{E}\sum_{k=1}^{K}\frac{n_{e,k}}{N_{T,e}}}{\sum_{e=1}^{E}\frac{T_e}{8760}} \tag{19}$$

where, λ denotes the failure rate per turbine per year, E is the number of intervals for which data are collected, K is the number of subassemblies, $n_{e,k}$ the number of failures during the specific interval, $N_{T,e}$ the number of turbines that were examined, and T_e represents the total time period in hours.

$\sum_{e=1}^{E}\sum_{k=1}^{K}\frac{n_{e,k}}{N_{T,e}}$ denotes the total number of failures in all periods per turbine while $\sum_{e=1}^{E}\frac{T_e}{8760}$ is equal to the sum of all time periods in hours divided by the number of hours within a period of a year.

Repairs are classified as minor repairs (repairs that cost up to 1,000€), major repairs (1,000–10,000€) or major replacements (> 10,000€); a categorisation adopted by the Reliawind project which has registered failure rate data for onshore wind turbines [57]. Data on the failure rates, average repair times, number of required technicians and material costs are enclosed in Table 11.The "No cost data" category refers to repairs for whose cost data are not registered.

The mean time between failures (MTBF) is a commonly used reliability metric for repairable items and it can be expressed as the inverse of the failure rate, as follows:

$$MTBF = \frac{1}{\lambda} \tag{20}$$

As demonstrated in Fig. 3, MTBF is connected to the mean time to repair (MTTR) and the Mean Time To Failure (MTTF) as follows [58,59]:

$$MTBF = MTTF + MTTR \tag{21}$$

The MTTF represents the reliability of the system while the MTTR denotes the competence of the maintenance strategy to recover the system back to normal operation (as well as the weather window to perform maintenance operations). The latter is hence a stochastic quantity that available reliability data cannot capture and needs to be processed in detail as will be described in Section 4.2.2. Since wind turbine components undergo failures usually less than once a year (therefore MTBF > 365 days), while the MTTR usually lasts for much shorter time, above expression can be assumed equivalent to $MTBF \cong MTTF$, which is the simplification that needs to be made in the application of the ECN O&M tool as will be described below.

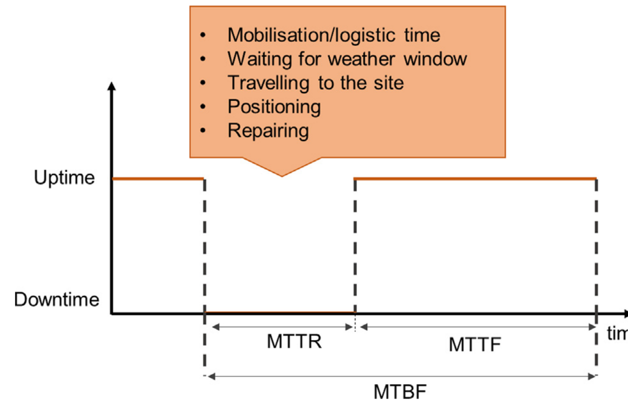

Fig. 3. Illustration of the MTTR, MTTF and MTBF.

4.2.2. Specification of settings for O&M costs

The detailed estimation of the O&M annual costs, downtime because of O&M activities and revenue losses caused by energy production loses was carried out through the ECN O&M tool [60], which has been used by numerous project developers and turbine manufacturers in the OW industry, and it is considered as the most comprehensive tool for O&M analysis to date [61]. It generates an average yearly estimation of the O&M cost over the lifetime of the wind farm; hence, long term average values of failure rates (as the ones outlined in Table 11) are needed as input to determine annual operating costs.

Apart from the general characteristic values of the wind farm (i.e. the number of turbines, the wind farm capacity, the power curve, etc.), met ocean data were also inserted in the software for an indicative installation site located in North Sea. Software allows for 1-hourly or 3-hourly significant wave height and mean wind speed data to be introduced; to this end, 3-hourly data was supplied by BTM ARGOSS [29].

For framing the maintenance strategy of the reference OW farm, a

Table 11
Average repair times (h), number of required technicians, material cost for different turbine components and repair category. FR: Failure rates (failures/turbine/year), ART: Average repair times (h), RT: Required technicians, MC: Material cost (€).
Source: [23].

	No cost data			Minor repair				Major repair				Major replacement			
	FR	ART	RT	FR	ART	RT	MC	FR	ART	RT	MC	FR	ART	RT	MC
Pitch/Hyd	0.072	17	2.8	0.824	9	2.3	210	0.179	19	2.9	1900	0.001	25	4	14,000
Other Components	0.15	8	2.3	0.812	5	2	110	0.042	21	3.2	2400	0.001	36	5	10,000
Generator	0.098	13	2.4	0.485	7	2.2	160	0.321	24	2.7	3500	0.095	81	7.9	60,000
Gearbox	0.046	7	2.2	0.395	8	2.2	125	0.038	22	3.2	2500	0.154	231	17.2	230,000
Blades	0.053	28	2.6	0.456	9	2.1	170	0.01	21	3.3	1500	0.001	288	21	90,000
Grease/oil/cooling liq.	0.058	3	2	0.407	4	2	160	0.006	18	3.2	2000	0	0	0	0
Electrical components	0.059	7	2.4	0.358	5	2.2	100	0.016	14	2.9	2000	0.002	18	3.5	12,000
Contactor/circuit/breaker/relay	0.048	5	2	0.326	4	2.2	260	0.054	19	3	2300	0.002	150	8.3	13,500
Controls	0.018	17	3.2	0.355	8	2.2	200	0.054	14	3.1	2000	0.001	12	2	13,000
Safety	0.015	2	2	0.373	2	1.8	130	0.004	7	3.3	2400	0	0	0	0
Sensors	0.029	8	2.7	0.247	8	2.3	150	0.07	6	2.2	2500	0	0	0	0
Pumps/motors	0.025	7	2.5	0.278	4	1.9	330	0.043	10	2.5	2000	0	0	0	0
Hub	0.014	8	2.4	0.182	10	2.3	160	0.038	40	4.2	1500	0.001	298	10	95,000
Heaters/coolers	0.016	5	2.7	0.19	5	2.3	465	0.007	14	3	1300	0	0	0	0
Yaw System	0.02	9	2.4	0.162	5	2.2	140	0.006	20	2.6	3000	0.001	49	5	12,500
Tower/foundation	0.004	6	2.3	0.092	5	2.6	140	0.089	2	1.4	1100	0	0	0	0
Power supply/converter	0.018	10	2.7	0.076	7	2.2	240	0.081	14	2.3	5300	0.005	57	5.9	13,000
Service items	0.016	9	2.2	0.108	7	2.2	80	0.001	0	0	1200	0	0	0	0
Transformer	0.009	19	2.8	0.052	7	2.5	95	0.003	26	3.4	2300	0.001	1	1	70,000

number of operational decisions (common within the O&M strategies of OW projects) needs to be taken. As such:

- Four workboats (crew transfer vessels, (CTVs)) are available for O&M operations and are permanently leased on a fixed contract. CTVs are used for the transportation of personnel and small components with 26knots maximum speed and maximum capacity of 15 workers.
- One helicopter is chartered to transfer technicians when response time is critical. Typically three technicians plus their equipment can be transferred by helicopter (top speed 245 km/h) [62].
- One jack-up vessel (heavy maintenance vessel) is chartered in the spot market in order to transfer and instal heavy components.
- One diving support vessel is chartered on the spot market to perform underwater inspections.
- One cable laying vessel for replacing any damaged power cables when required.

The site is close enough to shore ($D = 36$ km) and the maintenance activities are staged out of the O&M port; thus, an accommodation vessel (or mother vessel) was not considered necessary in the baseline case study and the access time for minor repairs and inspections as well as the fair weather window were evaluated in reference to the distance from shore.

General data such as maximum wave heights, wind speeds for the transportation equipment and vessel costs are shown in Table 2. Values included in the table have been retrieved and cross checked through a number of references [5,61,63–65], including a report [66] completed by the National Renewable Energy Laboratory (NREL) and the Energy Research Centre of the Netherlands (ECN) as well as from real data retrieved from 4C Offshore website [44].

The ECN O&M tool considers three types of O&M strategies, namely calendar-based, condition based and unplanned corrective. For unplanned corrective maintenance each component of the system (wind turbine and the Balance of the Plant (BOP)) is assigned an annual failure frequency. This may consist of several failure modes (fault type classes, (FTC)) with different severities and frequencies. The failure frequencies of each component of the system are introduced in the software through the MTTF. Annual failure rates from Table 15 are hence transformed on a per hour basis, as follows:

$$MTTF = \frac{8760}{\lambda}, \text{in h} \tag{22}$$

In the context of the baseline scenario, the components of the system considered are the ones summarised in Table 11, while the different FTCs are categorised as minor repairs, major repairs or major replacements (according to the Reliawind categorisation) with relative failure frequencies (RFF) calculated as:

$$RFF_{fc}(\%) = \frac{\lambda_{fc}}{\sum_{fc=1}^{numberofFTC} \cdot \lambda_{fc}} \cdot 100 \tag{23}$$

where, fc denotes the number of FTC. Apart from the RFF defined per FTC, the priority level as well as the repair and spare control strategy need to be defined; we set major repairs and major replacements to be of high priority and the rest to be of normal. Further data used for the definition of the unplanned corrective maintenance strategy constitute the average repair times, number of required technicians and material costs which were retrieved from Table 11. Finally, the logistic time for major replacements for unplanned corrective maintenance was assumed around 250 h. Due to the multiple uncertainties as well as the lack of data for predicting condition based maintenance activities, this maintenance type was ignored.

The period for calendar based maintenance is set between 01-May to 30-September to take advantage of the expected favourable weather conditions. For calendar based maintenance, all wind turbines are assumed to be maintained on an annual basis, through a lower cost maintenance mission, while every 5 year a larger preventive maintenance mission is assumed to take place.

The estimation on the total number of technicians to perform the O&M operations was based on having the maximum number of manpower for 4 workboats, resulting in a total of $4 \cdot 12 = 48$ technicians. The annual fixed technician's salary is 95 k£ for unplanned corrective maintenance, while additional crew for the calendar-based maintenance is hired with hourly wage £120/hour in the base case scenario [67].

4.2.3. Operation and maintenance phase (O&M) cost estimation

The costs for maintaining the OW farm were determined by both unplanned and corrective maintenance. The parameters exported through the tool were, among others, the range of availability of the wind farm, and the average annual repair cost and the power production. Results are summarised in Table 12.

4.3. Decommissioning and disposal phase (D&D)

Energy companies are obliged to remove all structures and verify the clearance of the area upon the termination of the lease. Decommissioning activities relate to the removal of the wind turbine (i.e. nacelle, tower and transition piece) as well as the balance of the plant (substation, cables and scour protection). Removal of the wind turbine and tower is done using a reversed installation method while the removal of foundation is carried out by the use of a cutting tool that removes the transition piece, while an ICM (Internal Cutting Manipulator) is used to cut the monopile at 2 m below the mud-line [68]. Cranes are used to lift the cut pieces of the turbine. Removal of mud and internal cutting can be realised by means of a workboat, while the lifting of the structure is performed by a jack up vessel. Two jack up vessels with deck space to load 5 complete WTGs with foundations are assumed. For the removal of the substation topside a heavy lift vessel is required while the jacket support structure of the substation also needs to be cut (the 4 piles) in order to get removed. As far as cables are concerned, they can be partially or wholly removed, depending on whether they are buried or not [69]. Cables can be cut in several sections while they are removed, hence, less expensive vessels can be employed, such as Special Operations Vessels (SOVs) or barges. In this analysis, 50% of the initial length of cables are assumed to be left in situ after the decommissioning of the wind farm (an assumption derived from discussions with wind farm operators). The scour protection may also be left in situ in order to conserve the marine life that would have grown on it. Site clearance is the final stage during decommissioning and it encompasses the removal of the debris accumulated in a specified radius of the structure throughout the 25 years of life of the wind farm. Vessels employed for the decommissioning of the structures are assumed to have similar characteristics to the ones summarised in Table 2. Input and output values of the removal process are included in Table 13.

Further to the removal of the wind turbine components, the balance of the plant and the clearance of the area, removed items need to be transported and disposed. Cost of transportation is a function of the total mass of the wind farm components, $W_{components}$, the cost per ton-mile of the transportation truck, $C_{truckperton-mile}$, the capacity of truck, W_{truck}, and the distance of port from the waste facility, $D_{port-facility}$, as follows [14]:

$$C_{transp,dd} = \frac{\sum W_{components}}{W_{truck}} \cdot D_{port-facility} \tag{24}$$

Table 12
Summary of OPEX in the baseline scenario.

OPEX estimation	Values
Availability (%)	92.5/92.2%
Repair costs	£28.38 million/year
Net annual energy production	1,734,792 MWh/year

Table 13
Removal costs of wind turbine.

Parameter	Value
Turbine and foundation removal – inputs	
Remove time per turbine with a self-propelled jack up vessel	15 h/turbine
Complete turbines (including foundations) capacity of a Jack up vessel	5 turbines/trip
Number of jack up vessels for the removal of the wind turbines	3
Number of workboats employed for the decommissioning of the turbines	2
Number of technicians per workboat	5
Offloading time of turbines/monopiles	8 h/item
Time to cut the foundation	6 h/foundation
Time to lift the item and place on the deck	11 h/item
Turbine and foundation removal – outputs	
Total duration of each trip which equals the sum of the travel time to and from site, the removal time of turbines and monopile, the loading time and the intra-field movement time of the jack up vessel	244 h
Total time per trip (adjusted to weather and working hours)	26 days
Total effective days for turbines and monopiles removal divided by the number of vessels, $T_{Effectdays,TF-Rem}$	243 days
Total cost of hiring technicians and workboats during the decommissioning of the wind turbines, $C_{vessel,dd}$	£4.13 million
Total cost for removing all wind turbines with monopiles, $C_{TF,dd}$	£83.5 million
Offshore substation removal – inputs	
Pile diameters of jacket substructure	2.6 m
Cutting rate of the pile	1 h/m
Lifting time of topside substructure	3 h
Cut time of topside	12 h
Reposition time of vessel to each leg of the jacket substructure	8 h
Offshore substation removal – outputs	
Time to cut the 4 piles	10.4 h
Total time for the removal of the two substations, $T_{Effectday,Substat-Rem}$	8.7 days
Total cost for removing the two substations, $C_{offSubst,dd}$	£1.18 million
Cables removal	
Rate of removal of inner-array cables	600 m/day
Rate of removal of export cables	875 m/day
Cost of cables removal, $C_{cables,dd}$	£11.9 million
Site clearance	
$Area = -51.5 + 0.41 \cdot d + 0.65 \cdot n_{WT}$, in km	83.37 km^2
Total cost for site clearance, $C_{clear,dd}$	£5.38 million

4.4. Revenue module

Levelised cost of electricity (LCOE) models consider the costs throughout the whole life of the asset. However, investors emerging in different phases of the OW farm are interested in the profitability profile of the investment from the purchasing instance until their exit point from the investment. Assessing the profitability of investing in an OW farm in different phases of its service life requires the estimation of the temporal profile of the revenues that the investment yields.

As far as the policy instruments supporting the OW industry are concerned, the Contract for Difference (CfD) scheme is currently in effect in the United Kingdom, which is a private law contract between a low carbon power producer and the Low Carbon Contracts Company (LCCC), a government-owned company. According to the CfD scheme, the low carbon power producer sells the produced electricity, as usual, through a Power Purchase Agreement (PPA), to a licenced supplier or trader at an agreed reference market price. However, in order to reduce investors' exposure to variations in electricity market prices, the CfD mandates that the power producer is paid the difference between a pre-determined "strike price" and the reference market price. If the reference price is lower than the strike price, the power generator receives the difference from LCCC; reversely, if the reference price is higher, the power producer has to pay back the difference. The bottom line is that the power producer always gets the strike price for the electricity generated. CfDs are awarded to power producers in allocation rounds and the amount of the strike price is determined through an allocation process, which is either based on administrative strike prices set by the Government (provided there are sufficient funds) or by means of a competitive auction run by the National Grid. The auctions ensure that the least expensive projects are awarded, reducing, thus, the cost passed to consumers. The scheme lasts for 15 years (while the average lifetime of an OW energy asset is 25 years), after which the electricity output is sold on the average UK electricity market price, hence imposing uncertainty to the revenues yielded by the investment after the 15th year of operation [70]. To this end, appropriate modelling of the cash inflows, along with the taxation imposed to the income needs to be conducted. For the reference case study, the baseline strike price value considered amounts to £140/MWh (which corresponds to the administrative strike price for 2018/19 [71]).

4.5. FinEX module

4.5.1. Depreciation and tax

Tax depreciation is available through the capital allowances regime, according to which $d_{rate} = 18\%$ of qualifying expenditure on equipment is reduced [72]. Depreciation is a term used in accounting in order to spread the cost of the capital assets over the life span of the investment, so that the net profit in any year will reflect all the costs required to produce the output. The effect of depreciation is estimated by dividing the equipment cost of the wind farm, $C_{equipment}$, over the total life span of the asset and deducting the 18% of this annual cost from the tax payment. The net tax, t_{net}, can then be calculated by deducting the depreciation credit, d_{credit}, from the yearly tax payment, $t_{payment}$, as shown below:

$$d_{credit} = \frac{C_{equipment}}{n} \cdot d_{rate} \tag{25}$$

$$t_{net} = t_{payment} - d_{credit} \tag{26}$$

$$t_{payment} = t_c \cdot P_{gr} \tag{27}$$

where, $t_c = 17\%$ is the nominal corporate income tax rate paid every year and P_{gr} represents the gross profit. Accordingly, the Net profit, P_{net}, of the investment can be calculated as:

$$P_{net} = P_{gr} - t_{net} \tag{28}$$

4.5.2. WACC and inflation

Inflation and interest rates are used to account for the time value of money. Inflation accounts for the reduction in the purchasing power of a unit of currency between two time periods, while the interest rate is the rate earned from a capital investment. In financial analysis, the nominal interest rate is the interest rate quoted by the banks, stock brokers etc. which includes both the cost of capital and the inflation. Real discount rate (or else real WAAC) integrates the inflation adjustment and the discount of cash flows according to Fisher Equation [73]:

$$WACC_{real} = \frac{1 + WACC}{1 + R_{infl}} - 1 \approx WACC_{nom} - R_{infl} \tag{29}$$

The discount rate is determined by the source of capital as well as the estimation of the financial risks associated with the investment. Projects gather their capital by raising funds through debt and equity. These sources of financing demonstrate individual risk-return profiles; hence their costs also fluctuate. The cost of capital will correspond to the weighted average of cost of its equity and debt, with weights determined by the amount of each financing source. The WACC is calculated by the following expression [74]:

$$WACC = \frac{VE}{V} \cdot RoE + \frac{VD}{V} \cdot Rd \cdot (1 - tc) \tag{30}$$

where, VE is the market Value of Equity, VD is the market Value of Debt, $V = VE + VD$, RoE denoted the Return on Equity, and Rd the interest rate on debt. The risk of the project significantly influences the amount of return on investment required by the investor. External capital is cheaper and, thus, it is often desirable to obtain the highest possible amount of debt; however, the cost of debt depends on the specific investment risk, namely the highest the investment risk, the lower the amount that banks will be willing to lend. Average values for the components of WACC were retrieved from [75,76] for OW energy and are summarised in Table 14. Further, the real WACC is calculated by taking into account the inflation rate (inflation rate was estimated equal to 2.5% in the baseline case study, which is a realistic assumption according to UK inflation rate predictions for 2017–2018 [77]).

5. Results and discussion

5.1. Cost breakdown

In this Section, an overview of the case study results is presented. Table 15 summarises the cost estimates of the different lifecycle phases. The total undiscounted CAPEX encompassing costs during the P&C, P&A, I&C and D&C phases amounts to £1.675 billion, while the annual OPEX was estimated £56.6 million.

In Fig. 4, the relative contribution of the 5 different phases of the life cycle to the total LCOE is presented. It is indicated that the costs incurred during the P&A phase have the largest share of the total costs (46%), followed by the O&M costs (30%). These results are consistent with a number of previous studies [14,78].

5.2. Sensitivity analysis

For the sensitivity analysis of the model, we have considered the wind farm general specifications, presented in Table 1 as design parameters (parameters that remain unchanged) and we have tested the sensitivity of variables found in the other modules of the model with respect to their influence on the Net Present Value (NPV) of the investment (as opposed to other works testing sensitivity of design parameters on the economic performance of the wind farm [14,79]). This should allow a targeted investigation of the impact of parameters that can be influenced during the lifecycle of a wind farm of a given location.

The results of the sensitivity analysis are illustrated in Fig. 5(a)–(d). The graphs include parameters which have an influence of at least ± 2% (cut-off point) on the NPV upon a 20% increase/decrease in their values. Under the baseline scenario, NPV of the investment was calculated £2 843 million at a real discount rate of 6.15% with an IRR = 10.3%. Further, LCOE was estimated £109/MWh.

Most influential CAPEX parameters appeared to be the wind turbine acquisition cost, the working hours of the personnel and the foundation acquisition cost increasing the NPV by 28% in absolute terms, upon a 20% decrease in their values, followed by the day rate of the jack up vessels and the weather adjustment factor inducing an approximately 9% change in the NPV.

As far as the OPEX parameters are concerned, the MTTF and the workboat wave height limit appeared to have the greatest influence on the NPV of the investment. In fact, a 20% drop of the wave height limit of the workboat, decreases NPV by 16%. Considering the significant effect of this factor on the feasibility of the project, the operator could consider measures to limit this risk; for example, through leasing workboats which could provide safe access at higher wave heights or through hiring other modes of transportation, which would allow rapid access to the WTGs regardless of weather (e.g. helicopters).

Table 14
Input data for the cost of capital calculation model.
Sources: [74–76].

	Values (%)
Share of equity, $\frac{VE}{V}$	30
Share of debt, $\frac{VD}{V}$	70
RoE	15.8
Rd	7
$WACC_{nom}$	8.8

Table 15
Overview of case study results.

Name	Value
CAPEX in k£	
Total P&C costs, $C_{P\&C}$	205,750
Project management cost $C_{proj,pc}$	42,327
Legal costs, $C_{legal,pc}$	16,698
Environmental surveys costs $C_{surveys,pc}$	19,162
Engineering costs, $C_{eng,pc}$	1,144
Contingency costs, $C_{cont,pc}$	126,419
Total P&A costs, $C_{P\&A}$	1,040,230
Wind turbine cost, $C_{T,pa}$	546,056
Foundation cost, $C_{F,pa}$	212,699
Cables cost, $C_{cables,pa}$	120,525
Offshore substation (x2), $C_{offSubst,pa}$	121,337
Onshore substation, $C_{onSubst,pa}$	30,334
SCADA cost, $C_{SCADA,pa}$	9,278
Total I&C costs, $C_{I\&C}$	305,742
Installation of wind turbines (tower, hub, nacelle and blades), $C_{T,ic}$	62,619
Installation cost of foundations, $C_{F,ic}$	102,224
Installation cost of cables, $C_{Cables,ic}$	115,070
Installation cost of substation, $C_{offSubst,ic}$	3,991
Installation cost of scour protection, $C_{Scour,ic}$	873
Insurance cost during installation $C_{insur,ic}$	20,966
Total D&D costs, $C_{D\&D}$	122,860
Removal cost of turbines and monopile foundations, $C_{TF,dd}$	83,526
Cable Removal, $C_{cables,dd}$	11,907
Removal of offshore substation, $C_{offSubst,dd}$	1,176
Scour Protection removal, $C_{scour,dd}$	1,612
Grout removal, $C_{grout,dd}$	60
Transportation cost, $C_{transp,dd}$	21
Disposal cost, $C_{disposal,dd}$	2,452
Site Clearance, $C_{clear,dd}$	5,376
Cost of hiring vessels and personnel, $C_{vessel,dd}$	4,130
Port preparation, $C_{port,dd}$	12,600
OPEX in k£/year	
Total O&M costs, $C_{O\&M}$	56,597
Repair cost, $C_{repair,om}$	28,403
Rent cost, $C_{rent,om}$	5,040
Insurance cost, $C_{insur,om}$	7,338
Project management cost, $C_{proj,om}$	15,816

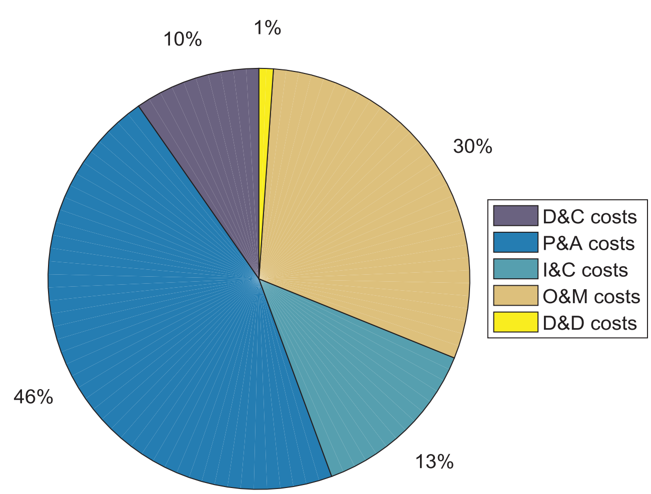

Fig. 4. Life cycle cost breakdown.

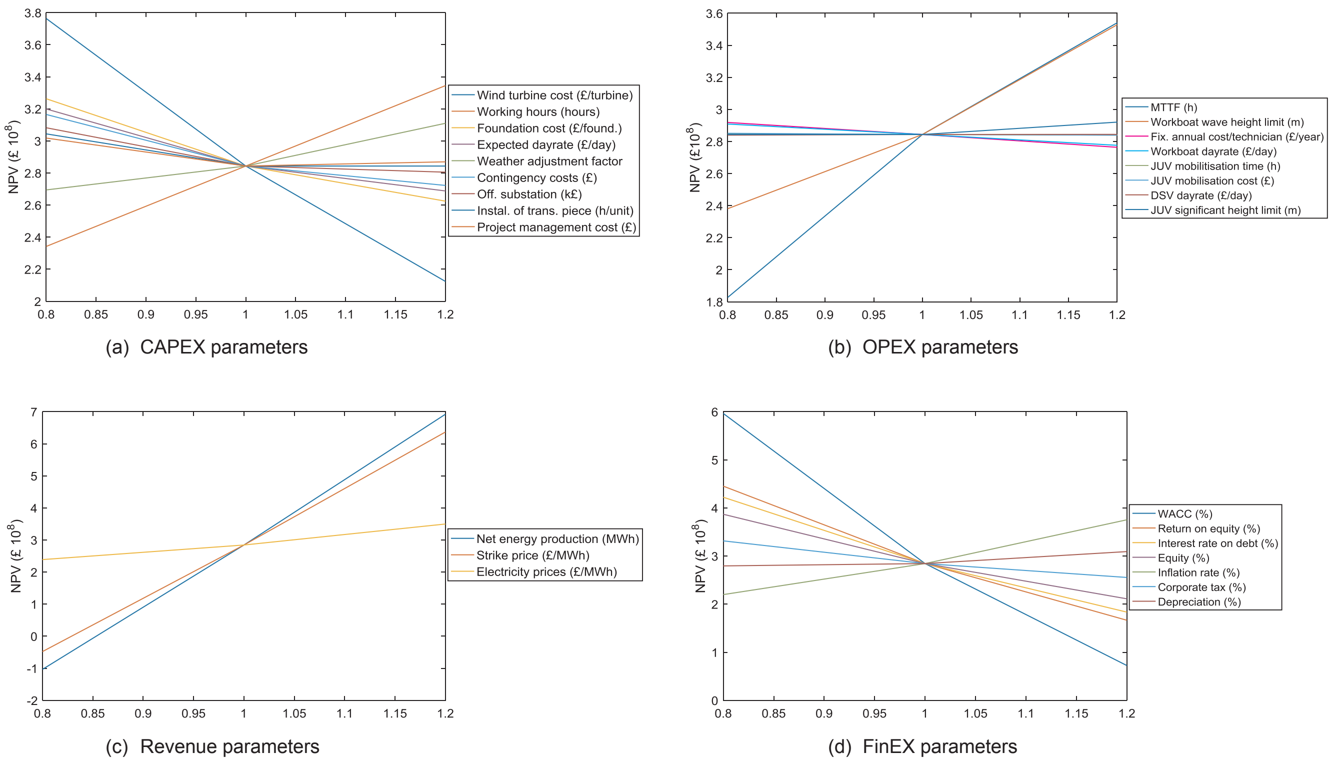

Fig. 5. Sensitivity analysis results.

Net present value demonstrated high sensitivity to the WACC value (with a 20% decrease in WACC more than doubling the NPV of the investment) and as a result, to its composing parameters. In fact, a 20% decrease in these parameters, namely the return on equity, the interest rate on debt and the equity ratio increase NPV by 52%, 44% and 32%, respectively. The last observation stresses the importance of financing costs on the feasibility of the investment, indicating that cost of equity is almost always expected to be higher than the cost of debt; thus, as the debt ratio increases, the WACC is expected to drop. Nevertheless, third party financing stakeholders would expect to see a reasonable equity being invested in the project in order to increase confidence in the investment. Hence, the final equity to debt ratio would be a balance of these opposite forces. Further, the inflation rate and the corporate tax appeared to have an effect of up to −26% and +13% in NPN upon a 20% decrease in their values, respectively.

A general observation from the four sensitivity analysis graphs is that FinEX and revenues parameters appear to have the greatest impact on the NPV of the investment in comparison to the other two modules of the model, with WACC, net energy production and strike price having the greatest impact.

5.3. Investor specific cost/revenue profiles

As mentioned above, one of the objectives of this paper is to assess the expected financial returns from an OW farm asset for investors investing and divesting the asset at different time instances across the entire lifecycle. Implementation of the model for the respective investment strategies can provide – among other outputs – information regarding the amount of return different investor classes will be looking to earn to get involved in the investment.

Fig. 6(a)–(c) illustrate cumulative cash flow profiles for the three different investor classes (Late entry investors, Pre-commissioning investors, Build-Operate-Transfer investors) identified in [3]. The "Build-Operate-Transfer" (BOT) type of investor suggests that a single investor owns the asset from the D&C up to the D&D phase; hence, this is the typical case that financial appraisal studies usually consider. The temporal cost/revenue profile of the BOT investor is illustrated in Fig. 6(a). In order to account for the range of potential WACC values this investor cluster is likely to accommodate, results for WACCs equal to 8% and 10% are presented. The graph can provide an estimate of the value of the asset across its life; the estimated break-even year can be found in the intersection of the cumulative costs and cumulative revenues curves (highlighted with the purple circle mark). As such, for WACC = 8% break-even year is the 18th year from the initiation of the project (including the pre-commissioning phase), while for WACC = 10% break-even year becomes the 20th year.

Departing from the BOT scenario, the model was, subsequently, applied to the other two investor profiles. "Pre-commissioning" (PC) investors undertake the development and construction of the wind farm, acting as turn-key developers, while they tend to sell the asset once the project is commissioned. Fig. 6(c) illustrates cumulative costs (dashed red and blue lines) and revenues (solid red line) for an investor entering from year 1 of the asset lifecycle (P&C phase) and exiting at the end of year 5. As expected, since PC investors sell the asset following its commissioning (i.e. before energy starts to be produced and injected to the grid), revenues are expected to be zero before the sixth year of the project's life cycle. The setting of the sale price of the asset needs to cover at least the construction cost of the asset plus their financing costs to that point. This cluster of investors comprising OEMs and EPCI contractors have generally weaker balance sheets in comparison to big power producers (belonging to the BOT cluster of investors), and hence, they have less financial strength to provide corporate finance to the project. Considering a WACC in the region of 12–15% [21], their cost/revenue profile for the construction period of the wind farm (from year 1 to year 5) is illustrated in Fig. 6(c) for the lower and upper bounds of potential WACC values. Assuming a 100% ownership, the PC investor is anticipated to balance the cost spent for the development of the asset and the financing cost (determined by the WACC values), in order to assess the minimum selling price of the asset. The application of the model indicated that the seller should ask for a minimum price of £1,078 million for a WACC = 15% under the baseline scenario, while the minimum asking price when WACC = 12% should be £1,170.5 million.

On the other hand, "Late entry" (LE) investors should consider future

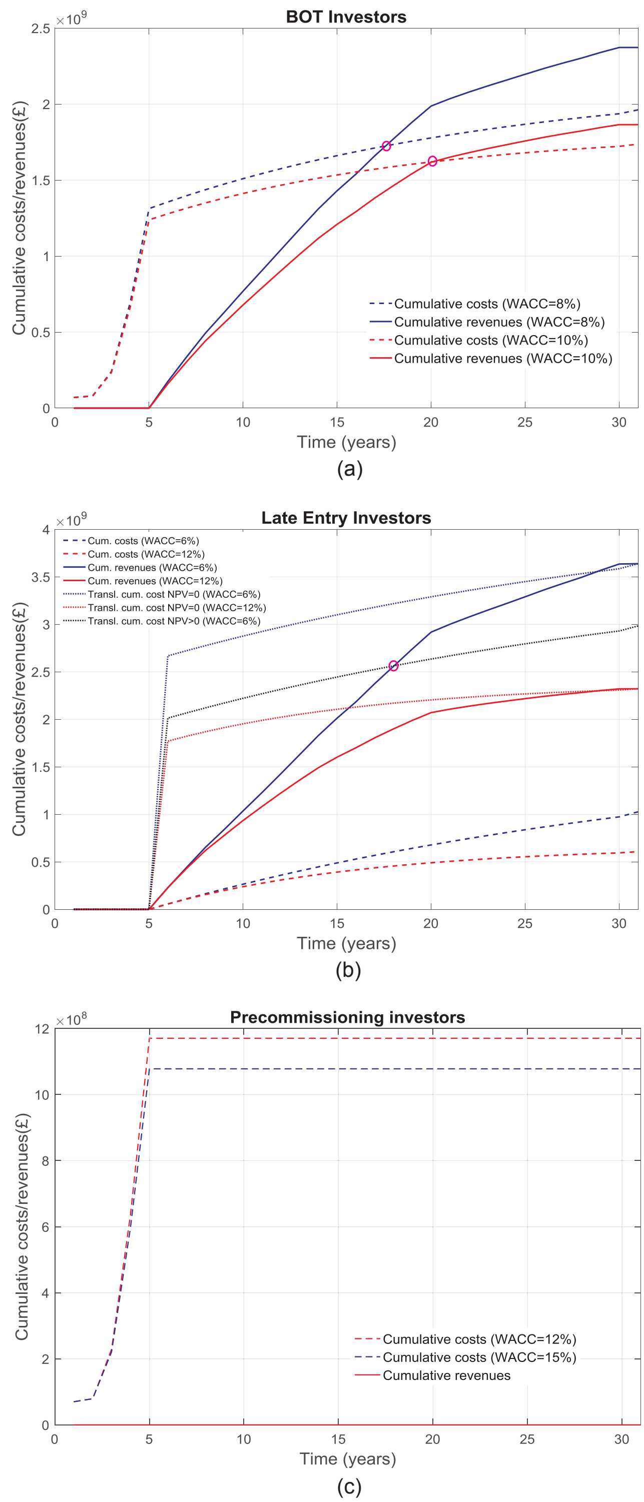

Fig. 6. Cumulative cost return profiles of the asset from the different investor perspectives.

expected costs and revenues, in order to evaluate the maximum price they can purchase the asset for. Taking into account the fact that this class of investors have more liquidity and stronger balance sheets, their WACC range is lower, approximately between 6% and 12% [21]. In Fig. 6 (b), the cost/revenue profiles of the asset from year 6 (commissioning year) up to the D&D phase are outlined for WACC values 6% and 12%. Further, the cumulative costs (denoted with the dotted lines) have been translated, so that they intersect with the cumulative revenues (solid lines) at the end of the service life of the asset (i.e. year 31st). This means that the break-even point is found at the extreme end of the service life and, hence, the NPV of the investment equals to zero. The blue dotted line corresponds to the translated cumulative costs for WACC = 6%, while the red dotted line represents the translated cumulative costs for WACC = 12%. Correspondingly, the blue and red solid lines reflect the cumulative revenues for the lower and upper WACC limit, respectively. Cumulative costs are discounted to the year of acquisition (i.e., beginning of year 6). The translation of the cumulative costs enables the identification of the extreme purchase price of the asset at the commissioning point, which will allow the late entry investor to make marginal profit. The translation of the cumulative cost is realised by the following expression:

$$DCC_{translated,t} = DCC_t + (DCR_{t=31} - DCC_{t=31}),\ \forall\ t = 6,7,8,\ldots,31 \tag{31}$$

where, $DCC_{translated,t}$ is the discounted translated cumulative cost at year t, DCC_t is the discounted cumulative cost and DCR_t is the discounted cumulative revenues at time t. If the acquisition price, at the point of the purchase, is less than this extreme, the two curves will be intersecting to a time earlier than the service life of the asset (i.e. the 31st year) and the profit margin will increase. For example, as illustrated in Fig. 6(b), if the acquisition price of the asset at year 6 (or else the discounted translated cumulative cost at year 6) amounts to £2 billion, the breakeven point will be reached during the 18th year, which is the intersection of the cumulative cost (black dotted line) with the cumulative revenues denoted by the blue solid line, assuming that WACC = 6%. The intersection point of the two lines is indicated by the purple circle mark. As such, the maximum acquisition price at the commissioning year of the wind farm (namely, the 6th year) can be calculated by subtracting the cumulative revenues of the asset from the translated cumulative costs at that year. Taking into account the upper and lower WACC bounds considered for this type of investor, the maximum price of purchase is £1,770 for WACC = 12% and 2668 million for WACC = 6%, as indicated by the red and blue dotted lines at the beginning of year 6, respectively. Therefore, it is deemed that the final price of the asset would, most probably, lie in the region between the minimum selling and the maximum purchase price, estimated by the PC and the LE investors, respectively. For the above mentioned example, the price of the wind farm is, thus, expected to lie in the region £1,078–£2,668 million, depending on the cost of capital of both investors.

However, it must be highlighted that the "price" and the "value" of the asset represent different concepts, with the price of the asset being determined by supply and demand, while the value is estimated by accounting for the cost and the return of an investment. In general, it is deemed that the price of an asset should be a result of adding a reasonable profit to a cost, which, however, is not always the case. Setting a price for an asset simply on the basis of its costs and revenues can, therefore, be considered a simplistic approach, although it makes sense to assume that the price is set by the value. The demand for investing in OW energy assets is influenced by a number of factors, in example the stability of the regulatory framework for the promotion of the technology, the lack of grid availability (particularly in markets where project sponsors are not in charge of the grid connection), etc. [21].

6. Conclusions

Offshore wind investments have reached reasonably maturity over the past decade. With 92 wind farms in operation in European countries, distinctive clusters of investors can be observed with new clusters expected to focus on the second half of the operational life of wind farms; in example, investors who will purchase assets approaching the end of their commercial life, at a low cost and extend its life in expense of higher O&M costs [80]. A detailed assessment of the returns is pertinent towards understanding the real cost and opportunity of investing in new or existing operational wind farms. Such an assessment could facilitate fair valuation of assets, supporting relevant investment/divestment decisions.

This paper has developed a methodological framework for the techno-economic analysis of a wind farm allowing for the assessment of the investment value from the perspective of different classes of investors. To this end, a life cycle cost/revenue model, which is decomposed further into CAPEX, OPEX and FinEX components, has been developed and applied for different investor classes.

The sensitivity analysis of the model has revealed that financial and revenue parameters have greater influence on the NPV of the investment in comparison to CAPEX and OPEX parameters. More in specific, the WACC along with the strike price and the energy production were found to cause the highest deviation, while the mean time to failure and the workboat wave height limit were the OPEX parameters with the highest impact. As far as CAPEX is concerned, reduction in the acquisition cost of wind turbines and foundations can yield the highest increase in the NPV of the investment.

Although several previous studies focus on the life-cycle cost assessment of OW farms and their economic feasibility, the consideration of different equity investors with different investment strategies that buy and sell stakes at different time instances during the life of an OW farm project, and the development of a relevant tool that enables such investors to assess the viability of their investment has not been previously investigated. Furthermore, in relation to other academic models in literature, the present study provides an integrated lifecycle cost revenue model of high fidelity aiming to increase accuracy of results, while there is, currently, no study to date to link the cost model to investment decisions. This is an element that is addressed from operators who have developed their own cost tools, but these are not included in the current body of literature.

Implementation of the lifecycle cost/revenue model from the perspective of different investors can contribute towards the fairer temporal evaluation of the wind energy asset. As such, the BOT class of investors (typically consisting of Major Utilities like DONG Energy, RWE, etc.), tend to keep the (majority stake of the) operating assets in their balance sheets. The temporal cost/revenue profile of the project can be used to estimate its value throughout its lifespan and derive the breakeven year. The PC investor cluster typically consists of OEMs and EPCI contractors with relatively higher costs of capital (in the range of 12–15%) than the BOT cluster. They would normally seek to sell the asset at a higher price in comparison to its construction cost to compensate for the risk to carry out the procurement and construction works. On the one hand, LE investors typically comprising third party capital investors, such as pension funds, are more likely to seek for a low risk investment with stable returns. When it comes to appraising the asset, they will need to assess the expected future costs and revenues and come up with an offer that will be lower than the breakeven point derived from the cash flow model. Above analysis, takes into account the different cost of capital values applicable to each investor class.

Acknowledgements

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Appendix A. Installation of foundations

The number of voyages (from the staging port to the installation site and vice versa) is calculated as:

$$N_{F,voy} = \frac{n_{WT}}{VC_{F,JU}} \tag{A.1}$$

where, $VC_{F,JU}$ is the jack up vessel capacity of foundations. The time of jacking at port can be estimated as:

$$T_{j,port} = \frac{WD_{port}}{V_j} \tag{A.2}$$

where, WD_{port} denotes the water depth at the port (m) and V_j the jacking up speed (in m/h). The jacking (up/down) time at the wind farm site is estimated as:

$$T_{j,site} = \frac{WD}{V_j} \tag{A.3}$$

where, WD is the water depth at wind farm site (m). The time to travel from port to farm can be found as:

$$T_{port\ to\ farm} = 2 \cdot T_{JU,voy} \cdot N_{F,voy} \tag{A.4}$$

The voyage time, $T_{j,voy}$ is estimated by taking into account the vessel speed, $V_{S,JU}$ (in km/h), and the distance, D (in m), between the wind farm site and the port:

$$T_{JU,voy} = \frac{D}{V_{S,JU}} \tag{A.5}$$

The time to travel between turbines can be estimated as:

$$T_{F,mov} = (VC_{F,JU} - 1) \cdot T_{betwtrb,F} \cdot N_{F,voy} \tag{A.6}$$

The travel between turbines time is estimated by:

$$T_{betwtrb,F} = \frac{d_{trb}}{V_{S,JU}} \tag{A.7}$$

where, d_{trb} is the mean distance between consecutive turbines. Assuming 12 working hours per day, $T_{workhrs}$, along with a time adjustment factor for the consideration of potential adverse weather conditions during the offshore operations ($ADJWEATHER$), the number of effective days was estimated as:

$$T_{effectdays,F} = \frac{T_{F,Instal}}{T_{workhrs} \cdot ADJWEATHER} \tag{A.8}$$

Input data that were used for the calculation of installation time of foundations are summarised in Table A.1.

Table A.1
Parameters used for the calculation of installation time of foundations.

Parameter	Value
$VC_{F,JU}$	4 Units/trip
$V_{N,JU}$	3
WD_{port}	20 m
V_j	30 m/h
$T_{F,Load}$	2 h/turbine
$T_{workhrs}$	12 h
$T_{F,Lift}$	4 h/turbine
$R_{F,pile}$	0.65 h/m
$D_{F,driv}$	30 m
$ADJWEATHER$	0.85
d_{trb}	800 m
$n_{workers}$	30

Appendix B. Installation of wind turbines

The cost components throughout the turbine installation are outlined in this Appendix. Calculations were based on the work of [46] under the conditions described below. The total travel time for transporting the turbines was calculated by the following expression:

$$T_{T,Travel} = \frac{n_{WT}}{V_{S,JU}\cdot V_{N,JU}}\left[(2\cdot D - d_{trb} + t_{PL}\cdot V_{S,JU})\cdot\left(\frac{A_{Tj}\cdot e^{q_1\cdot(P_{WT}-2)}}{A}\right) + 2V_{N,JU}\cdot d_{trb} + t_{FS}\cdot V_{N,JU}\cdot V_{S,JU}\right] \tag{B.1}$$

where, n_{WT} represents the number of wind turbines, $V_{S,JU}$ is the vessel speed (km/h), $V_{N,JU}$ is the number of vessels, t_{PL} symbolizes the pre-loading time in the port (h), t_{FS} is the pre-loading time at site, A_{Tj} is the area required for one reference turbine with rated power 2 MW during transport (m^2), A is the free deck area for transportation of components (m^2), and q_1 is the constant coefficient (0.1019). The total lifting time was estimated by the following expression:

$$T_{T,Lift} = \frac{2^b\cdot(n_{WT}\cdot N_{Lj})^{1+b}\cdot e^{q_2\cdot(P_{WT}-2)}}{R_L}(\alpha_1\cdot P_{WT}^2 + b_1\cdot P_{WT} + c_1 + H_{JU}) \tag{B.2}$$

where, $b = \frac{\log(L_R)}{\log 2}$ with the learning rate $L_R = 0.95$, $b < 0$, N_{Lj} is the number of lifts for each turbine during loading or installation, q_2 is a constant (0.3214), R_L is the lifting rate $\left(40\frac{\text{m}}{\text{hour}}\right)$, α_1 is a constant (0.5714), b_1 is a constant (0.7714), c_1 is also a constant (77.12), and H_{JU} represents the jack up height [m]. The total assembly (onshore and offshore) time is further described below:

$$T_{T,Assemb} = \frac{n_{WT}^{1+b}e^{q_2(P_{WT}-2)}}{R_A}((M - N_{Lj})^{1+b} + W\cdot N_{Lj}^{1+b}) \tag{B.3}$$

where, R_A is the rate of assembly $\frac{1 assembly}{2h}$, M is the number of parts in each turbine (7) and W is the weather multiplier for offshore lift. Finally, the total jack up time is calculated by the following equation: (See Table B1)

$$T_{JU} = \frac{n_{WT}\cdot \mathrm{H_{JU}}}{V_{S,JU}}\left(\frac{A_{Tj}\cdot e^{q_1(P_{WT}-2)}}{A} + 4\right) \tag{B.4}$$

Table B.1
Parameters used for the calculation of installation time of wind turbines.

Parameter	Value
M	7
W	2
$V_{N,JU}$	2
A	7000 m^2
A_{Tj}	550 m^2
N_{Lj}	3
t_{PL}	5 h
t_{FS}	1 h
R_L	$40\frac{m}{h}$
R_A	$1\ \frac{assembly}{2\ h}$
H_{JU}	35 m
L_R	0.95
q_1	0.1019
q_2	0.3214
α_1	0.5714
b_1	0.7714
c_1	77.12

Appendix C

(See Table C1).

Table C.1
List of symbols.

A	Free deck area for transporting equipment (m^2)
A_{Tj}	Area required for one reference turbine with rated power 2 MW during transport (m^2)
A_{TR}	Rated power of transformer (MVA)
α_1	Constant
$ADJWEATHER$	Weather adjustment factor
b_1	Constant (0.7714)
$C_{Cables,ic}$	Total installation cost of cables (£)
$C_{cables,dd}$	Total cost of cables removal (£)
$C_{cables,pa}$	Total cost of cables (£)
$C_{C-export,ic}$	Installation cost of export cables (£)
$C_{C-array,ic}$	Installation cost of array cables (£)
$C_{clear,dd}$	Total cost for site clearance (£)
$C_{cont,pc}$	Contingency costs (£)
C_{DG}	Diesel generator cost (£)
$C_{disposal,dd}$	Disposal cost (£)
$C_{eng,pc}$	Engineering costs (£)
$C_{equipment}$	Cost of equipment (capital assets) over the lifetime of the investment (£)
$C_{F,ic}$	Total installation cost of foundations (£)
$C_{grout,dd}$	Grout removal cost (£)
$C_{insur,ic}$	Installation insurance cost (£)
$C_{insur,om}$	Operation insurance cost (£)
$C_{legal,pc}$	Legal costs (£)
$C_{offSubst,ic}$	Total installation cost of the two substations (£)
$C_{offSubst,pa_f}$	Substation platform cost (£)
$C_{offSubst,pa}$	Cost of offshore substation (£)
$C_{onSubst,pa}$	Cost of onshore substation (£)
$C_{offSubst,dd}$	Total cost for removing the two substations (£)
$C_{proj,pc}$	Project management cost during predevelopment and consenting (£)
$C_{proj,om}$	Project management cost during operation of the wind farm (£)
$C_{D\&D}$	Total disposal and decommissioning costs (£)
$c_{F,mat}$	Cost of materials for foundations (£/foundation)
$c_{F,manuf}$	Cost of manufacturing of foundations (£/foundation)
$c_{F,pa}$	Unit cost of foundation (£/foundation)
$C_{I\&C}$	Total installation and commission costs (£)
$C_{P\&A}$	Total production and acquisition costs (£)
$C_{P\&C}$	Total predevelopment and consenting costs (£)
$C_{protection}$	Cost of protective equipment for cables (£)
$C_{port,dd}$	Cost of port preparation (£)
$C_{repair,om}$	Repair costs (£/year)
$C_{rent,om}$	Rent costs (£/year)
$C_{SG,HV}$	HV switchgear cost (£)
$C_{SG_{MV}}$	MV switchgear cost (£)
$C_{SCADA,pa}$	Cost of monitoring (£/turbine)
$C_{Scour,ic}$	Total installation cost of scour (£)
$C_{Scour,dd}$	Scour protection removal cost (£)
$C_{surveys,pc}$	Environmental survey costs (£)
$C_{TF,dd}$	Total cost for removing all wind turbines with monopiles (£)
C_{TR}	MV/HV transformer cost (£)
$C_{vessel,dd}$	Total cost of hiring technicians and workboats during the decommissioning of the wind turbines (£)
$C_{transp,dd}$	Total cost for the transportation of decommissioned parts (£)
$C_{truckperton-mile}$	Cost per ton-mile of the transportation truck (£/ton/mile)
$C_{T,ic}$	Total installation cost of turbines (£)
$c_{T,pa}$	Unit cost of wind turbine (£/turbine)
$C_{TF,dd}$	Removal cost of turbines and monopile foundations (£)
c_{BB}	HV busbar cost (£)
c_i	Unit cost of the cable (£/km)

(*continued on next page*)

Table C.1 (*continued*)

c_1	Constant
D	Distance of installation site from port (km)
D_{pile}	Depth of pile under the soil (m)
$D_{port-facility}$	Distance of port from the waste facility (km)
$D_{F,driv}$	Distance of monopile driven into the seabed
$DCC_{translated,t}$	Discounted translated cumulative cost at year t (£)
DCC_t	Discounted cumulative costs at year t (£)
DCR_t	Discounted cumulative revenues at year t (£)
d	Rotor diameter (m)
d_{credit}	Tax depreciation credit reduced from the total tax payment (£)
d_{rate}	Tax depreciation rate (%)
d_{trb}	Mean distance between consecutive turbines (m)
E	Number of intervals for which reliability data are collected
FTC	Fault type classes
H_{JU}	Jack up height (m)
h	Hub height (m)
K	Number of subassemblies
L_i	Length of cable of type i (km)
L_1	Length of array cables (km)
L_2	Length of export subsea cables (km)
L_3	Length of export onshore cables (km)
L_R	Learning rate
M	Number of parts comprising each turbine
$MTBF$	Mean time between failures (h)
$MTTF$	Mean Time To Failure (h)
$MTTR$	Mean time To Repair (h)
N_i	Number of cables of type i
$N_{F,voy}$	Number of voyages for the transportation of foundations
N_{Lj}	Number of lifts for each turbine during loading or installation
$N_{T,e}$	Number of turbines that were examined for deriving the failure rates
$N_{trips,scour}$	Number of trips required for the installation of scour protection
n	Lifetime of the investment (years)
$n_{e,k}$	Number of failures
$n_{Subst,pile}$	Number of piles per substation foundation
n_{TR}	Number of transformers
n_{WT}	Number of turbines
$n_{workers}$	Number of workers
P_{WF}	Capacity of the wind farm (MW)
P_{WT}	Capacity of the wind turbine (MW)
P_{gr}	Amount of gross profit (£)
P_{net}	Amount of net profit of the investment (£)
q_1	Constant coefficient 1 (0.1019)
q_2	Constant coefficient 2 (0.3214)
RFF_{fc}	Relative failure frequencies (%)
R_A	Assembly rate (assembly/hour)
Rd	Interest rate on debt (%)
R_{infl}	Inflation rate (%)
R_L	Lifting rate (m/hour)
RoE	Return on Equity rate (%)
$R_{Subst,pile}$	Rate of piling the piles of the substructure (h/m)
$R_{F,pile}$	Rate of piling the monopile (h/m)
SPU	Tonnage of scour protection per unit (ton/turbine)
$T_{C-array,Inst}$	Effective days required for the installation of array cables (days)
$T_{C-export,Inst}$	Effective days required for the installation of export cables (days)
$T_{Effectdays,F}$	Number of effective days for the installation of the foundations (days)
$T_{Effectdays,Scour}$	Total effective days for scour installation (days)
$T_{Effectdays,Substat-Rem}$	Total effective days for the removal of the substations (days)
$T_{Effectdays,TF-Rem}$	Total time effective days for the removal of turbines and monopiles (days)
$T_{Effectdays,T}$	Total effective days of turbines installation (days)
$T_{F,Instal}$	Total installation time of foundations (h)
$T_{F,Lift}$	Offshore lifting time (h)
$T_{F,Load}$	Pile loading time (h)
$T_{reposit}$	Reposition time of the vessel (h)
$T_{HL,voy}$	Voyage time of heavy-lift vessel from the port to the installation site (h)

(*continued on next page*)

Table C.1 (*continued*)

T_{JU}	Total jack up time (h)
$T_{Scour,Inst}$	Total time for scour installation (h)
$T_{Scour,Tr}$	Travel time from/to port (h)
$T_{Scour,Dump}$	Dumping time per trip (h/trip)
$T_{Scour,Load}$	Loading time per trip (h/trip)
$T_{Subst,Inst}$	Total installation time of the substation (days)
$T_{Substjacket,Inst}$	Installation time of the substation's jacket (h)
$T_{T,Assemb}$	Assembly time of wind turbine (h)
$T_{T,Instal}$	Total installation time of turbines (h)
$T_{T,Lift}$	Lifting operation time of wind turbine (h)
$T_{T,Travel}$	Travel/transportation time of turbines (h)
$T_{betwtrb,F}$	Travel time from one turbine to the next (h)
T_e	Total time period during which failures are counted (h)
T_j	Total jacking up operational time (h)
$T_{j,port}$	Time of jacking of the jack-up vessel at port (h)
$T_{j,site}$	Time of jacking of the jack-up vessel at installation site (h)
$T_{porttofarm}$	Travel time from port to farm (h)
$T_{workhrs}$	Working hours (h)
t_c	Nominal corporate income tax rate (%)
t_{net}	Amount of net tax (£)
t_{FS}	Pre-loading time at site (h)
t_{PL}	Pre-loading time in the port (h)
$t_{payment}$	Amount of tax payment over the gross profit (£)
V	Sum of Equity and Debt (£)
$V_{DR,CLV-array}$	Day rate of Cable Laying Vessel for the installation of array cables (£/day)
$V_{DR,CLV-export}$	Day rate of Cable Laying Vessel for the installation of export cables (£/day)
$V_{DR,Trench}$	Day rate of trenching ROV (Remotely Operated underwater Vehicle) for the installation of subsea cables (£/day)
$V_{DR,HLV}$	Day rate of Heavy Lift Vessel (HLV) for the installation of the substation units (£/day)
$V_{Mobil,CLV}$	Mobilisation cost of Cable Laying Vessel (£)
$V_{Mobil,HLV}$	Mobilisation cost of Heavy Lift Vessel (£)
$V_{N,JU}$	Number of identical jack up vessels used for the installation of the wind turbines
V_n	Nominal voltage (kV)
$V_{scour,Mobil}$	Mobilisation cost of rock-dumping vessel (£)
$V_{S,HL}$	Speed of heavy lift vessel (km/hour)
$V_{S,JU}$	Speed of jack-up vessel (km/hour)
V_j	Jacking speed (m/hour)
$VC_{F,JU}$	Deck capacity of jack-up vessels for foundations (number of foundations per voyage)
VC_{Scour}	Rock-dumping vessel capacity (ton/trip)
VD	Market Value of Debt (£)
VE	Market Value of Equity (£)
W	Weather Multiplier for offshore lift
$W_{components}$	Total mass of the wind farm components (ton)
$W_{Subst,top}$	Mass of the topside substation (ton)
W_{truck}	Load capacity of truck (ton)
$WACC$	Weighted average cost of capital (%)
$WACC_{nom}$	Nominal weighted average cost of capital (%)
$WACC_{real}$	Real weighted average cost of capital (%)
WD	Water depth at the installation site (m)
WD_{port}	Water depth at the port (m)
λ	Failure rates per turbine per year

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D. Parametric CAPEX OPEX and LCOE expressions for offshore wind farms based on global deployment parameters

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Parametric CAPEX, OPEX, and LCOE expressions for offshore wind farms based on global deployment parameters

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ABSTRACT

Installed wind energy capacity has been rapidly increasing over the last decade, with deployments in deeper waters and further offshore, with higher turbine ratings within new farms. Understanding the impact of different deployment factors on the overall cost of wind farms is pertinent toward benchmarking the potential of different investment decision alternatives. In this article, a set of parametric expressions for capital expenditure, operational expenditure, and levelized cost of energy are developed as a function of wind turbine capacity (P_{WT}), water depth (WD), distance from port (D), and wind farm capacity (P_{WF}). These expressions have been developed through a series of simulations based on a fully integrated, tested cost model which are then generalized through the application of appropriate nonlinear regression equations for a typical offshore wind farm investment and taking into account most current published cost figures. The effectiveness of the models are countersigned through a series of cases, estimating the predicted values with a maximum error of 3.3%. These expressions will be particularly useful for the preliminary assessment of available deployment sites, offering cost estimates based on global decision variables.

KEYWORDS

CAPEX; LCOE; nonlinear regression; offshore wind farm; OPEX; parametric expressions

Introduction

Latest targets for Europe as reported from Wind Europe aim for 320 GW of wind energy capacity to be installed by 2030, 66 GW of which is planned to come from offshore wind (OW) energy (EWEA 2015). Deployment in deeper waters and further offshore is driven by the higher wind speeds, unrestricted space, and lower social impact in the marine environment (Kolios et al. 2016; Regueiro-Ferreira and Villasante 2016), where it is estimated that the same wind turbine can produce around 50% higher power output compared to onshore. High construction costs, especially foundation and electrical connection, and limitations in operation and maintenance are key barriers that need to be overcome in order to deploy in such environments in a cost-effective way. Figure 1 presents processed data from commissioned wind farms with respect to deployment depth, distance from shore, and wind farm capacity, while Figure 2 shows the increase in installed wind turbine ratings from 1995 to 2017 based on data from 4C Offshore 2017.

Reference to cost figures across the life cycle of existing wind farms has been limited to date with high volatility of cost components, primarily due to the fact that the industry and its supply chain have not yet been fully developed. Understanding, however, the impact of different deployment

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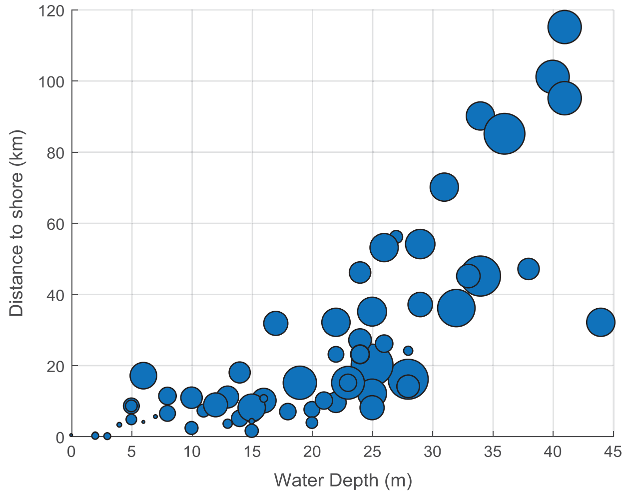

Figure 1. Water depth vs. distance to shore vs. wind farm capacity.

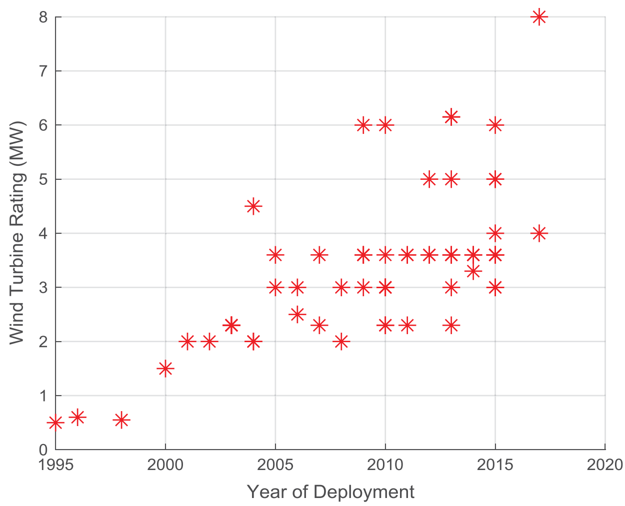

Figure 2. Turbine rating vs. wind farm year of commissioning.

factors to the overall cost of wind farms becomes pertinent toward benchmarking the potential of different investment decision alternatives.

This article reports the development of a set of parametric models for capital expenditure (CAPEX), operational expenditure (OPEX), and levelized cost of energy (LCOE) as a function of a set of global variables for potential deployment sites. These account for the wind turbine capacity (P_{WT}), water depth (WD), distance from port (D), and wind farm capacity (P_{WF}). These variables were selected due to their significant effect on the cost-effectiveness of the investment (Shafiee et al. 2016). After mapping the multidimensional cost domain based on these variables, through a series of simulations performed by a fully integrated and tested cost model developed by the author, results are translated into analytical expressions to interpolate cost figures for potential wind farms within the applicability range of the expressions. A parametric analysis and a number of test cases illustrate the effectiveness of the models, drawing useful conclusions.

These expressions are expected to assist investors, researchers, and other stakeholders to undertake an initial estimate of CAPEX, OPEX, and LCOE values for OW farm projects with varying design parameters, as well as use them as reference for estimating the effect in the change of one of the selected design parameters. The cost model developed incorporates the most up-to-date available parametric expressions in the literature, while where such equations were not available, most recent data were gathered in order to model specific costs.

Cost model of OW farm with fixed monopile

The main components of the life-cycle cost of a fixed OW farm are distinguished and further decomposed to cost subcomponents as shown in Figure 3, while in Figure 4, the cost model framework that has been developed is presented. Throughout the model, the most up-to-date expressions for cost subcomponents have been employed. The life-cycle phases under which costs

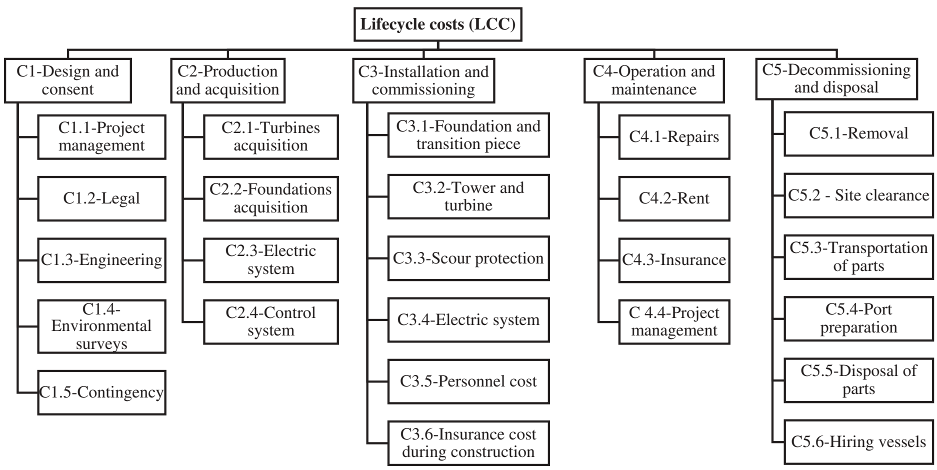

Figure 3. Breakdown of life-cycle costs.

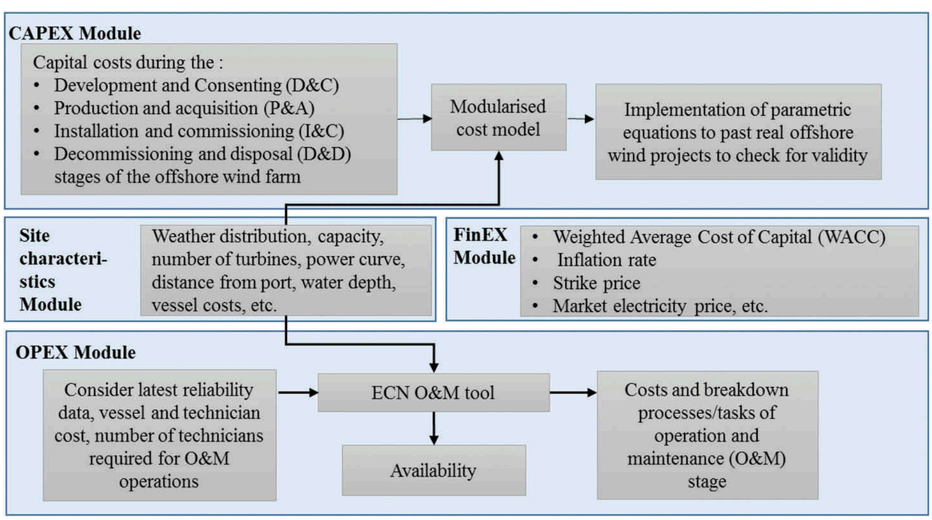

Figure 4. Integrated cost model structure.

were categorized are as follows: design and consent (C_1), production and acquisition (C_2), installation and commission (C_3), operation and maintenance (C_4), and decommissioning and disposal (C_5), a categorization scheme adopted by numerous recent studies (Myhr et al. 2014; Shafiee et al. 2016; The Crown Estate 2010). Total life-cycle cost is, thus, defined as

$$\mathrm{LCC} = C_1 + C_2 + C_3 + C_4 + C_5 \tag{1}$$

The design and consent costs were further decomposed to legal ($C_{1.1}$), environmental survey ($C_{1.2}$), engineering ($C_{1.3}$), contingency ($C_{1.4}$), and project management ($C_{1.5}$) costs. The costs of this stage were considered to be proportional to the wind turbine capacity (P_{WT}) according to Shafiee et al. 2016, although other parameters such as the water depth and marine life in the installation location can also affect the cost because of the lack of data.

The production and acquisition stage can be further decomposed to the following: the acquisition of the turbine ($C_{2.1}$), the foundation ($C_{2.2}$), the electric system ($C_{2.3}$), and the control system ($C_{2.4}$). The cost of the turbine was estimated as a function of the wind turbine capacity ($C_1 = \mathrm{f}(P_{WT})$, while the cost of foundation as a function of the P_{WT}, WD, h, and d ($C_{2.2} = \mathrm{f}(P_{\mathrm{WT}}, \mathrm{WD}, h, d)$; Dicorato et al. 2011).

The cost of the electric system comprises the cost of array, export and onshore cables ($C_{2.3.1}$), and the cost of the substation ($C_{2.3.2}$); the first, depending on the number of the wind turbines (N_{WT}), the rotor diameter (d), and the distance from shore (D)—$C_{2.3.1} = \mathrm{f}(N_{WT}, \mathrm{d}, \mathrm{D})$; the second, depending on the number of the wind turbines, rated power of transformer (A_{TR}), the nominal voltage transformer (V_n), and the wind farm capacity (P_{WF}) according to Dicorato et al. 2011—$C_{2.3.2} = \mathrm{f}(N_{WT}, A_{TR}, V_n, P_{WF})$. Onshore substation cost was assumed to be half the cost of the offshore substation. The control system cost was also taken from the same source to be equal to $C_{2.4}$ = 75 k£/turbine.

Next, the installation and commissioning costs of the OW farm comprise the installation of the wind turbine and tower ($C_{3.1}$), foundation and transition piece ($C_{3.2}$), scour protection ($C_{3.3}$), electric system ($C_{3.4}$), and the insurance costs ($C_{3.5}$), a categorization also used by BVGA 2010, Dicorato et al. 2011, and Shafiee et al. 2016. The installation cost of the wind turbines is a function of the vessel day rates (VDR), the number of vessels (workboats, heavy lift vessels, Special Operations Vessels (SOVs), and jack up vessels; N_v), the duration of the installation (T_{Instal}), and the cost for the personnel (C_{pers}) required for carrying out the installation. Specifically for the installation of the wind turbines, the onshore pre-assembly method ($M_{\mathrm{Assemb,T}}$) is also expected to greatly affect the cost of installation (Sarker and Faiz 2017). Although installation usually takes place during spring and summer time in order to avoid adverse weather conditions, they still play an important role to activities taking place offshore (Kaiser 2009); hence, for estimating the final installation cost of the wind farm, a weather adjustment factor (Adj$W$) was also considered, an approach used also by other authors in the literature (Sarker and Faiz 2017; Kaiser and Snyder 2012). Therefore, the cost is expressed as $C_{3.1} = \mathrm{f}\left(\mathrm{VDR}, N_v, T_{\mathrm{Instal,T}}, C_{\mathrm{pers,T}}, M_{\mathrm{Assemb,T}}, \mathrm{Adj}W\right)$. Roughly, the installation of all components of the wind farm depends on similar factors; nevertheless, vessels with different load capacity and different procedures are followed for the installation of each component.

The operation and maintenance stage of the life cycle is further decomposed into the repair ($C_{4.1}$), the rent ($C_{4.2}$), the insurance ($C_{4.3}$), and the project management cost ($C_{4.4}$). The estimation of the repair cost was carried out through the Energy Research Centre of the Netherlands Operation and Maintenance (ECN O&M) tool (Van De Pieterman et al. 2011), which divides O&M strategies into calendar-based, condition-based, and unplanned corrective operations. For unplanned corrective maintenance, each structural component of the system is assigned a number of failure modes bearing different severity and frequency levels, which is introduced in the software by means of a mean time to failure. The different fault type classes are classified as minor repairs, major repairs, and major replacements following the Reliawind categorization scheme (Wilkinson et al. 2010). Further data needed for the prediction of the unplanned corrective maintenance costs include the average repair times, number of required technicians, and material costs, which were adopted from Carroll et al. 2016. For the condition-based maintenance, a certain number of repairs can be set for inclusion, while the calendar-based maintenance applies to all turbines of the wind farm. For calendar-based maintenance, a yearly small maintenance operation and a longer one occurring every 5 years were considered.

Decommissioning and disposal cost of the wind farm includes the following: 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; $C_{5.1}$), the site clearance ($C_{5.2}$), the onshore transportation to the disposal sites ($C_{5.3}$), the port preparation ($C_{5.4}$), the disposal process ($C_{5.5}$), and finally the hiring vessels costs ($C_{5.6}$). To accomplish this stage of the life cycle, jack-up vessels are used to transport the removed items to shore, as well as workboats to transfer personnel who will support the operation. Substations are also removed by means of a reverse installation process (with the support of a heavy lift vessel), and the jacket foundations are also cut and removed. Removal costs depend on the removal duration per turbine (t_{rem}), the capacity of the jack-up vessel (VC), the vessels' day rate (VDR), the number of vessels (workboats, heavy lift vessels, SOVs, and jack-up vessels) (N_v), and the cost of technicians (C_{pers}). As such, $C_{5.1} = \mathrm{f}\left(t_{\text{rem}}, \mathrm{VC}, \mathrm{VDR}, N_v, C_{\text{pers}}\right)$. The site clearance cost depends mainly on the area of the wind farm, which can be calculated by taking into account the rotor diameter and the number of wind turbines, as well as a mean clearance cost per km^2 (c_{clear}), as in (Kaiser and Snyder 2012) $C_{5.2} = \mathrm{f}(d, N_{WT}, c_{\text{clear}})$. The transportation cost is associated to the total mass of the wind farm components (W_{comp}), the truck cost per ton-mile ($C_{\text{tr,ptm}}$), the capacity of truck ($\mathrm{CP_{tr}}$), and the distance of port from the waste facility (D_{p-f}): $C_{5.3} = \mathrm{f}\left(\mathrm{W_{comp}}, C_{\text{tr,ptm}}, \mathrm{CP_{tr}}, D_{p-f}\right)$.

Case study presentation and application

Key assumptions of the wind farm site under the baseline scenario are included in Table 1. The 504 MW wind farm is located in the North Sea region. For the calculation of the energy produced under the baseline scenario, the availability factor derived from analysis through the O&M simulation was used (calculated 91.2%). Further, an efficiency factor of 90% was assumed accounting for losses due to wake effects, cable losses, and so on. The electrical system consists of 33 kV array cables and two offshore substations of 336 MW HVAC transmission system. Additionally, the transmission assets are connected to the onshore substation by three AC export cables of 132 kV.

The total undiscounted CAPEX aggregating C_1, C_2, C_3, and C_5 were estimated equal to 1,698.3 M £, while the mean undiscounted annual OPEX was found around 56.3 M£/year under the baseline scenario. Nevertheless, the above figures need to be adjusted for the inflation rate and the interest rate, in order to account for the time value of money considering that the service life of an OW farm is approximately 25 years. All costs were therefore discounted and inflated with the real discount rate ($WACC_{real}$) integrating the nominal cost of capital ($\mathrm{WACC_{nom}}$) with the inflation rate (R_{infl}), according to Fisher equation (Barro 1997)

Table 1. Baseline specifications.

Characteristic values of the 3.6 MW wind turbine used for the baseline scenario	
Total wind farm capacity, P_{WF}	504 MW
Nameplate capacity, P_{WT}	3.6 MW
Distance to port, D	36 km
Water depth, WD	26 m
Service life of the wind farm	25 years
Rotor diameter	107 m
Hub height	77.5 m
Pile diameter	6 m
Rated wind speed	13.5 m/s
Cut-in wind speed	4 m/s
Cut-out wind speed	25 m/s

Table 2. Results from the application of the model to a number of scenarios.

Scenario	P_{WT} (MW)x_1	WD (m)x_2	D (km)x_3	P_{WF} (MW)x_4	dOPEX (£)	dCAPEX (£)	LCOE (£/MWh)
Baseline	3.6	26	36	504	559,000,000	1,351,900,000	112.6
#1	**1.8**	26	36	504	709,750,000	1,512,500,000	135.2
#2	**7**	26	36	504	481,420,000	1,281,400,000	106.1
#3	**5.3**	26	36	504	510,370,000	1,274,100,000	110.3
#4	3.6	**13**	36	504	559,000,000	1,318,500,000	110.7
#5	3.6	**52**	36	504	559,000,000	1,418,800,000	116.6
#6	3.6	**39**	36	504	559,000,000	1,385,400,000	114.6
#7	3.6	26	**18**	504	557,590,000	1,303,500,000	107.6
#8	3.6	26	**72**	504	573,260,000	1,448,700,000	126.9
#9	3.6	26	**54**	504	559,390,000	1,400,300,000	115.0
#10	3.6	26	36	**252**	341,250,000	743,920,000	130.0
#11	3.6	26	36	**1008**	989,090,000	2,600,300,000	109.9
#12	3.6	26	36	**756**	771,040,000	1,970,300,000	111.2

Note: Bold numbers indicate which values change (in relation to the baseline case) at each scenario analysed.

$$\mathrm{WACC_{real}} = \frac{1 + \mathrm{WACC}}{1 + \mathrm{R_{infl}}} - 1 \approx \mathrm{WACC_{nom}} - R_{\mathrm{infl}} \tag{2}$$

where $\mathrm{WACC_{nom}}$ was assumed equal to 8.81% (BVGA 2015) and R_{infl} 2.5%. Further, the levelized cost of energy (LCOE), which estimates the net present value of the unit cost of electricity produced over the lifetime of the OW asset, can be calculated as

$$\mathrm{LCOE} = \frac{\sum_{t=0}^{T_{\mathrm{farm}}} \frac{\mathrm{LCC_t}}{(1+\mathrm{WACC_{real}})^t}}{\sum_{t=0}^{T_{\mathrm{farm}}} \frac{\mathrm{E}}{(1+\mathrm{WACC_{real}})^t}}, \text{ in } /\mathrm{MWh} \tag{3}$$

where T_{farm} (£) is the life time duration of the wind farm (from construction to decommissioning) and E (MWh) is the total energy produced. Taking the above into consideration, the baseline LCOE was estimated 112.6 £/MWh, the discounted total OPEX (dOPEX) 559 M£, and the discounted CAPEX (dCAPEX) 1,351.9 M£. The above results conform well with the literature levelized cost estimates for Round 3 OW projects commissioned in 2020 (BEIS 2016). Finally, the resulting capacity factor was calculated (38.8%).

The parametric relationships linking the four key design parameters—namely, the wind turbine capacity, water depth, distance from port, and wind farm capacity with the OPEX, CAPEX and LCOE figures—were derived through nonlinear regression from a number of simulations of the integrated cost model aiming to map the cost performance across the multidimensional domain of the four independent variables. A set of complex relationships was assumed for this study based on the observation of the relationship between the input global parameters and the output variables (dCAPEX, dOPEX, and LCOE), ensuring a realistic approximation and avoiding cases of overfitting which may reduce accuracy in the results. The outcome of the finite number of scenarios that were run in order to map the cost domain is listed in Table 2, where the effect of the variable variation on CAPEX, OPEX, and LCOE can also be observed. It was shown that wind turbine and wind farm capacity have the greatest effect on CAPEX, OPEX, and LCOE. In fact, doubling the P_{WT} while keeping the rest of the variables stable results in 14%, 5.2%, and 5.8% decrease in the respective investment performance indicators; the corresponding effect of $\mathrm{P_{WF}}$ resulted in 77%, 92.3%, and −2.4% variation from the baseline case. The next most impactful variable on LCOE proved to be the distance from port.

Results and discussion

Based on the data presented in Table 1, which illustrate the results of the different scenarios derived from the high fidelity cost model, each of the chosen variables (P_{WT}, WD, D, and P_{WF}) was studied

Table 3. Testing scenarios and results produced by model and parametric expressions.

Testing scenarios			#t1	#t2	#t3	#t4
	P_{WT}		**6**	3.6	3.6	3.6
	WD		26	**15.6**	26	**15.6**
	D		36	36	**21.6**	**21.6**
	P_{WF}		504	504	504	**302.4**
dOPEX (£)		Par. expression	4.872E+08	5.680E+08	5.680E+08	3.984E+08
		Cost model	5.036E+08	5.590E+08	5.569E+08	3.909E+08
		Error (%)	−3.3%	1.6%	2.0%	1.9%
dCAPEX (£)		Par. expression	1.269E+09	1.336E+09	1.324E+09	8.055E+08
		Cost model	1.293E+09	1.325E+09	1.313E+09	8.108E+08
		Error (%)	−1.8%	0.8%	0.8%	−0.7%
LCOE (£/MWh)		Par. expression	108.4	110.9	109.3	116.3
		Cost model	107.6	111.1	107.2	115.7
		Error (%)	0.8%	−0.2%	1.9%	0.5%

Note: Bold numbers indicate which values change (in relation to the baseline case) at each scenario analysed.

independently in order to qualify the most appropriate regression expression to capture the trend in the overall dependent variables. This allowed for a series of nonlinear expressions to be developed, which would better represent these trends not only for interpolation between the limits that were set through the different scenarios but also for extrapolation near these limits. More specifically, it was found from the results of the scenarios that for variable P_{WT}, all three dependent variables were better fitted through power equations. For WD, OPEX was constant (independent from water depth), while CAPEX and LCOE were better fitted through linear equations. Accordingly, for D, OPEX and LCOE were fitted through exponential and polynomial equations, respectively, while for CAPEX a linear equation was chosen. Finally, for P_{WF}, linear equations were fitted for CAPEX and OPEX and a power equation for the LCOE.

Once the most appropriate regression expressions were determined, a set of overall relationships were developed for each of the dependent variables, and the nonlinear coefficients were estimated through application of the maximum likelihood method for a predetermined shape of the target equation. The analysis also returned the overall value for the regression coefficients, providing an indication on the overall quality of fit of the quantities considered. Based on the above, the following three expressions are proposed, considering the most up-to-date information and high-fidelity cost modelling structure in order to link the macro variables, namely P_{WT} (MW), WD (m), D (km), and P_{WF} (MW) to the OPEX, CAPEX, and LCOE figures.

$$\mathrm{dOPEX} = -6.349\cdot10^{8}\cdot \mathrm{P}_{WT}{}^{0.187} + 2.595\cdot10^{-19}\cdot\exp(0.830\cdot\mathrm{D}) + 8.413\cdot10^{5}\cdot\mathrm{P}_{WF} + 9.506\cdot10^{8},\ \text{in} \tag{4}$$

$$\begin{aligned}\mathrm{dCAPEX} = &-1.485\cdot10^{11}\cdot P_{\mathrm{WT}}{}^{0.001} + 2.353\cdot10^{6}\cdot\mathrm{WD} + 2.530\cdot10^{6}\cdot\mathrm{D} + 2.451\cdot10^{6}\cdot\mathrm{P}_{WF}\\ &+ 1.487\cdot10^{11},\ \text{in}\end{aligned} \tag{5}$$

$$\begin{aligned}\mathrm{LCOE} = &\ 110.370\cdot\mathrm{P}_{WT}{}^{-2.260} + 0.167\cdot\mathrm{WD} + 0.004\cdot\mathrm{D}^2 + 0.001\cdot\mathrm{D} + 2.889\cdot10^{9}\cdot\mathrm{P}_{WF}{}^{-3.399}\\ &+ 95.045,\ \text{in } /\mathrm{MWh}\end{aligned} \tag{6}$$

The R^2 for each of the expressions are 0.986, 0.999, and 0.983, respectively, denoting a satisfactory fit to the original data. Further, the data for the independent variables for the different scenarios were used as predictors using the regression coefficients, and the average value of the absolute errors that were measured in each case were 1.62%, 0.83%, and 0.82%. Finally, a series of separate test scenarios were run in order to test the performance of the model while interpolating, and the results are summarized in Table 3.

Following the test scenarios that were run, a series of plots were also produced and are presented in Figure 5, illustrating the effect of each of the independent variables to the dependent ones.

Increase in the wind turbine rating results in an inverse exponential reduction in all three costs: CAPEX and OPEX due to the fact that less units need to be installed and maintained, and LCOE due to the reduced costs and increased expected power production. Distance from shore increases

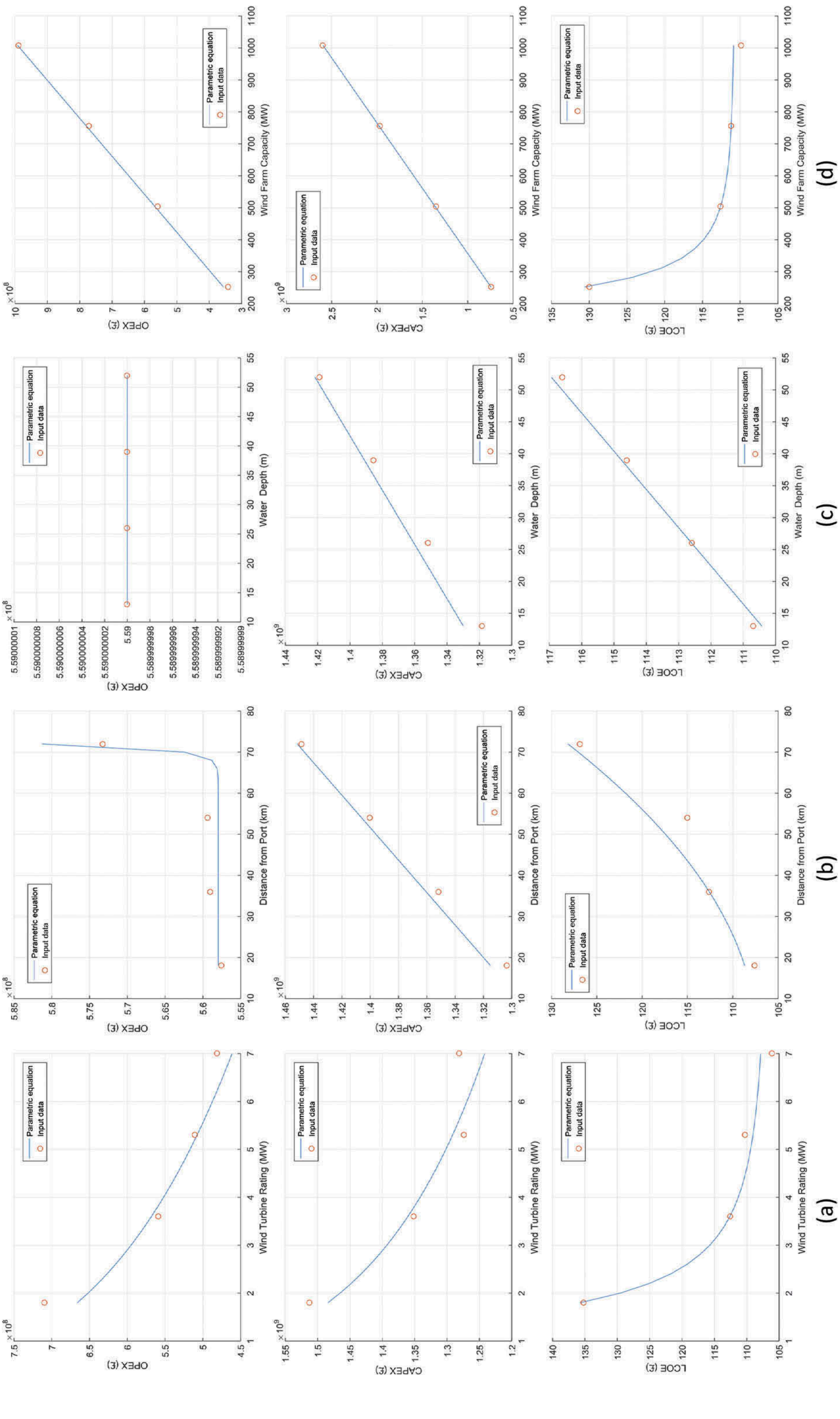

Figure 5. Sensitivity analysis of each parameter: (a) wind turbine rating, (b) distance from port, (c) water depth, and (d) wind farm capacity.

CAPEX linearly, while OPEX and LCOE increase exponentially. Increase in water depth does not affect OPEX, while it results in almost a linear increase in CAPEX and LCOE mainly due to the additional cost of the foundation and support structure as well as installation. Finally, increase in total wind farm capacity increases proportionally the amount of OPEX and CAPEX, while presents an inverse exponential reduction trend to LCOE for the given wind turbine rating due to the higher energy production and the reduced costs per wind turbine. It should be noted that the applicability range of these equations yields mainly for interpolation of values for independent variables, i.e., selection of values within the upper and lower limits included in Table 2. Extrapolating for values significantly out of this range would introduce higher errors as coefficients should be calibrated following a new set of initial simulations with the integrated cost model.

Conclusions

As the OW energy industry is developing, understanding the key cost factors of wind farm developments is a pertinent condition toward benchmarking the suitability of different deployment options. In this work, a set of parametric equations linking wind turbine capacity, water depth, distance from port, and wind farm capacity with the discounted total OPEX, CAPEX, and LCOE figures were developed, based on a number of high-fidelity cost simulations and regressions of the results. Further, this article characterizes the effect of these variables on CAPEX, OPEX, and LCOE. It was shown that wind turbine and wind farm capacity have the greatest effect on CAPEX, OPEX, and LCOE. A future expansion of the model could potentially include more variables, so as to increase the accuracy of results, such as the interest rate which has a considerable effect on LCOE and on the discounted values of capital and operational costs. Further, the inclusion of the wind resource of the installation site could potentially improve the energy output prediction and hence, provide a better informed expression for LCOE; while the inclusion of the soil conditions, aerodynamic, and wind and wave loads at the installation site would increase the accuracy of the production and acquisition cost of the foundations and wind turbines, leading, however, to more complex relationships requiring more input data.

The high-level expressions developed in this work are expected to assist investors, researchers, and other stakeholders to derive initial estimates for wind farm projects based on global variables within the applicability range as defined above. Additionally, it should be highlighted that results from the above expressions should be treated with caution as input data have been adopted from wind farms mainly installed in North Europe, since no data currently exist for the USA or Asian OW farms.

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E. Stochastic valuation of offshore wind farms through the application

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Stochastic valuation of offshore wind farms through the application of advanced numerical methods

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Abstract

Increasing investment activity in offshore wind energy projects has induced the need for an improved valuation framework of the assets. As opposed to the deterministic valuation models currently available, a probabilistic analysis can provide decision support with assigned confidence levels, taking into account uncertainties inherent in the analysis. To this end, departing from an integrated lifecycle techno-economic model developed by the authors, the present study develops a probabilistic approach considering time-dependent and independent stochastic variables. To this end, advanced numerical methods, namely Artificial Neural Network (ANN) approximation model and an Auto-Regressive Integrated Moving Average (ARIMA) time series model are combined with Monte Carlo simulations in order to assess the impact of the system uncertainties on the performance of the asset. Joint probability distributions of the output variables, namely the NPV, capital cost, annual operating cost and LCOE are presented, providing insights regarding the profitability of the asset within defined confidence intervals.

Keywords: offshore wind; stochastic valuation; ARIMA; Artificial Neural Networks; Monte Carlo simulation

1 Introduction

WindEurope's Central Scenario projects 323 GW of cumulative wind energy capacity to be installed in the EU by 2030, out of which 253 GW will originate from onshore and 70 GW from offshore wind (OW) energy installations [1]. In 2017, 3,148 MW net additional offshore wind capacity was installed in Europe, reaching a cumulative capacity of 15,780 MW, corresponding to approximately 22.5% of target attainment, while almost half of this capacity (7.1GW) is installed in the UK. Investments in offshore wind amounted to 7.5 billion Euros, reaching cumulatively 74.3 billion Euros since 2010 [2]. For the aforementioned ambitious targets to be achieved, accurately assessing the costs of offshore wind generation is pertinent towards evaluating the economic aspect of the offshore wind technology and associated investments.

Offshore wind levelized cost of electricity (LCOE), which is the net present value of the unit-cost of electricity over the lifetime of a generating asset, can be estimated by calculating the following components: 1) capital expenditures (CAPEX), 2) operating expenditures (OPEX), 3) financial expenditures (FINEX) and 4) the amount of energy production. Fig. 1 and 2, gather ranges of CAPEX and OPEX cost estimates for offshore wind installations based on historical data of installed projects and surveys of project developers. These figures suggest that there is significant scatter of data between different sources denoting a high degree of uncertainty across the industry. This is mainly due to the ongoing development of the supply chain, upscaling of new generation offshore wind farms, increased demand of new assets pushing upwards the CAPEX and reduced confidence in the assessment of Operation and Maintenance (O&M) costs of aging assets.

Literature in cost modelling of offshore wind energy assets has been recently expanding. In [3] a general cost model taking into account the pre-investment and investment stages of OW farms is proposed; the model is, then, applied to indicate the most suitable wind farm layout. Installation and decommissioning costs of offshore wind farms have been analysed by Kaiser and Snyder, based on existing data of European wind farms [4,5]. A lifecycle cost model of different offshore floating wind turbine concepts was developed in [6]. Authors in [7] have developed a parametric whole life cost model of offshore wind farms, which requires less input data compared to other models available, aiming to provide a simple framework for estimating the LCOE of the investment. Finally, Ioannou et al [8] have proposed a high-fidelity cost model taking into account the different stages and key cost components of the life cycle costing of an offshore wind farm, based on the most up to date available parametric equations and developing further ones based on available real data.

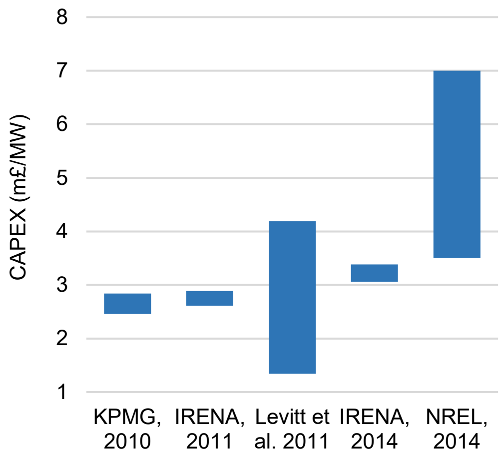

Figure 1 Range of capital costs (£m/MW) converted to 2015 £ currency (Sources:[9–13])

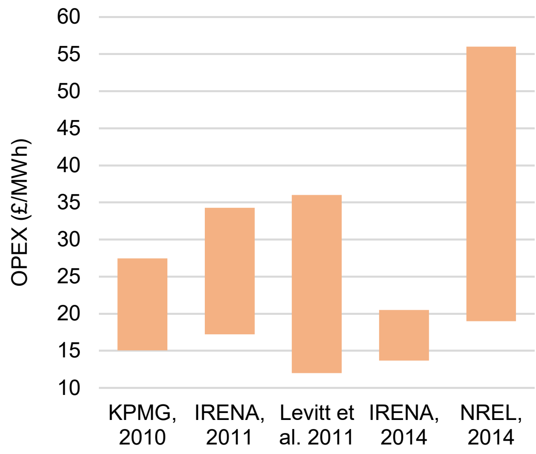

Figure 2 Range of operating costs (£/MWh) converted to 2015 £ currency (Sources:[9–13])

Several tools have been developed to date to predict costs of offshore wind energy. A basic LCOE prediction tool has been developed by BVGA [14] in the context of the Department of Energy and Climate Change (DECC) Offshore Wind Programme to enable identification of high-impact (in terms of LCOE reduction) technological developments in offshore wind farm reaching financial investment decision (FID) in 2020. The tool incorporates a number of benchmark base case scenarios with a few predetermined design parameters: nameplate capacity, water depth, foundation style, currency year. It can be used for evaluating the impact of change in OPEX, CAPEX, decommissioning costs, energy generation and WACC (weighted average cost of capital) on the final cost of energy. A stochastic expansion of the last model through the employment of Monte Carlo simulations was performed in [15]. Another model widely available is the Cost of Renewable Energy Spreadsheet Tool (CREST) provided by the National Renewable Energy Laboratory (NREL), which calculates the cost of energy (COE) and the LCOE for a range of solar, wind and geothermal electricity generation projects [16]. System Advisor Model (SAM) is a performance and financial model designed to facilitate decision making in the renewable energy industry. SAM includes several libraries of performance data and coefficients that describe the characteristics of system components such as photovoltaic modules and inverters, parabolic trough receivers and collectors, wind turbines, and biopower combustion systems. For those components, the user can simply choose an option from a list, and SAM applies values from online databases [17]. ECN has developed an offshore wind energy costs and potential (OWECOP) model, evaluating the cost of energy for offshore wind energy using a GIS database. A probabilistic analysis was implemented into the OWECOP cost model to form OWECOP-Prob [18].

Although deterministic models can support decisions pertinent to the development and operation of an offshore wind farm, they lack the ability to systematically account for the inherent uncertainty of input parameters when predicting the economic feasibility of a wind power project. To this end, a probabilistic/stochastic approach can significantly increase value of the outputs of the analysis, assigning confidence levels to the predictions towards better informed decisions. Stochastic cost modelling of power generation technologies has been applied in numerous studies focusing on fossil fuel [19], nuclear [20] as well as renewable power plants [21]. A probabilistic cost model for a solar power plant in USA was developed in [22]. Pereira et al. [23] presented a methodology based on Monte Carlo simulation to estimate the behaviour of economic parameters and applied it in a rooftop photovoltaic system in Brazil. Arnold et al. [24] and Amigun et al. [25] focused on analysing economic uncertainties regarding renewable energy technologies with a case study on bio-energy infrastructure. The profitability of wind energy investments was investigated by Caralis et al. [26] for different regions in China. Wind intermittency related to long-term cost analysis that compares the wind power to non-renewable generating technologies was studied by Li et al. [27].

The aim of this paper is to develop a stochastic financial valuation framework for offshore wind energy investments based on a high-fidelity techno-economic model, incorporating the uncertainties arising from stochastic inputs systematically. For this to be achieved Monte Carlo simulations have been adopted to account for time-independent stochastic variables, while Auto-Regressive Integrated Moving Average (ARIMA) time series model has been considered for time dependent stochastic variables. Adoption of a machine learning algorithm, Artificial Neural Network (ANN), allowed for regression from a finite number of simulations of the O&M costs, to reduce the complexity of the model and hence allow for a computationally efficient iterative process. Although employment of these methods is reported independently in literature, there is limited reference for their application in the systematic stochastic cost modelling of renewable energy applications. This work will be of value to researchers and practitioners working on the planning and optimisation of offshore wind energy assets, while the approach followed can be extended to a wide spectrum of similar applications.

The rest of the paper is structured as follows; section 2 provides an overview of the high-fidelity deterministic cost model and the methodological approach that was followed for the stochastic expansion of the model. In section 3, the advanced numerical methods applied to model stochastic inputs (time dependent and independent variables) are analysed, while in section 4 we present the case study characteristics, the stochastic variables that were modelled as well as the outputs of the deterministic cost model under the baseline scenario. Finally, in section 5, the results of the stochastic analysis are described and section 6 includes the main conclusions of this work.

2 Deterministic lifecycle techno-economic model

2.1 Structure of the model

The profitability of an offshore wind farm is evaluated through a high-fidelity deterministic lifecycle (LC) techno-economic model developed by the authors [8]. The conceptual framework of the model is illustrated in Fig. 3. Briefly, the model consists of: (a) the CAPEX module, compiling costs throughout the development and consenting (D&C), production and acquisition (P&A), installation and commissioning (I&C) and decommissioning and disposal (D&D) stages of the OW farm, (b) the general site characteristics module with details on the weather conditions, site water depth, distance from port, etc., (c) the FINEX module with parameters related to the financing expenditures, namely the Weighted Average Cost of Capital (WACC), inflation rate, corporate tax and the equity to debt ratio, (d) the OPEX module incorporating latest reliability data, vessels weather limits data and vessel and technician costs, in order to derive O&M cost estimates and (e) the revenue module which encapsulates the net power generation and the selling price of power output.

In more detail, for the CAPEX costs, the design and consent (D&C) phase costs consist of the legal, environmental survey, engineering, contingency and project management costs. The production and acquisition (P&A) phase can be further decomposed to: the acquisition of the turbine, the foundation, the electric system and the control system. The cost of the electric system comprises the cost of array, export and onshore cables and the cost of the substation. The installation and commissioning (I&C) costs of the OW farm comprise the installation of the wind turbine and tower, foundation and transition piece, scour protection, electric system, and the insurance costs. For the development of the CAPEX module and the estimation of total capital costs, the most up-to-date parametric expressions were integrated from literature while where latest data were available, new parametric equations were developed.

The OPEX module has been modelled by the use of the commercial ECN O&M Tool [28]. Inputs required by the tool include: an updated database of failure rates, the weather limits of the vessels, the number of technicians required for repairs, cost of repairs, and historic weather data, among others. Output of the analysis is the availability of the wind farm and the annual O&M costs to be integrated to the LC cost assessment.

Finally, for the decommissioning and disposal (D&D) cost of the wind farm the following aspects are taken into account: 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), the site clearance, the onshore transportation to the disposal sites, the port preparation, the disposal process and finally the hiring vessels costs.

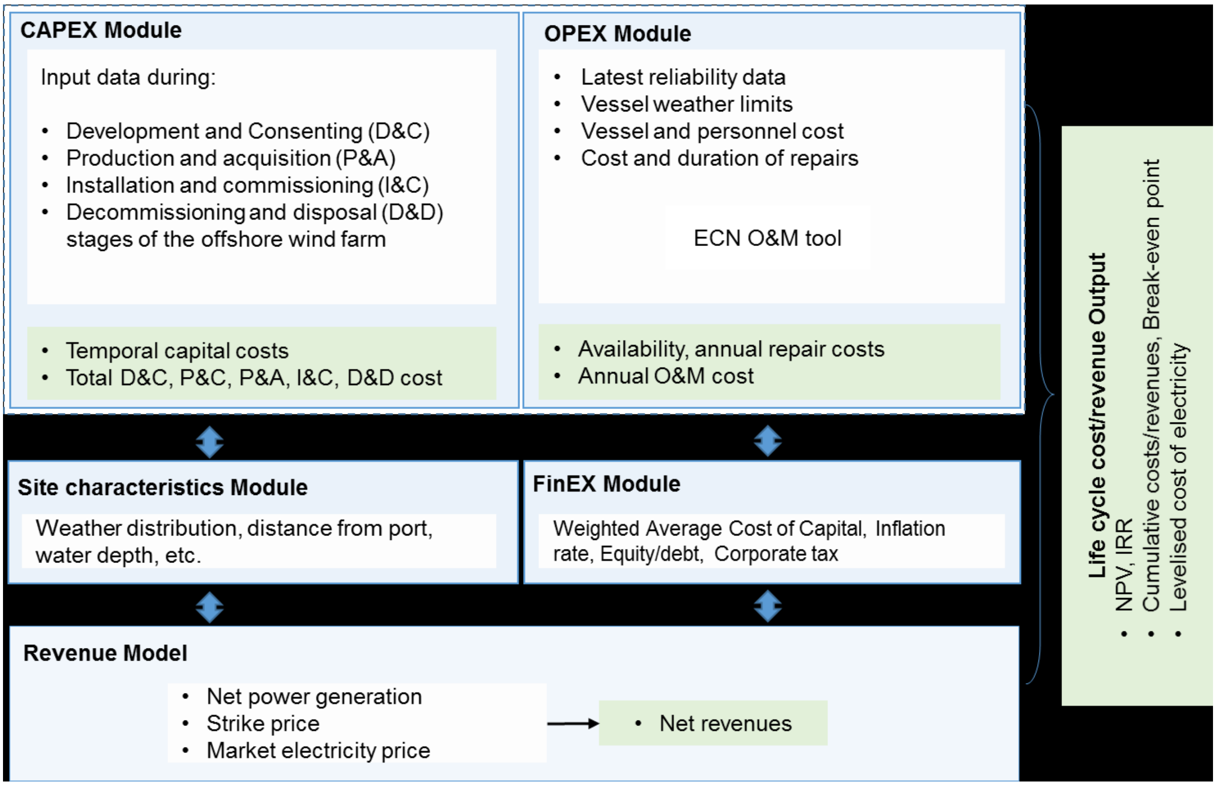

Figure 3 Overview of deterministic techno-economic model

The deterministic techno-economic model has been programmed in Matlab, to facilitate parametric simulations and visualisation of the results. It derives a series of cost outputs for each of the five phases described above, as well as costs and key profitability indicators for the lifecycle cost/revenue profile of the offshore wind farm (OWF) investment, namely the net present value (NPV), internal rate of return (IRR), break-even point, as well as the levelised cost of electricity (LCOE). The model has been verified through comparison with available data and can be considered a reliable option for further analysis [7,29,30]. Within this present work, this cost model is extended to allow for a number of iterative Monte Carlo simulations to be executed to evaluate the effect of stochasticity of inputs to the outputs. For this to be achieved, a surrogate model is constructed through an ANN, based on a finite number of numerical simulations, in order to avoid the time consuming high-fidelity simulations required for the O&M tool initially employed; further, consideration of the electricity price will be modelled through an Auto-Regressive Integrated Moving Average (ARIMA) model to account for the time-dependent variability of this specific variable. These additional features are presented in detail in section 3.

2.2 Stochastic expansion of the lifecycle techno-economic model

The approach followed herein constitutes a non-intrusive formulation allowing for a set of well-established discrete steps to be followed. In order to extend the applicability of the model, an approximation model will be adopted integrating Artificial Neural Networks (ANNs) in order to link deterministic inputs with outputs alleviating the need of analytical calculations through the analytic O&M tool and also allow for combination of Monte Carlo simulations at a reasonable computational effort and further consideration of the ARIMA model to derive forecasting values for the future electricity market price which is a time-dependent stochastic variable. The sequence of steps to be followed is shown in Fig. 4 and presented further below.

i. *Development of cost model:* This step accounts for the high-fidelity deterministic cost model that has been presented in section 2.1 and in reference [8].
ii. *Identification of stochastic input variables:* Selection of the stochastic variables should be carefully selected as their number will significantly influence the computational effort required for the analysis. The selected variables have been chosen following a sensitivity analysis and setting of a cut-off point, gradually increasing/decreasing by 20% the value of each variable and comparing with a baseline case.
iii. *Identification of key output variables:* For the expression of the results of this study, the NPV, IRR, cumulative cost/revenues, break-even point, LCOE are relevant.
iv. *Generalization of the O&M costs through an ANN model:* In order to be able to integrate the high-fidelity O&M tool initially employed, a surrogate model will be developed based on a series of deterministic simulations in order to map the response of the system. Starting from a baseline case, a series of combinations of the stochastic variables will be planned in order to provide an appropriate data set of input and output values that will later on be approximated. Selection of the total number of simulations will be a compromise between the number

and computational effort required per simulation. A finite number of simulations is then executed in the commercial O&M tool as described above and data will be recorded in an inputs/targets format. Then, an Artificial Neural Network (ANN) is developed. Outcome of this model is a non-analytic expression that can provide approximations of key outputs as a function of given inputs.

v. *For time dependent stochastic variables*, the Auto-Regressive Integrated Moving Average (ARIMA) approach is adopted to generate time series based on available historical data. This will allow for a random data set of values of electricity price to be considered, for each of the simulations that will run.

vi. *For time independent stochastic variables*, appropriate probability distribution functions will be assigned. In the absence of real data, normal and uniform distributions will be chosen for the analysis, which is a common practice followed by other researchers such as in [31].

vii. *Run a number of Monte-Carlo Simulations:* Once the above steps are completed, a series of Monte Carlo simulations will be executed in order to derive the joint probability distribution of the key performance indicators determined in step (iii). Following a convergence study, it was found that 10,000 iterations would be sufficient for results that converge in specific values. Transition from deterministic to stochastic expression of results, implies that instead of a set of fixed output values (i.e. LCOE) derived from a deterministic set of input values, the output is expressed as the probability that the output value lies within a set threshold.

viii. *Interpretation of results and sensitivity analysis:* Once the algorithm has been developed, a sensitivity analysis of the input variables will take place distinguishing those with the higher impact to the output variables as well as investigating the impact of statistical modelling of input variables. Results are best presented through tornado graphs.

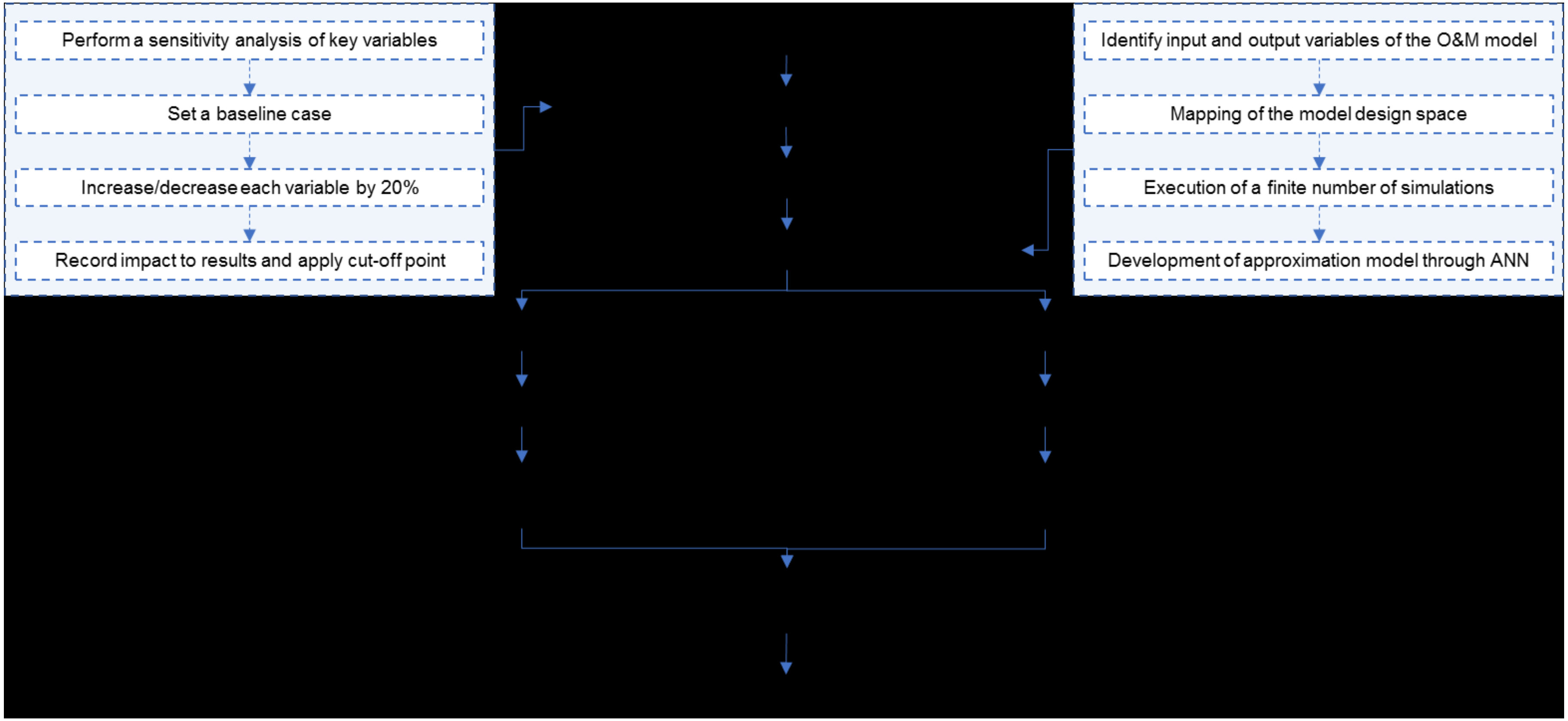

Figure 4 Methodological steps

3 Advanced numerical methods for stochastic modelling

3.1 Development of approximation models for O&M costs

3.1.1 Artificial Neural Network (ANN) modelling approach

An Artificial Neural Network (ANN) is a powerful data modelling tool able to capture and simulate complex input/output relationships [32]. It comprises a large number of interconnected neurons with linear and nonlinear transfer functions and can be even used to predict the nonlinear behaviour of a system [33]. In general, the structure of ANNs consists of an input layer, one or more hidden layers and an output layer. Conventional mathematical models, such as common approximation models, use an algorithmic approach following a set of steps to solve a problem; unless these steps are known, the problem cannot be solved, restricting the problem-solving capability of conventional models. ANN ‘learns’ the relations between the inputs and outputs by training.

The input to each neuron can be the network input from the input layer, the output of the neuron in the previous layer, and an externally applied bias [34]. The output of each neuron is the function of the weighted sum of the neuron inputs, with the hyperbolic tangent sigmoid transfer function (Eq. (1)) used in the hidden layer and the linear function (Eq. (2)) used in the output layer. The weights and bias are determined in the training process by minimising the error between the ANN outputs and the design matrix [31].

$$f(\varphi) = \frac{2}{1 + \varepsilon^{-2(\sum_{i=1}^{k} w_i \cdot u_i + \theta)}} - 1 \tag{1}$$

$$f(\varphi) = \sum_{i=1}^{k} w_i \cdot u_i + \theta \tag{2}$$

where, φ is the Neuron output; θ is the ANN layer bias; w_i is the ANN node weight and u_i is the stochastic variable.

In this analysis, the MATLAB Neural Network Fitting toolbox was used, with a two-layer feed-forward ANN with ten sigmoid hidden neurons and linear output neurons, to map the system response generated from the process model (based on the design matrix inputs).

To ensure an accurate prediction by the ANN, the data in the design matrix were divided between training (70%), validation (15%) and testing (15%) samples. Neural network training was performed to adjust the weights of all the connecting nodes until the desired network performance was reached. The evaluation of network performance is essentially a nonlinear optimisation process and the objective function involves minimisation of an error function, e.g. mean squared error (MSE). In this study, the Bayesian Regularisation training algorithm was used as it can provide a better solution than other available algorithms for smaller problems to obtain the optimal values of the adjustable parameters, weights and biases. The MSE performance function (Eq. 3) was used to assess the network performance.

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(z_i - y_i)^2 \rightarrow min \tag{3}$$

where, z_i: the targets, y_i: network outputs and N:data size.

ANNs have been commonly applied in energy-related problems. Kalogirou has performed a literature review in energy systems applications, including solar steam generators and water heating systems, photovoltaic systems, as well as in forecasting and prediction of solar radiation and wind speed, among others [35]. In the more recent literature, a number of studies have used ANN for estimating building energy consumption [34,36,37]. In [38], authors present a methodology to forecast the diurnal cooling load for institutional buildings, by training and forecasting with ANNs the next day energy use based on five previous days' data. Smrekar et al. developed ANN models of a coal-fired boiler of a CHP plant in Slovenia in order to predict mass flow, pressure and temperature of steam exiting the boiler [33]. ANNs were also used in [39] to solve a number of problems in photovoltaic systems applications. A recent study combined ANN approximation models and Monte Carlo simulations (MCS) to map the response domain of an innovative energy recovery system under varying inputs [31].

The ANN method was employed in this study as a robust approximation method that can derive outputs relevant to the O&M phase of the investment in an efficient way through mapping the response of the system under varying sets of input parameters. This method was considered appropriate since stochastic analysis through the high-fidelity O&M Tool would require a large number of direct simulations to take place. Hence, this study utilises the deterministic O&M tool to produce a design matrix which is accordingly used to generate the ANN approximation model. The latter is, then, able to use the input variables to return the output values, even when their relationship is nonlinear. In this study, input parameters were considered the following: the average repair cost, the Mean Time To Failure (MTTF), the workboat significant height limit, the workboat work day rate, the jack up (JUV) vessel day rate, the JUV mobilisation/ demobilisation cost and the fixed annual cost per technician. Output variables were: the repair cost, the total OPEX and the net power production of the wind farm.

3.1.2 Accuracy of the ANN model

To validate the capacity of the derived ANN to accurately predict the values of the dependent variables, a series of tests were run as part of the analysis. Firstly, the regression plots, which can be found in Fig. 5 display the network outputs with respect to targets for training, validation, and test sets. As shown in Fig. 5, all data fall along the fit line, indicating that the network outputs are equal to the targets. In this case, the outputs of the networks are: the repair cost, the net energy production and the annual operating cost. This is summarised to obtained R values equal to 1.

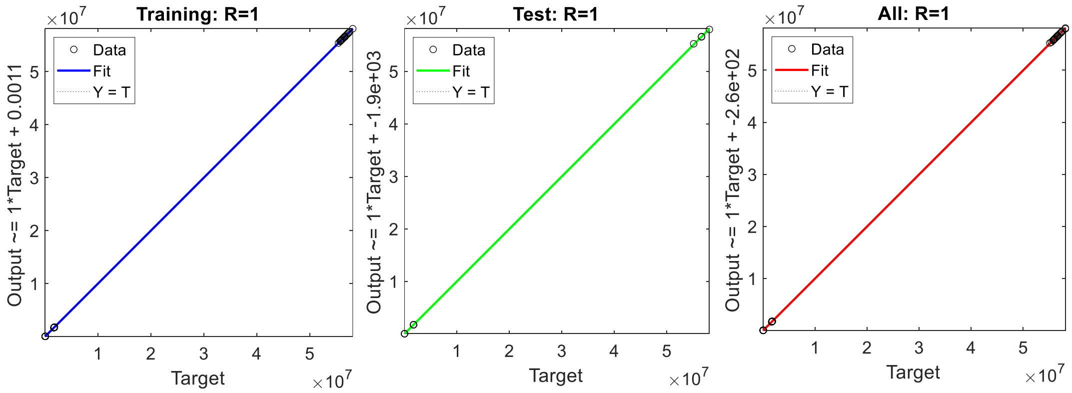

Figure 5 Regression plots

Further, an error histogram is compiled (Fig. 6) providing an indication of outliers, which are data points where the fit is significantly worse than the majority of data. In this case, the mode bar coincides well with the zero-error value, denoting a good fit with a very small number of values lying outside the range of this bar. The process was repeated to account for the stochasticity of the process and similar results were obtained. An analysis of the performance of the network calculating the mean square error of the prediction, shows converging trend in performance after epoch 150, denoting a sufficient number of epochs selected (i.e. 1,000). Finally, on an additional analysis of the ANN capability, using the inputs of the initial decision matrix to predict the outputs has returned an average absolute error in prediction of 0.05%.

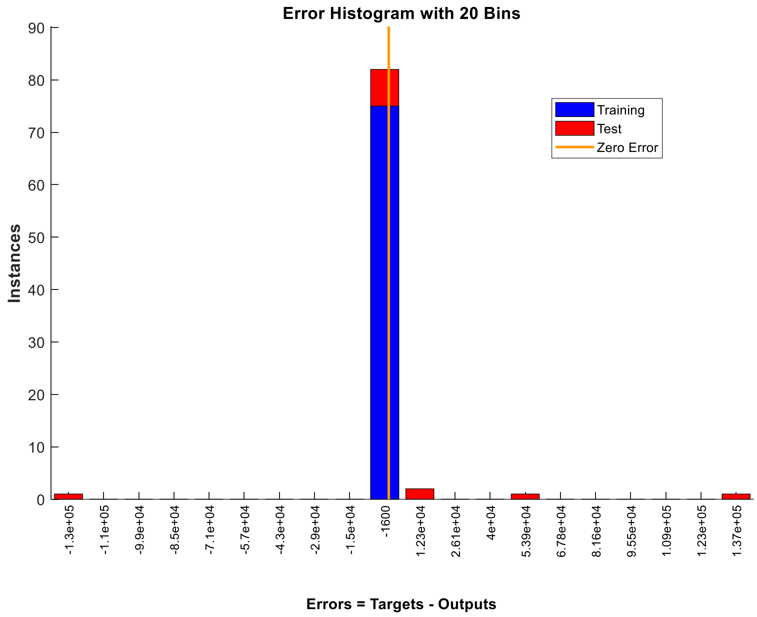

Figure 6 ANN error plot

3.2 Stochastic modelling of electricity prices

3.2.1 ARIMA model approach

In this section, the modelling approach of monthly wholesale electricity prices is presented. Electricity prices appeared to have a considerable impact on the profitability of the investment according to the sensitivity analysis on the Net Present value (as will be presented later on). Further, considering the zero-subsidy bids lately awarded to offshore wind projects [40], it becomes evident that accurate forecasting of market electricity prices can significantly contribute towards a more informed assessment of revenues.

Numerous forecasting techniques for electricity prices can be found in literature. In [41], electricity price forecast techniques are categorised into: multi-agent, fundamental methods, reduced-form models, statistical approaches and computational intelligence techniques. Statistical methods forecast the current value of a time series by applying a mathematical correlation of the previous values with the current values. ARIMA or Box-Jenkins model [42] is a statistical method standing for autoregressive (AR) integrated (I) moving average (MA) and it is a generalisation of the Autoregressive Moving Average model (ARMA), where “I” (standing for Integrated) is a differencing step that is used to remove trend or seasonality from the time series. ARIMA models use standard notation of ARIMA(p,d,q) and (P,D,Q) for their seasonal counterparts. In power systems applications, ARIMA models have been used for load forecasting [43,44], with good results, as well as to model and forecast day-ahead electricity prices [45,46] and weekly prices [47]. ARIMA method was deemed appropriate for this study considering the ability of the method to take into account the seasonal trend of the dataset of electricity prices.

- The Autoregressive part (p) specifies which previous values from the data series are used to predict the current values or else the number of autoregressive orders.
- The Difference part (d) specifies the order of differencing of the time series before the application of the model. To apply the ARIMA model, the dataset is required to be stationary; if not, a transformation of the series to the stationary form needs to take place. Differencing is one of the simplest ways to achieve this. Box and Jenkins (1976) introduced a model that contains not only the autoregressive and moving average parts, but also the differencing part [42].
- The moving average part (q) specifies the moving average orders in the model, namely how the mean values deviation of the previous time series are used to predict the current values.

As such, the mathematical formulation of the ARIMA(p,d,q) model can be described using a lag operator notation (defined as $L^i X_t = X_{t-i}$) as follows:

$$\varphi(L)(1-L)^d X_t = c + \theta(L)\varepsilon_t \tag{4}$$

where, X_t is the price at time t, c a constant term, d the differencing order, ε_t is the random error at time t; further, $\varphi(L)$ are the parameters of the AR model formulated as:

$$\varphi(L) = 1 - \varphi_1 L - \ldots - \varphi_p L^p \tag{5}$$

where, p refers to the autoregressive terms, while $\theta(L)$ are the parameters of the MA(q) model expressed as:

$$\theta(L) = 1 + \theta_1 L + \ldots + \theta_q L^q \tag{6}$$

where q refers to the moving average terms [48].

3.2.2 Application of ARIMA model

In this study, monthly data of the wholesale electricity prices were collected from different sources [49,50] to compile a monthly dataset starting from March 2003 to February 2018. The dataset (178 observations) was divided into two parts, the first consisting of 142 observations, which was used to build the model and the second of 36 observations for testing the model (corresponding to a ratio 80% (for building) / 20% (for testing the model)).

In order to identify the best-fitting ARIMA model for the monthly electricity prices, the time series Expert Modeler of SPSS was used, eliminating the need to identify an appropriate model through a manual trial and error process [51]. The tool indicated an ARIMA(2,1,2)(1,0,1) model consisting of non-seasonal and seasonal parts with a periodicity set to 12, while the tool was also set to automatically detect outliers of different types. Above notation means that the series was differenced once at lag-1; further, the model includes X_{t-2} and ε_{t-2}, as well as a seasonal lag-12 AR term and a seasonal lag-12 error term. Accordingly, we simulated 10,000 sample paths from the ARIMA model. The 50% upper and lower confidence limits of the resulting model for the first part of the dataset, as well as the observed data for 2015-2017 (2^{nd} part of the dataset) are illustrated in Fig. 7. The mean absolute percentage error between the observed data and the average values of the forecasted data (mean annual probability distributions of forecasted prices are depicted in Fig. 8) was calculated 7%, indicating a relatively good fitness of the model to the dataset.

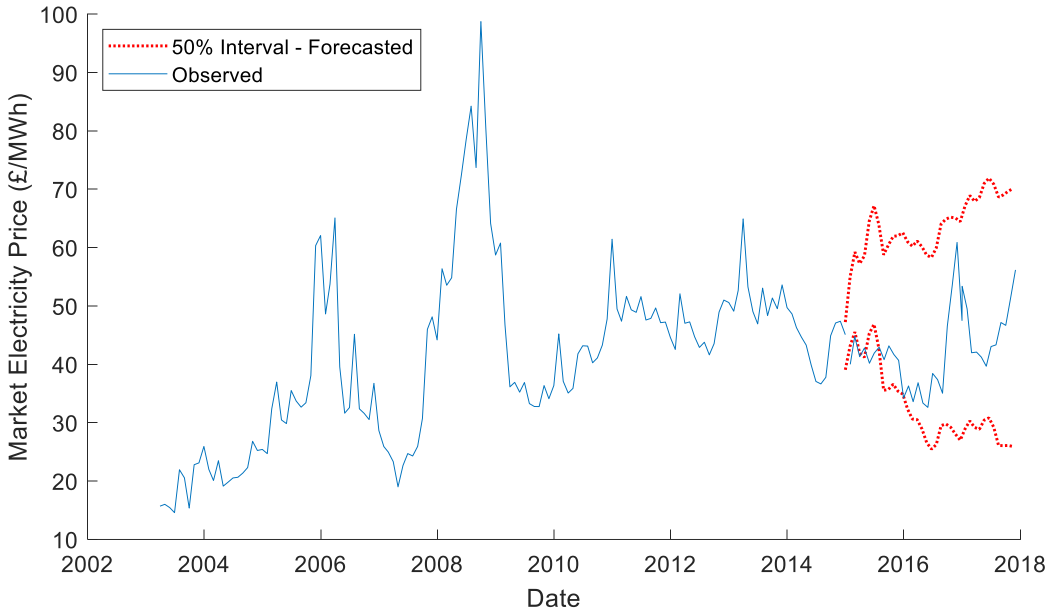

Figure 7 Testing of ARIMA(2,1,2)(1,0,1)$_{12}$ model for the prediction of wholesale electricity prices

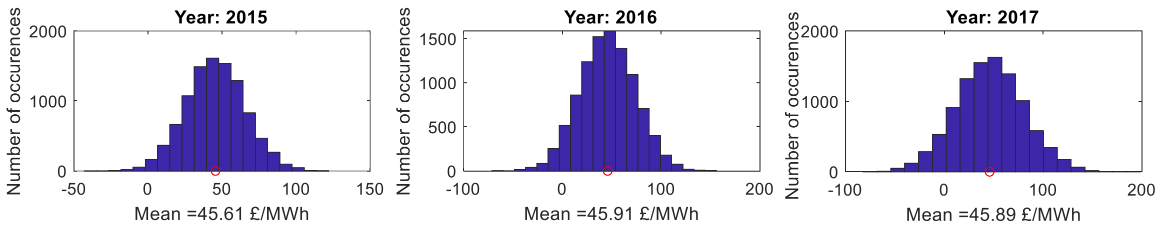

Figure 8 Mean annual probability distributions of forecasted electricity prices between 2015-2017

Assuming that the power output of the offshore wind farm is sold on the wholesale electricity prices from 2018 onwards for ten years, the ARIMA model built, was further applied to forecast values of wholesale electricity prices from 2018 to 2027. Table 1 summarises the goodness-of-fit measures of the time series model. The R-squared value is an estimate of the proportion of the total variation in the series that is explained by the model; hence values closer to 1 signify a better fit. The stationary R-squared measure is an appropriate measure when there is a trend or a seasonal pattern in the time series, since it compares the stationary part of a model with a simple average model [52]. The mean absolute percentage error of the model (MAPE) was estimated 7.5%, i.e. a similar magnitude of the deviation found when testing the model by means of the two dataset parts. MaxAPE stands for the maximum average percentage error and captures the worst-case scenario of the forecast. Further, the Ljung-Box statistics showed that the model is specified correctly by returning a significance value of greater than 0.05. Finally, after simulating 10,000 sample paths of the model for the period 2015-2017, the mean annual probability distributions were included in Fig. 9, while Fig. 10 illustrates the 50% upper and lower confidence limits of the forecasted values. Predicted mean annual values illustrated in Fig. 9 were introduced in the stochastic cost model to predict cost inflows after the 15-year period that CfD tariff scheme is in effect.

Table 1 Model statistics

Fit Statistic	Model Fit
Stationary R-squared	0.669
R-squared	0.930
MAPE	7.448
MaxAPE	32.746

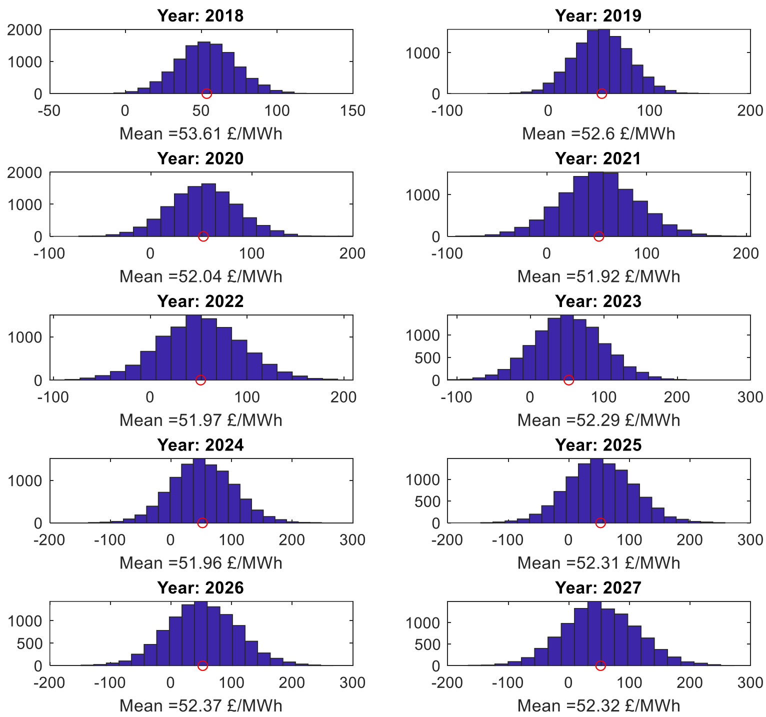

Figure 9 Mean annual probability distributions of forecasted electricity prices between 2018-2027

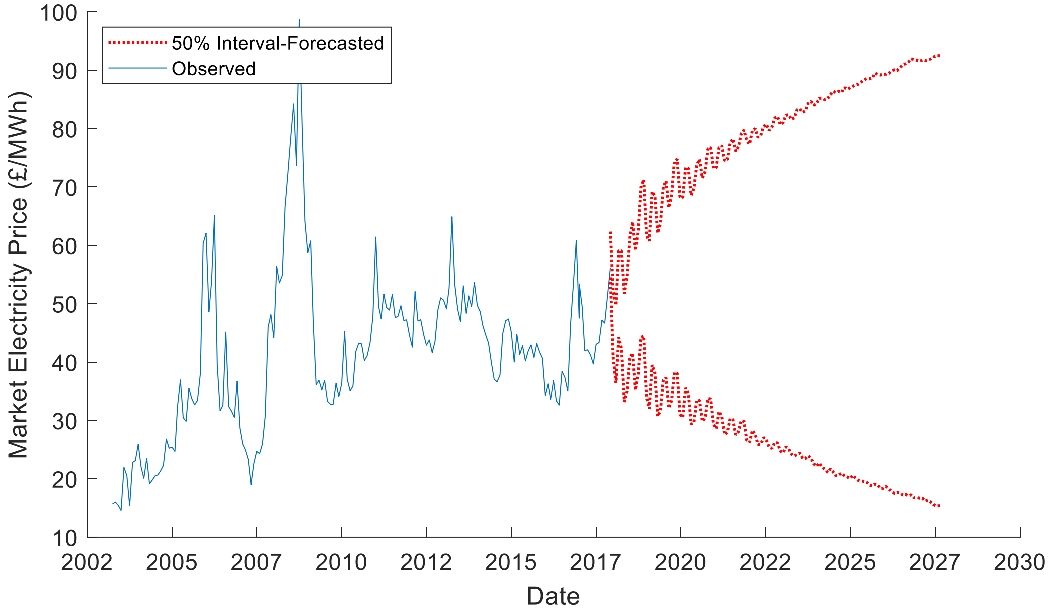

Figure 10 Applying the ARIMA(2,1,2)(1,0,1)$_{12}$ model for forecasting the 2018-2025 wholesale electricity prices

4 Case study

4.1 Specifications of the case study

The baseline case study refers to a 504 MW wind farm located in the North Sea region, 36km away from shore. Weather data were retrieved from BTM ARGOSS [53] for modelling the operational phase of the asset. In Table 2, the wind farm specifications are summarised.

Weather limits of the vessels, along with the day rates, speed, mobilisation/ demobilisation time/cost are included in Table 3. The wind speed limit measurements are referenced at 10m above the mean water level. The mobilisation activities refer to the planning and modifying of a vessel for a marine mission, while the demobilisation to the restoring of the vessel for release and reassignment to other operations. As far as the personnel cost is concerned, a rate of £270/day is assumed for additional professionals hired to perform mechanical/electrical operations for the installation, erection and other services [6,54].

Inputs required by the ECN O&M tool include: an updated database of failure rates, the weather limits of the vessels, the number of technicians required for repairs, cost of repairs, and historic weather data, among others. The classification scheme of repairs was adopted from the Reliawind project [55]. As such, repairs were divided into minor repairs (up to 1,000€), major repairs (1,000€-10,000€) or major replacements (>10,000€). Data on the failure rates, average repair times, number of required technicians and material costs were retrieved from [56].

Table 2 Case study wind farm specifications

Wind farm characteristics		Values
Wind farm	Total wind farm capacity	504MW
	Projected operational life of the wind farm	25years
	Construction years	5years
General Site characteristics	Number of turbines	140
	Distance to port	36km
	Water depth	26m
Wind turbine	Rotor diameter	107m
	Hub height	77.5m
	Pile diameter	6m
	Rated power	3.60MW
	Cut-in speed	4m/s
	Cut-out speed	25m/s

Table 3 Transportation equipment specifications (Source: [8]**)**

Vessel type	Technician space	Vessel speed (knots)	Weather limits: Sign. wave height (m)	Weather limits: Wind speed (m/s)	Mob. / Demob. Cost (k£)	Mob. / Demob. Time (h)	Day rate (k£/day)
Crew transfer vessel	12	26	1.8	16	-	-	3.25
Jack-up vessels	-	10	2	10	405	720/48	112.6
Heavy lift vessel	-	9	-	-	500	-	135
Helicopter	6	-	99	20	4.7	8/4	4.7
Diving support vessel (DSV)	-	16	2	25	185	360	60
Cable laying vessel	-	14	1	10	445	720	80 (Array) 100 (Export)
Rock dumping vessel	-	13.5	-	-	10.6	-	13.8

4.2 Deterministic profitability assessment

The results of the evaluation of the profitability of the investment in deterministic terms are presented in this section. The total CAPEX was estimated £1.67 billion, annual OPEX £56.6 million, NPV=£284.36 million at a real discount rate of 6.15%, while the LCOE=108.9 £/MWh. The results indicate that P&A costs have the highest contribution to the LCOE value, accounting for 46%, while O&M costs correspond to 30% of the total cost. A breakdown of the costs per Phase of the wind farm under the baseline case is illustrated in Fig. 11.

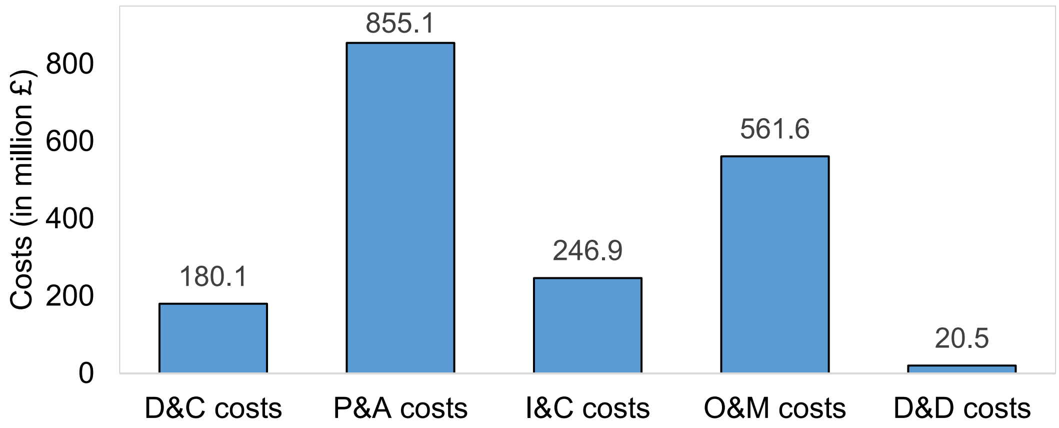

Figure 11 Lifecycle costs breakdown

4.3 Selection of stochastic variables

A global sensitivity analysis (Fig. 12) of the deterministic cost revenue model was conducted using a ± 10/20% increase or decrease in the mean value of the key statistical parameters to determine their effect on the net present value. It was concluded that there are 23 input variables that can have a considerable effect on the NPV of the investment (>2% cut-off point). Particularly influential parameters appeared to be the strike price, the return rates of equity and debt, the MTTF, the share of equity, the cost of turbine, the inflation rate, the working hours per shift, the wholesale electricity prices and the workboat significant wave height limit, inducing an absolute variation of higher than 15% to the NPV of the investment.

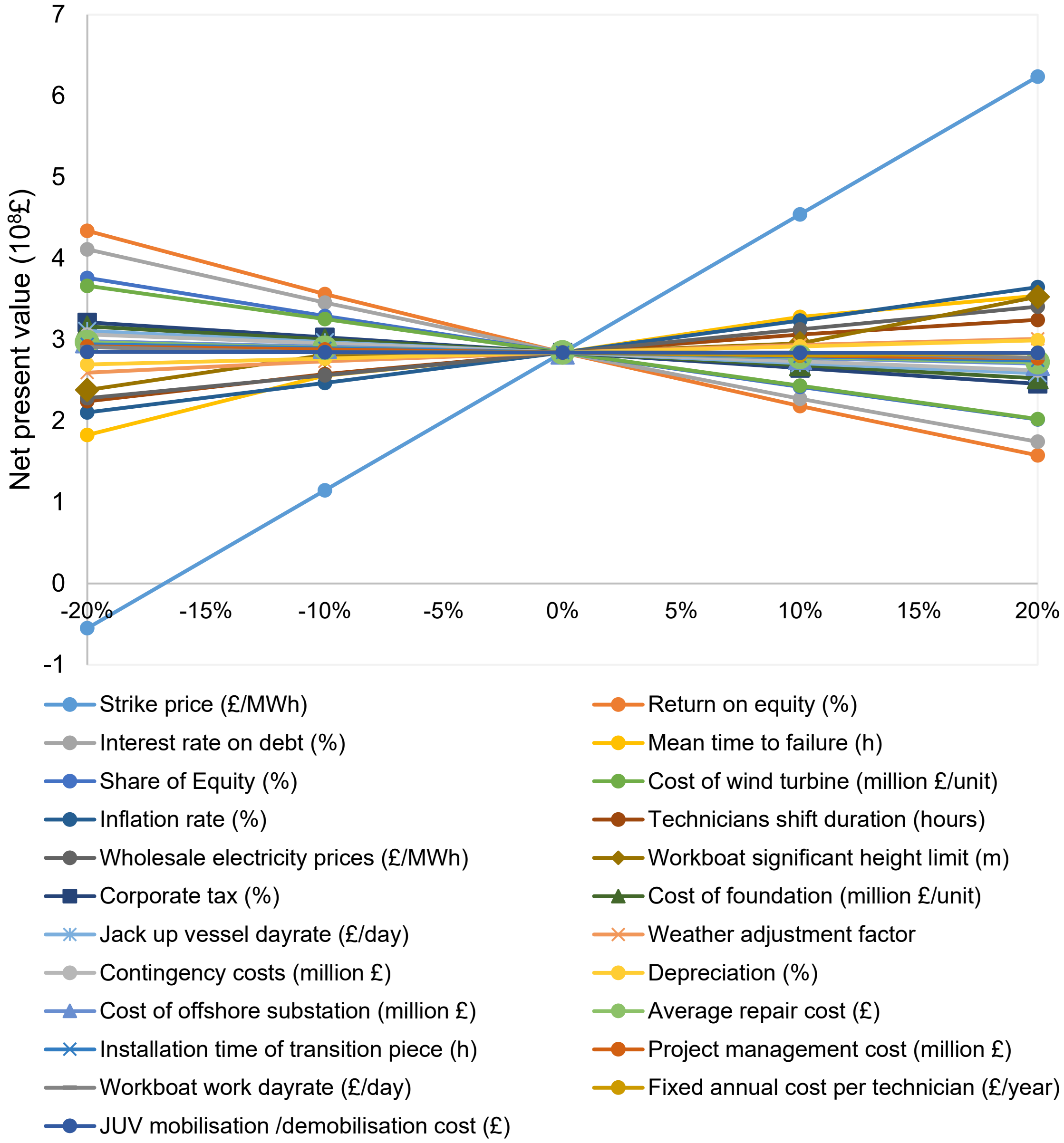

Figure 12 Global sensitivity analysis of the deterministic model (variables are listed in descending order of effect on NPV)

Above listed variables were assumed to be normally distributed, when the distribution of the random variables was unknown, with mean value their initial deterministic value and a 10% coefficient of variation (COV). The cost of turbines and foundations was calculated based on the different up-to-date parametric expressions available in literature as shown below. Wind turbine cost is usually expressed as a function of the turbine capacity and different parametric models have been developed in literature (as shown in Table 4).

Table 4 Wind turbine cost prediction expressions

Source	Parametric model	Reference case study *
[7]	$c_{WT} = 3 \cdot 10^6\ ln(P_{WT}) - 662{,}400$	3.90 m£ / turbine
[3]	$c_{WT} = -255016 + 2 \cdot 10^6 \cdot \log(\mathrm{P_{WT}})$ in € (2011)	£ 2.85 million/turbine plus the tower cost
[57]	$c_{WT} = 1374 \cdot \mathrm{P_{WT}}^{0.87}$ in k€ (2016)	£ 3.37 million/turbine for the acquisition, shipping and assembling, and electrical installation

* Costs are adjusted to a single currency (Pounds) at a single year (2017) to allow meaningful comparisons.

Further, Table 5 summarises results from the application of different expressions found in the literature, linking foundation costs with water depth, turbine capacity, hub height and rotor diameter.

Table 5 Foundation cost prediction expressions

Sources	Parametric model	Reference case study*
[57]	$c_f = 363 \cdot \mathrm{P_{WT}}^{1.06}$, in k€ (2017)	1.14 £ million/foundation
[3]	$c_f = 8.17 \cdot \mathrm{WD} + 389.3$, in k€ (2011)	2.77 £ million/foundation
[6]	$c_f = 320 \cdot 1000 \cdot P_{WT} \cdot (1 + 0.02 \cdot (WD - 8)) \cdot \left(1 + 8 \cdot 10^{-7} \cdot \left(h \cdot \left(\left(\frac{d}{2}\right)^2 - 100000\right)\right)\right)$	2.07 £ million/foundation

* Costs are adjusted to a single currency (Pounds) at a single year (2017) to allow meaningful comparisons.

Uniform distributions were assumed for modelling the cost of foundations and turbines, by considering as the upper and lower limits, the highest and lowest costs respectively from the expressions summarised in Tables 4 and 5. Table 6 presents the stochastic variables, probability functions and the characteristic values of their probability distribution.

The average repair costs of all wind turbine components were extracted, as mentioned above, from [56], while in order to account for the stochasticity of this set of parameters a multiplier following a normal distribution with mean value 1 and 10% COV was applied to all average repair costs of each sub-assembly/component. The same approach was followed for the MTTF variable.

Table 6 List of stochastic input parameters

Variable	Type of distribution	Characteristic values
CAPEX parameters		
Cost of wind turbine (million £/unit)	Uniform	Min: 2.85, Max: 3.37
Cost of foundation (million £/unit)	Uniform	Min: 1.14, Max: 2.77
Technicians shift duration (hours)	Normal	μ= 11, σ=1.1
Weather adjustment factor	Normal	μ= 0.85, σ=0.085
Contingency costs (million £)	Normal	μ=126.4, σ=12.6
Cost of offshore substation (million £)	Normal	μ= 29.5, σ=2.95
OPEX parameters		
Average repair cost (£)	Normal	μ= 1, σ=0.1
Mean time to failure (h)	Normal	μ= 1, σ=0.1
Revenue parameters		
Strike price (£/MWh)	3 Scenarios	
Wholesale electricity prices (£/MWh)	ARIMA	
FINEX parameters		
Share of Equity (%)	Normal	μ= 30.00%, σ=3.00%
Inflation rate (%)	Normal	μ= 2.50%, σ=0.25%
Corporate tax (%)	Normal	μ= 17.00%, σ=1.70%
Depreciation (%)	Normal	μ=18.00%, σ=1.80%
Return on equity (%)	Normal	μ= 15.80%, σ=1.58%
Interest rate on debt (%)	Normal	μ= 7.00%, σ=0.70%
General parameters		
Workboat significant height limit (m)	Normal	μ= 1.8, σ=0.18
Workboat work dayrate (£/day)	Normal	μ= 3,250, σ=325
Jack up vessel dayrate (£/day)	Normal	μ= 112,600, σ=11,260
JUV mobilisation /demobilisation cost (£)	Normal	μ= 405,000, σ=40,500
Fixed annual cost per technician (£/year)	Normal	μ=95,000, σ=9,500

5 Results

5.1 Stochastic profitability assessment

The joint probability distributions of the NPV, CAPEX, annual OPEX and LCOE are plotted in Fig. 13-16. Due to the significant impact of the strike price on the NPV of the investment, probability plots under three different scenarios of strike prices, namely 100, 120, 140 £/MWh, are presented. The resulting NPVs follow an approximately normal distribution. As expected, increasing the guaranteed tariff (strike price) on the wind farm energy output shifts the NPV probability distribution to the right, towards higher values of NPV, thus, increasing the value of the asset. As such, under a strike price of 120£/MWh, the chance of a negative NPV amounts to 47%, while for a strike price of 140 £/MWh, there is just 1% chance for the investment to yield a negative NPV. Finally, it is concluded that a strike price of 100 £/MWh would render the investment no longer profitable for the investor, since the chance of a positive NPV would fall below 1% under the specifications of the baseline scenario.

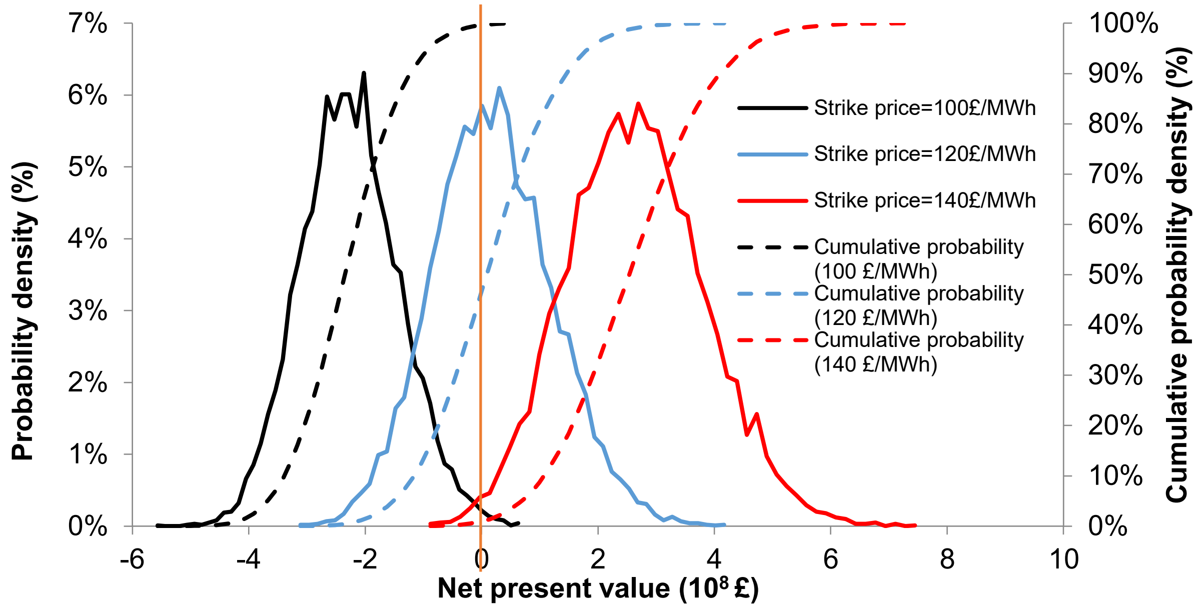

Figure 13 Probabilistic results of NPV under three different strike prices (100, 120 and 140 £/MWh).

Further, the probability plot of LCOE is illustrated in Fig. 14 and it demonstrates there is a high probability at a 90% confidence interval for the investment cost of energy to lie within 93.6-115.5 £/MWh. The deterministic analysis of the LCOE has indicated a value of 108.9 £/MWh; nevertheless, according to the probabilistic analysis, it is deemed that there is an approximately 20% probability that the NPV can achieve higher values. Accordingly, the probability plot of investment cost approximates a normal distribution shape as depicted in Fig. 15. The CAPEX output lies in the range of £1.60-1.77 billion at a 90% confidence interval. The outcome of the deterministic model (£1.67 billion) was concluded to lie in approximately the median value of the distribution derived from the stochastic analysis. The probabilistic results of annual OPEX (Fig. 16) indicated a range of £55.0-58.4 million per year for a CI of 90%.

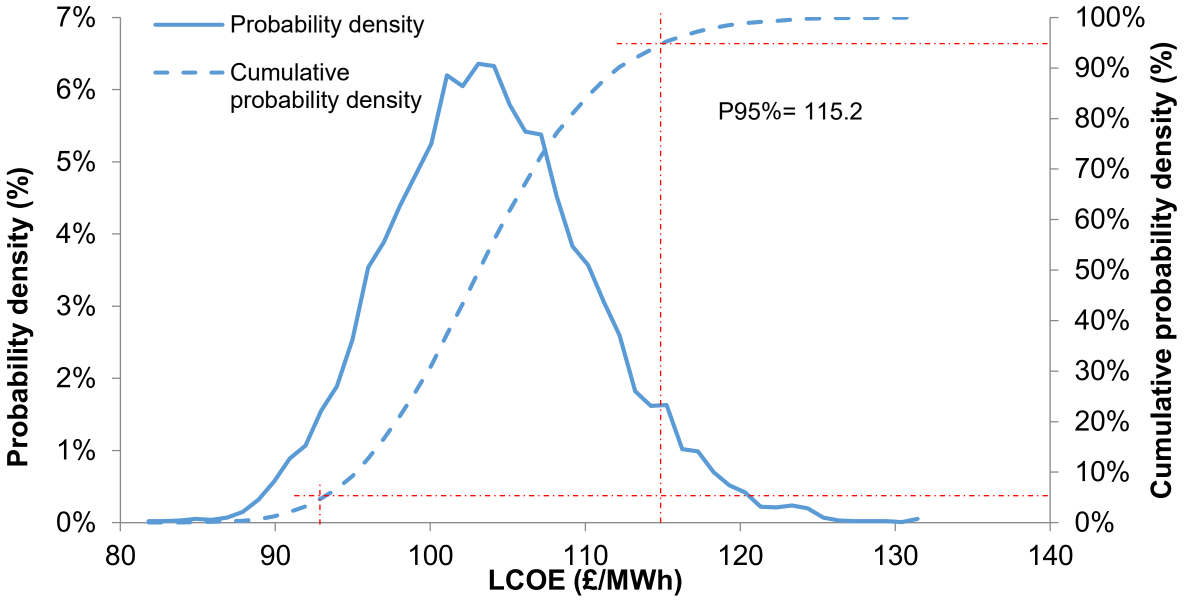

Figure 14 Probabilistic results of LCOE (£/MWh)

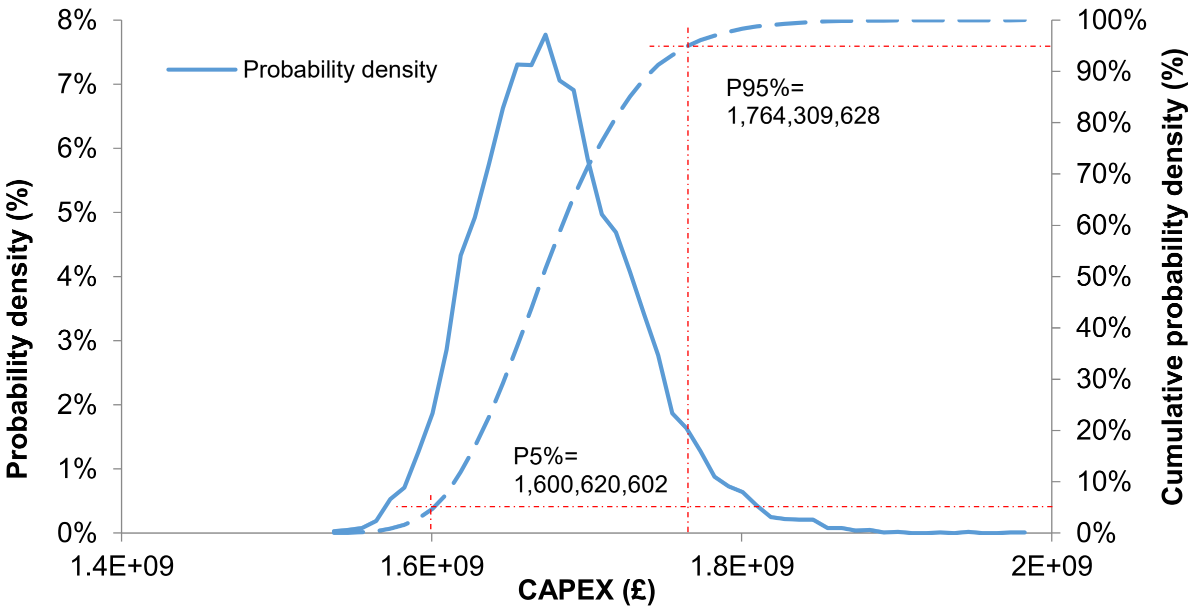

Figure 15 Probabilistic results of Capital costs

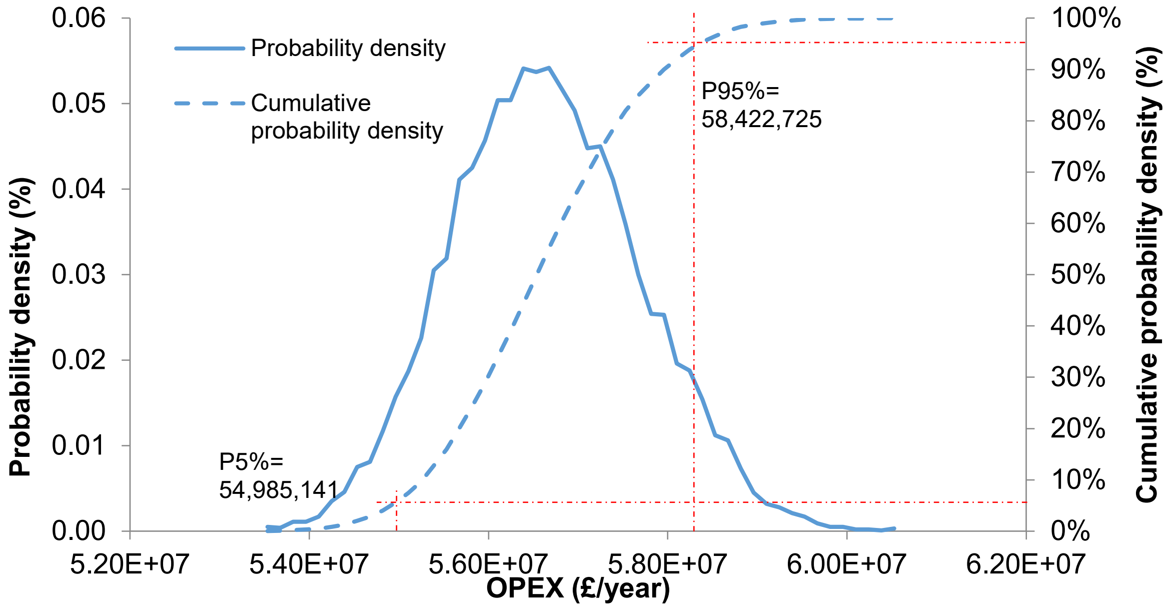

Figure 16 Probabilistic results of O&M costs

5.2 Sensitivity analysis

A sensitivity analysis of the variability of the stochastic variables was accordingly applied, based on an assessment of an increase or decrease of 20% of the standard deviations of the key statistic parameters on the key performance indicator of the profitability of the investment. Considering the mean NPV resulting from the probabilistic analysis under strike price=140£/MWh (reaching a value of £ 266.1 million) as the baseline case, the outcomes of the sensitivity analysis are presented in the Tornado plot of Fig. 17. It should be noted that since strike prices were modelled by means of scenarios and electricity prices by means of time series the sensitivity of NPV on their variability has not been included in this analysis.

Variables whose variance appeared to have notable impact on the NPV were in descending order of impact: the cost of turbine component, the mean time to failure, the cost of foundation, the working hours and the weather adjustment factor. The general conclusion that can be drawn from this graph is that the increase in the standard deviation of key variables, results in increasing investment risk, hence reducing the profitability of the investment. Nevertheless, increasing the variance of some parameters such as the return on equity and the contingency costs appears to result in slightly higher NPVs, which can be explained by the randomness of each Monte Carlo simulation. As shown above, considerable differences compared to the standard deterministic sensitivity analysis were observed, where the return rates of equity and debt, the MTTF, the share of equity, the cost of turbine, the inflation rate, and the working hours per shift were among the most significant variables.

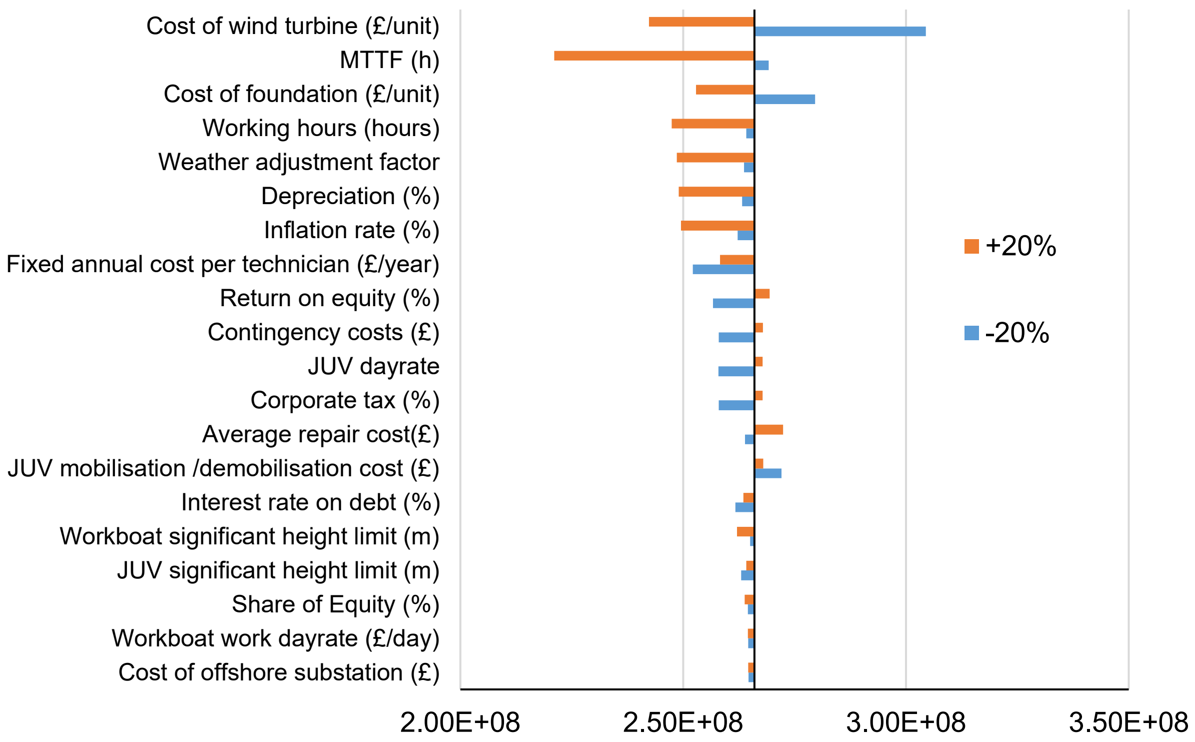

Figure 17 Tornado Chart - Sensitivity Analysis of standard deviations on NPV (£)

6 Conclusions

Uncertainty of key parameters needs to be considered when predicting the economic feasibility of offshore wind energy investments. This approach has the potential to increase the value of the outputs of the analysis, by assigning confidence levels to the predictions towards better informed decisions. The present paper proposes a probabilistic/stochastic approach which is based on the expansion of a high-fidelity deterministic lifecycle techno-economic model to account for numerous time independent and dependent uncertain inputs by applying advanced numerical methods, such as Artificial Neural Networks (ANNs) and the Autoregressive Integrated Moving Average (ARIMA) model.

To this end, following a global sensitivity analysis of the deterministic model, the most influential parameters were indicated and further modelled as either time-dependent or independent stochastic variables. ANNs were used to map the response of the O&M cost model under varying values of key input parameters, while forecasting of stochastic future wholesale market electricity prices was performed through an ARIMA model aiming to capture standard temporal structures of the time series dataset. Accordingly, Monte Carlo simulation was used to produce multiple sets of the stochastic variables and produce probability distributions of the output variables, namely the NPV, capital cost, annual operating cost and LCOE.

The probabilistic analysis highlighted the strike price impact over the total value of the asset, indicating that a strike price of 140 £/MWh can give 99% probability for a profitable investment, while when this value decreases by 14%, the respective probability falls to 53%. Further, a significant deviation between the deterministic NPV of the project (estimated £284.36 million) and the probabilistic mean value (£ 266.1 million) was observed under the specifications of the baseline case.

To the authors' best knowledge, the present study is the first one to combine above mentioned advanced numerical techniques in order to provide a better-informed valuation of an offshore wind farm asset. Stochastic analysis has proven to be more insightful than a deterministic approach since instead of returning a deterministic value with limited context, it can respond with an evaluation of performance for an associated confidence interval

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F. Informing parametric risk control policies for operational uncertainties of offshore wind energy assets

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Informing parametric risk control policies for operational uncertainties of offshore wind energy assets

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Abstract

The aim of this paper is to investigate uncertainties present during operation of offshore wind energy assets with a view to inform risk control policies for hedging of the incurring losses. The parametric framework developed is subsequently applied across a number of different locations in the south east coast of the UK, so as to demonstrate the effect of weather conditions and resulting downtime on a number of operational key performance indicators (KPIs), such as downtime due to planned and unplanned interventions, wind farm availability, O&M costs and power production losses. Higher availability levels were observed in areas closer to shore of the specified region, while the distribution of O&M cost per MWh demonstrated a general trade-off of higher power generation in locations further from shore due to better wind speed profiles and higher O&M costs, as a result of the decreasing vessels accessibility. It was highlighted that the amount of power production losses throughout the service life of the asset is not necessarily proportional to the entailed risk of surpassing a set threshold. Above analysis aspires to contribute to the development of better-informed risk control policies, through parametrically estimating the probability of exceedance of a specified revenue loss threshold.

Keywords: Offshore wind energy, O&M cost modelling, loss of revenue, weather risk, risk control.

1 Introduction

Most relevant decisions throughout planning, construction and operation of offshore wind energy assets made by market agents involve a significant level of risk due to technical conditions and project externalities. Generally, loss of revenue risk (as a result of project delays, turbine components damage/losses during transport, construction and operation) can substantially affect the value of the asset. During the construction phase, weather risks can result in delay of the commissioning date due to lack of accessibility of installation vessels (which bear specific working limits for various marine operations), while throughout the operation phase, in the occurrence of a failure, weather can increase the total downtime of the wind farm by impeding the access of the support vessels dispatched to perform maintenance activities, leading to revenue losses. Both cases can lead to significant impact in cash flows and the project's ability to meet debt service requirements.

In order to estimate the loss of revenue risk, the downtime of the asset needs to be estimated as accurately as possible through modelling the planned and unplanned maintenance activities during the O&M phase of the asset. The development of high-fidelity models would assist in the calculation of the total availability, power production losses and O&M costs throughout the service life of the asset, which typically account for approximately 30% of the levelised cost of electricity in offshore wind (Carroll et al., 2016a; Ioannou et al., 2018).

Most offshore wind O&M models currently available are used to inform project developers/owners on the expected costs and performance of their assets. They typically use turbine and BOP reliability data coupled with meteorological prediction models in order to predict the operational state of the wind farm throughout its service life and the maintenance activities required. Common outputs of such models comprise the downtimes per subsystem/failure type and per maintenance stage, the wind farm/turbine availability, the total number of failures occurred, the number of spare parts and the revenue loss, among others. A review in offshore wind O&M models is provided in (Hofmann, 2011; Martin et al., 2016).

The aim of this paper is to investigate uncertainties present in the operational phase of offshore wind investments with a view to inform risk control policies for hedging of the incurring losses. The framework developed is subsequently applied parametrically in a reference region, so as to demonstrate the effect of weather conditions and resulting downtime on a number of operational key performance indicators (KPIs), such as downtime due to planned and unplanned interventions, wind farm availability, O&M costs and power production losses. The proposed framework for calculation of O&M KPIs, incorporates latest databases of failure rates and cost components throughout the O&M phase of the wind farm, while it also allows rapid simulations for a number of locations within a region allowing development and visualisation of parametric expressions. Above analysis aspires to contribute to the development of better-informed revenue loss risk control policies, through parametrically estimating the probability of exceedance of a specified revenue loss threshold.

The rest of the paper is set out as follows: Section 2 presents an overview of risk control options available for renewable energy assets, along with an introduction to key reliability concepts widely used in the O&M cost analysis of offshore wind turbines. Section 3 presents the framework developed for the calculation of operational KPIs. Subsequently, results from the application of the framework to a baseline wind farm installed at a specific location are presented in Section 4, followed by the parametric estimation and illustration of O&M related KPIs across a number of locations in the south east coast of the UK. Furthermore, this section expands the applicability of the proposed method to estimate the expected production losses due to the downtime of the wind farm and estimate the probability of exceedance of a pre-determined threshold which would activate a potential risk control policy. Finally, Section 5 summarises the findings of this work.

2 Power production uncertainties and risk control options

2.1 Risk control options for renewable energy assets

Investing in renewable energy assets, e.g. an offshore wind farm, is typically subject to downside risks, which is the combination of the probability of occurrence of a negative event and its associated financial effect (International Standardisation

Organisation, 2009). The likelihood and impact of negative events are reflected in the financing costs (quantified by the weighted average cost of capital (WACC)) of the technology; higher investment risk tends to increase both the bank's interest rates and the equity owners' return expectations. Furthermore, considering the fact that renewable energy technologies are typically capital-intensive investments, their lifecycle costs are very sensitive to an increase in financing expenditures (Schmidt, 2014). It can therefore be concluded that financial risk mitigation can play an important role in reducing the levelised cost of electricity (LCoE) of the technology.

General risk control options include: i) risk retention, ii) risk avoidance, iii) risk mitigation and iv) risk transfer. Companies retain a risk, when they have determined that transferring the risk is costlier than covering all or part of the losses out of their reserve budget (also called self-insurance) or when they decide to consciously take a risk to potentially achieve a higher gain. Avoiding the risk implies deciding not to get involved in a high-risk investment or operating within a (geographic or operational) region where the underlying hazard is not present. Mitigating the risk involves limiting the impact of a risk by taking appropriate measures. Finally, risk transfer involves the contractual shifting of a risk from one party to another, usually from the project owner to one or more insurance providers.

As far as the risk insurance market is concerned, there is currently a number of commercial risk control products that are expanding as the technology becomes more established (UNEP, 2004). Construction is a phase of the service life of an offshore wind asset which involves considerable risks, mainly due to the likely occurrence of incidents during the transportation and/or installation of wind turbines and BOP (balance of plant) components. Such risks can be mitigated through effective project management and contracting; however, project owners tend to seek to extend their risk coverage to protect their investment against delay in start-up (DSU), or the Advanced Loss of Profit (ALOP) incurred through the inability of the construction contractor to commission the project on time. Developers can claim back lost revenues resulting from delays in construction (Swiss Re & Bloomberg New Energy Finance, 2013). Another common risk transfer product available is the Construction All Risks (CAR), covering physical loss and damage during the construction phase of a project (UNEP, 2004).

Following the construction of the wind farm, project owners often rely on manufacturer yield/availability warranties by signing an O&M contract that guarantees a certain uptime or availability level; if the minimum yield levels are not met, the O&M contractor will be liable for availability liquidated damages (LDs) (Clifford Chance, 2017). The O&M contract comprises the most common risk control method ensuring the provision of spare parts and maintenance labour. The loss of revenue due to component failure or natural catastrophy is critical for offshore wind owners (U.S. Department of Energy, 2013). In example, faults in the transformer of the offshore substation, which from a reliability perspective is the 'weak link' of the wind farm, may result in the shut down of the whole wind farm inducing large financial losses. It is, therefore common apart from the manufacturer's warranties (which usually last for 5 years, after which the contract can either be renewed or the owner proceeds with alternative O&M risk coverage ways) to undertake Business Interruption (BI) coverage to insure against losses that are not already covered by O&M contracts. Loss of revenue can also be induced by severe weather, preventing vessels to access offshore wind turbines to perform scheduled or unscheduled maintenance. In such cases, the owner of the asset can purchase an insurance product to hedge the financial impact of adverse weather on the project. These risk control products dealing with the inability of the Operations and Maintenance Contractor to gain access to the OWF Facility through short or sustained periods of unusually high waves can be financially mitigated through the use of parametric (finite risk) products. These products are called parametric because they are triggered by a weather-related parameter such as the significant wave height or the wind speed (Swiss Re & Bloomberg New Energy Finance, 2013). Such products are gaining popularity as investors become more risk averse.

2.2 The concept of availability

The service life of the wind farm asset typically consists of uptime and downtime periods, with uptime representing the intervals during which the turbine is able to produce energy and downtime the time that the turbine stops working, as a result of a subsystem failure until the turbine is restored. Time-based availability can be defined as the ratio of the total uptime of the wind farm to the total time in consideration (sum of uptime and downtime), while production-based availability is estimated as the ratio of the energy actually produced to the amount of energy that would ideally be produced based on actual wind speeds and site conditions (DNV GL, 2017; Scheu et al., 2017).

$$A_{time} = \frac{Uptime}{Uptime + Downtime}$$
$$A_{production} = \frac{Actual\ energy\ produced}{Energy\ production\ potential} \quad (1)$$

Figure 1 demonstrates the mean time to failure (MTTF) which equals the uptime period when the turbine is able to produce power and the mean time to repair (MTTR) which reflects the total downtime of the wind farm and includes a number of activities related to planned and unplanned maintenance. Activities listed during the downtime can be divided into passive and active downtime. Passive downtime relates to the activities required until the execution of the actual maintenance activity (active downtime). Improving availability can be achieved through decreasing passive downtime through better planning.

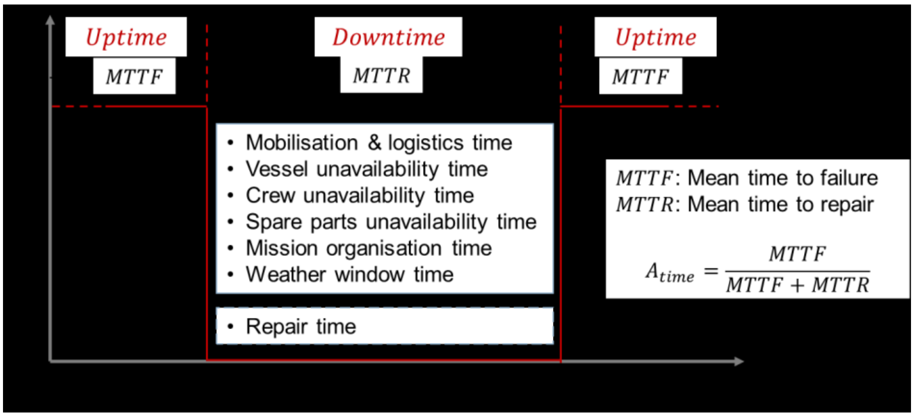


Figure 1 Operational states of the turbine

3 Development of an efficient model for calculation of operational KPIs

3.1 Overview of the model

An overview of the integrated O&M analysis framework is illustrated in Figure 2. The main modules are: (1) the failure modelling module, (2) the weather modelling module, and (3) the cost modelling module.

The failure modelling module is further divided into the mean time to failure estimation (namely the uptime of the asset) and the mean time to repair estimation throughout the planned and unplanned maintenance operations (namely the downtime of the asset). The mean time to repair calculation is based on the annual failure rates, while the planned and unplanned maintenance operations require data related to the resources required for the repairs. Resulting downtime depends on the availability of the required vessels, technicians, weather window, spare parts, mission organisation time, duration of navigation and repair, as well as the required number of technicians' shifts.

The weather modelling module enables the prediction of the future sea states, namely future significant wave heights and wind speeds. Weather conditions play an important role in the total downtime of the wind farm, as when the related parameters surpass the set wave height and wind speed limits of the vessels, travelling to wind turbines and accessing them becomes impossible. Therefore, unfavourable weather conditions will delay repairs, thus increasing downtime and decreasing the wind farm's availability.

The cost modelling module takes into account the actual duration of all stages required to perform the repair and maintenance operations and uses vessel and crew day-rates, along with material costs to predict the total O&M cost. Other outputs of the model are the time-based and production-based availability, and the power production losses.

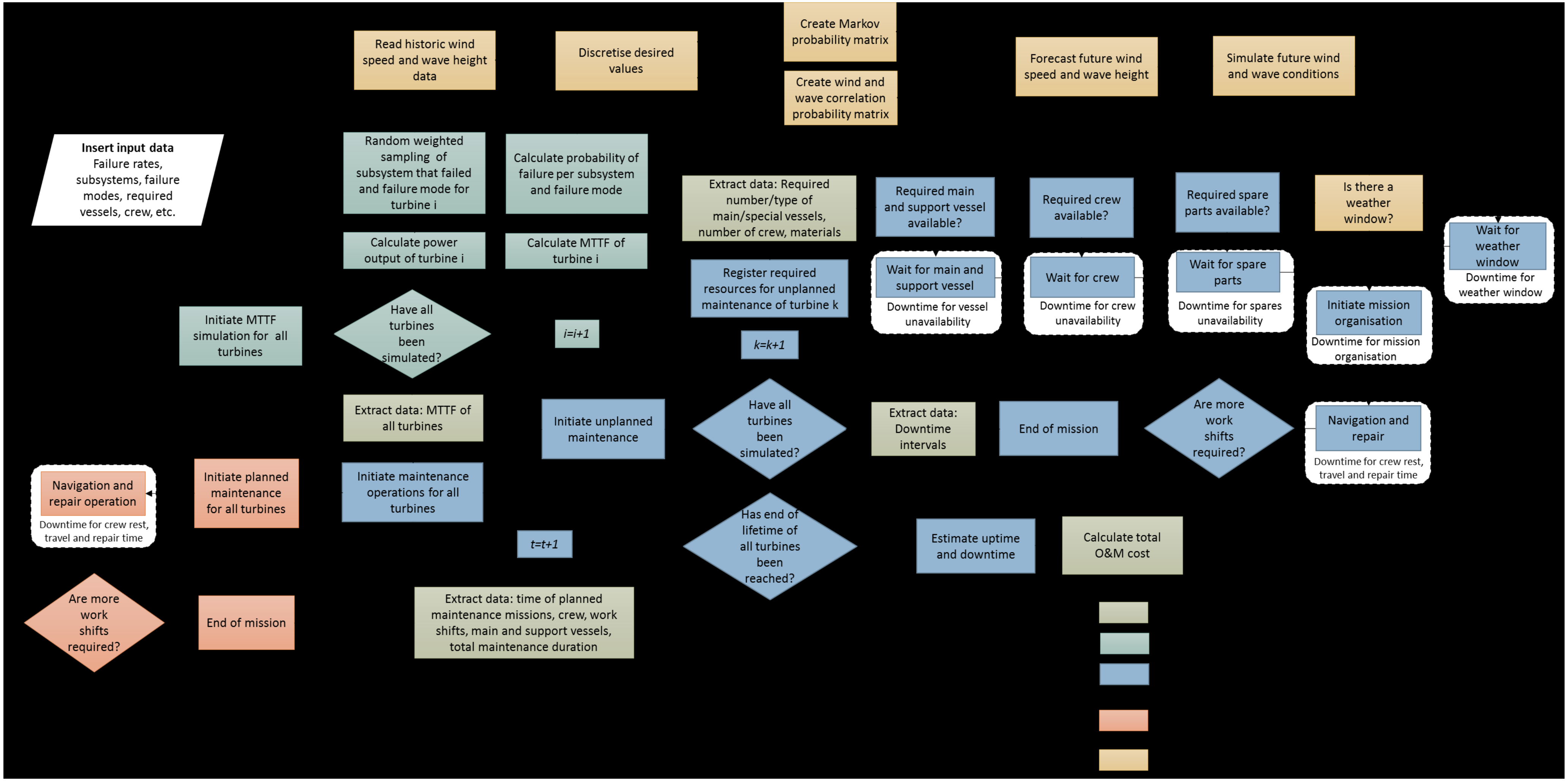


Figure 2 Flowchart of O&M cost model

It should be noted that the development of decisions for the different steps of the model have taken into consideration not only the accuracy of the calculation but also the computational efficiency required so as to allow a serial execution of simulations which is relevant to the comparative analysis which is the aim of this study. A high-level validation based on the results of published cases has been performed, while further calibration of the model for more accurate results can take place through a specific case study.

3.2 Failure modelling module

3.2.1 Estimation of Mean time to repair (MTTR)

In this study, the repair categorisation of Reliawind project (Garrad Hassan, 2007) was adopted which classifies repair classes of subsystems into minor repairs, major repairs and major replacements. A total of 19 subsystems of the wind turbine were considered, while data used for the application of the model on failure rates, average repair times, average material costs and number of required personnel were retrieved from (Carroll et al., 2016b). Assuming that the reliability of the turbine follows an exponential distribution, the probability of failure (PoF) can be expressed as:

$$PoF = 1 - Reliability = 1 - \ e^{-\lambda_{turb} \cdot t} \tag{2}$$

$$t = MTTF = -\frac{1}{\lambda_{turb}} ln(1 - PoF) \tag{3}$$

Where, λ_{turb}=$\sum_{i=1}^{Subsyst} \lambda_i$, is the sum of the failure rates of each turbine's subsystems in series. Monte Carlo simulation is, then, performed to generate numerous random PoFs and subsequently returns an average MTTF value for each wind turbine. Once, MTTFs are calculated, Equation (2) can be used to estimate the probability of occurrence of each subsystem's failure, as:

$$PoF_{subsyst} = 1 - \ e^{-\lambda_{subsyst} \cdot MTTF_{subsyst}} \tag{4}$$

where, $\lambda_{subsyst} = \sum_{k=1}^{Repair\ class} \lambda_i$ is the sum of the failure rates of the different repair classes of the subsystems. Once the probabilities of each subsystem's failure is known, the model performs random weighted sampling to determine which subsystem will fail once the MTTF has elapsed along with the repair class, which is also randomly selected following the same logical process. Along with the MTTF calculation, the model calculates the absolute time set of the simulation, which is interpreted as the actual time from the beginning to the end of life of the wind farm. The duration of the individual activities is added to the absolute time set, enabling the calculation of the uptime and downtime of the turbine and registering the time when a certain failure happens.

3.2.2 Planned and unplanned maintenance

Unplanned (corrective) maintenance is carried out following the occurrence of a failure on the turbine or the BOP, which may affect several turbines. The procedure after the occurrence of a new failure is illustrated in Figure 2. Once a failure has occurred on the first turbine, the required resources - namely, the number and type of main and special vessels, number of crew and materials, depending on the subsystem and the repair class - are registered. If a major repair, or a major replacement is needed, the turbine instantaneously shuts down. The process begins with the availability check of the required main and support vessels. It is assumed that a predetermined number of vessels will be continuously operating in the wind farm, hence they will be available to access the wind turbine that failed if the weather conditions allow so and the same applies for a predetermined number of personnel and the spare parts needed for the repair. If, however, all available vessels are occupied, the failure remains unresolved and the check is repeated once the required number of vessels are released from the previous mission. All required resources can also be inserted by the user as per each subsystem and repair class. Once the required vessels, crew and spare parts are available, the weather conditions are checked. The weather window is sufficient as long as the significant wave height and the wind speed conditions at the wind farm site are below the operational threshold limits of the vessels commissioned throughout the whole intended time offshore. Subsequently, the organisation of the mission, including the mobilisation of the vessel(s) (if required), take place. Once the crew accesses the subsystem that failed, the repair is carried out; it is assumed that one work shift lasts for up to 12 hours, which includes the total repair time, transitioning from harbour to the site and vice versa, as well as a mid-shift break. In case that more than one shifts are required, the crew returns to harbour and the mission restarts 12 hours later. When the damage is restored, the wind turbine starts producing power again, and the MTTF of the subsystem is reset to its original value. Finally, the transit back to the harbour and the demobilisation time are added to the total downtime of the wind farm. The durations of all unplanned maintenance activities are registered and added to the absolute total time set. Once the absolute total time set equals the service life of the wind farm, the simulation stops.

Planned maintenance (else calendar-based maintenance) operations are carried out periodically and deal not only with one subsystem of the wind turbine, but with groups of subsystems or the entire wind turbine. Planned maintenance can be scheduled ahead of time, during periods of favourable weather conditions when delays to missions due to exceedance of vessels' safety limits (weather window downtime) are not likely to occur, so that the availability of the wind turbine and amount of generated electricity is affected the least possible. The same applies for vessels, crew and spare parts unavailability downtimes. In this analysis, calendar-based maintenance is assumed to take place every one year with a deviation of ±1 month, to simulate the real life operations. Downtime due to planned maintenance is assumed to originate exclusively from the navigation and repair time, together with the potential downtime due to crew rest. In this analysis, it is assumed that planned maintenance can only restore minor repairs, i.e. once each mission terminates the mean time to failure of minor repairs is reset. It is expected that unplanned maintenance will incur higher downtimes in relation to planned maintenance considering the longer expected downtimes and types of maintenance activities.

3.3 Weather modelling

As described in the previous sections, predicting weather conditions for the operational lifetime of an offshore wind farm is crucial to predict its availability. If wave height and wind speed conditions exceed vessels' safety thresholds, transit from harbour to the wind farm is not possible leading to delays in performing repairs, thus increasing downtime and decreasing the wind farm's availability (Scheu et al., 2018).

Commonly used methods for generating sea state time series comprise Gaussian and Langanian approaches for short term wave modelling, Autoregressive Moving Average (ARMA) methods and Markov-based models which work well for long term forecasting and can capture persistence of sea state parameters (Anastasiou and Tsekos, 1996; Scheu et al., 2012).

In this study, the discrete time Markov chains was chosen as the weather forecasting method. To this end, historic weather datasets from 1992 to 2017 with a 3-hour time step were retrieved from BTM ARGOSS database (BTM ARGOSS, 2017). Discrete time Markov chains method is based on having a finite number of states in a system and estimating the probability, *pij* of state *i* to evolve into state *j*. Markov probability matrices are generated for each month, to account for seasonality, as shown below:

$$P(sea\ state\ parameter)_{month} = \begin{pmatrix} p_{11} & p_{12} & \cdots & p_{1n} \\ p_{21} & p_{22} & \cdots & p_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ p_{n1} & p_{n2} & \cdots & p_{nn} \end{pmatrix}_{month} \quad (5)$$

Where, $p_{i,j}$ equals the number of transitions of sea state parameter *i* to *j*, divided by the total number of times, state *i* appears. As such, initially, the weather data is discretised with a resolution of 0.2 for wave height and 1 m/s for wind speed data, resulting in a finite number of possible values, namely 23 and 25 values, respectively. A time step of 3 hours is also considered for the forecast, during which wind speed and wave height are assumed to remain constant. Based on the probabilities of each transition matrix, the wave height for the starting month is randomly selected, successively all sea state conditions are predicted as a function of the previous state and the transition probability.

3.4 Cost modelling

The cost modelling module gathers the data recorded during each iteration, which are required to estimate the O&M cost. For unplanned maintenance of wind turbines, the time that a failure occurs is registered with reference starting point the beginning of operation of the wind farm. Further, the subsystem that failed and the type of failure will define the required main and support vessels (to match the correct day rates) and the number of crew members required for the repair. Downtimes of crew unavailability, spare parts unavailability, weather window, navigation time and demobilisation time are taken into account and assigned to the respective day rates of vessels, crew, cost of materials, mobilisation and demobilisation costs, to estimate the total O&M cost.

4 Results and discussion

4.1 Baseline wind farm

4.1.1 Characteristics of wind farm

Typical wind farm characteristics were used for the application of the integrated cost estimation framework across a number of different locations in a region by the south east coast of the UK. This case study is considered representative of a modern wind farm located in European waters and its characteristics are summarised in Table 1.

Table 1 Reference wind farm characteristics

Parameter	Value
Number of turbines	140
Turbine rated power	3.6MW
Service life	25 years
Cut in speed	4 m/s
Cut out speed	25 m/s

Weather data were obtained from the BTM ARGOS database for a set of 204 different locations with latitude and longitude coordinates ranging between

[0.000°, 2.667°] and [50.000°, 53.667°], respectively, covering the south east coast of the UK as illustrated in Figure 3. This region was selected due to its high concentration of currently operating and under construction Round 1, 2 and 3 wind farms (The Crown Estate, 2017).

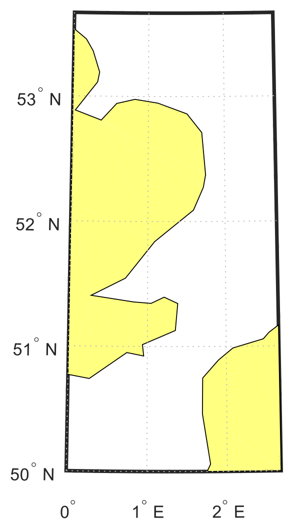


Figure 3 Focus region located in the south east coast of the UK

Existing ports near the locations of the focus region were identified from 4C offshore (4C Offshore, 2018) and their coordinates are summarised in Table . It was assumed that these ports provide their adjacent wind farms with maintenance support services; hence, the distances of all harbours from all potential wind farm locations were calculated and the ports with the minimum distances were assumed to serve the maintenance operations of the respective site.

Table 2 Coordinates of nearby ports

Port	Longitude	Latitude
Wells	52.954	0.853
Great Yarmouth	52.583	1.735
Lowestoft	52.473	1.755
Harwich Navyard	51.948	1.288
Sheerness	51.443	0.748

Ramsgate	51.327	1.412
Newhaven	50.7903	0.0546
Shoreham	50.8311	0.2381

4.1.2 Assumptions on the operating cost components

Cost components taken into consideration in the present study comprise the cost of main and support vessels, crew and materials. Herein, material is anything that is used or replaced in the turbine; from consumable materials to whole replacement parts such as full generators. The required cost parameters of the maintenance vessels are summarised in Table 3. The material costs are adopted from Carroll et al.'s publication (Carroll et al., 2016b) while the vessel and crew day rates as well as the cost of materials used in the present study were adopted from a recent publication of the authors (Ioannou et al., 2018). To estimate the revenue loss due to the downtime of the wind farm, a strike price of 100 £/MWh was assumed.

Table 3 Characteristic values of vessels used during the O&M phase of the wind farm (Source: (Ioannou et al., 2018))

Vessel type	Technician space (#)	Vessel speed (knots)	Weather limits		Mob. / Demob. Cost (k£)	Mob. / Demob. Time (h)	Day rate (k£/day)
			Sign. wave height (m)	Wind speed (m/s)			
Crew transfer vessel	12	26	1.8	16	-	-	3.25
Jack-up vessel	-	10	2	10	405	720/48	112.6
Heavy lift vessel	-	9	-	-	500	-	135
Helicopter	6	-	99	20	4.7	8/4	4.7
Diving support vessel (DSV)	-	16	2	25	185	360	60
Cable laying vessel	-	14	1	10	44	720	90

4.2 Risk-based revenue loss modelling

4.2.1 Operation and Maintenance results for a specific location

The model was initially applied for the prediction of the operational KPIs of the reference wind farm installed in a single location with coordinates [0°, 50.334°]. The power output of each of the 140 turbines as well as the breakdown of downtimes are illustrated in Figures 4 and 5, respectively.

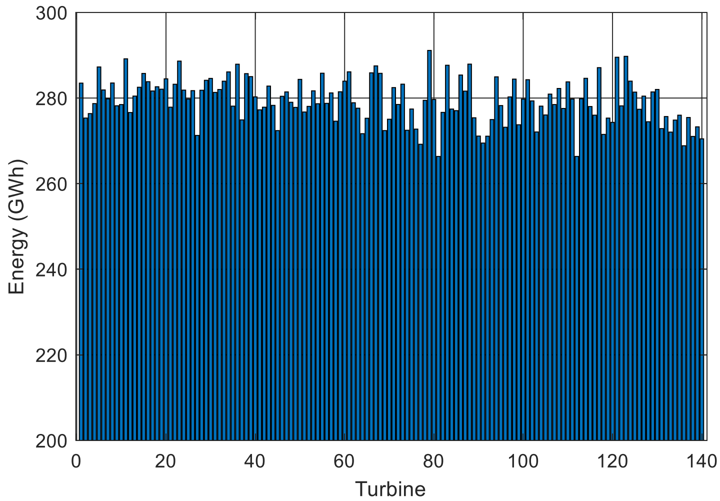


Figure 4 Power output per each turbine

Total power produced was calculated at 38,823 GWh and the total downtime $3.6658 \cdot 10^6$ hours with a power-based availability of 90.3% and a time-based availability of 89.1%. The downtime due to weather unsuitability had the highest share of the total downtime (21%) followed by the repair time (18.3%) and the spare availability downtime (12.6%).

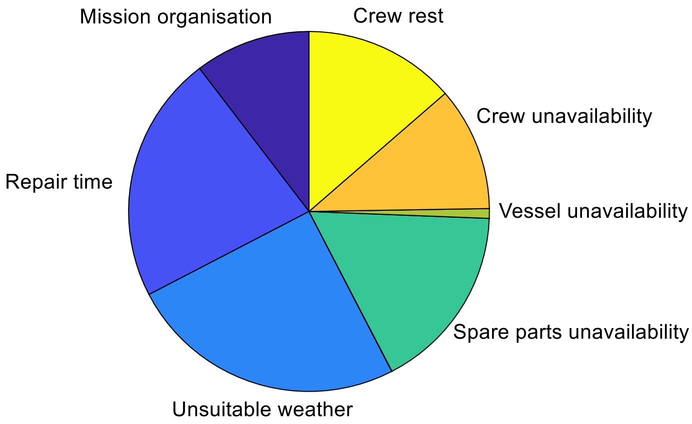


Figure 5 Breakdown of downtimes

The temporal O&M costs throughout the service life of the wind farm are shown in Figure 6 for unplanned maintenance of both wind turbines and the BOP, as well as for planned maintenance. Total wind farm O&M cost during the entire service life was estimated at £686.5 million. Above results on the availability and O&M total costs show good agreement with a benchmarking study estimating O&M costs of an offshore wind farm located also in the south coast of the UK (Martin et al., 2016).

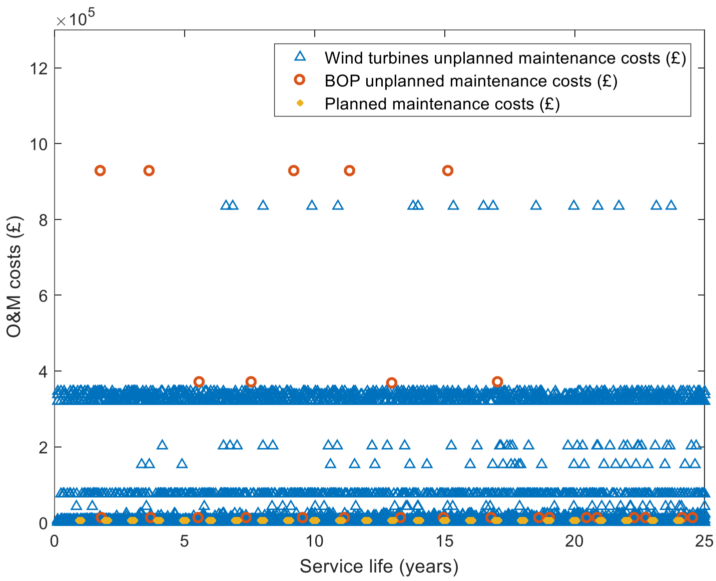
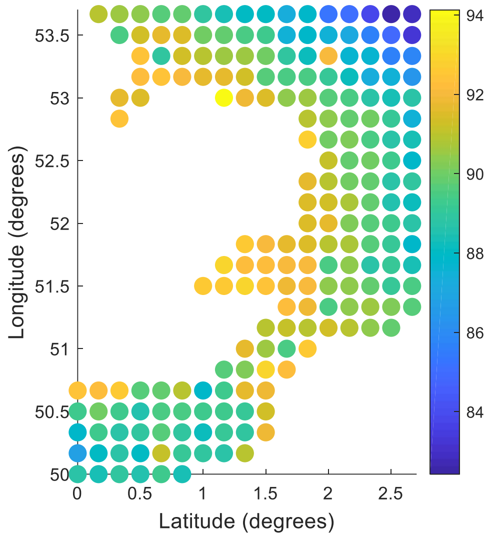


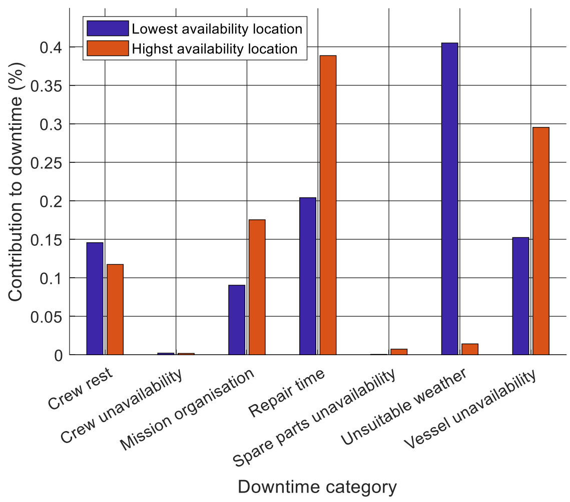
Figure 6 O&M costs throughout the service life of the wind farm

4.2.2 Parametric estimation of operational KPIs

Subsequently, the model was applied for 204 locations in the south east coast of the UK (illustrated in Figure 3), using the respective historic weather data for each set of coordinates retrieved from the BTM ARGOSS database. A sufficient number of iterations of the model was conducted to allow for the generation of robust results through the stochastic process. Accordingly, a number of location-specific colour-coded plots, illustrating resulting operational KPIs across the whole region, were generated.

The production-based wind farm availability results are plotted in Figure 7 (a) for each of the 204 sets of coordinates under investigation. Higher availability levels can be observed in areas closer to the coast of the specified region (noting that half a degree is equivalent to approximately 56 km). This can be attributed to the smaller distances between the port and the wind farm site, as well as the lower magnitudes of significant wave height and wind speed limits, improving the accessibility of the maintenance vessels for the performance of unplanned maintenance, hence reducing the total downtime of the asset. In general, results demonstrate a smooth transition from high availability values in locations positioned closer to the coast to gradually decreasing further from shore. Nevertheless, a number of outliers can be observed, for example in the location point [2.000^{o} 53.334^{o}], where an availability peak is noted; this can be explained as the result of measurement uncertainty of the historic met ocean data. Figure 7 (b) illustrates the breakdown of downtimes for the location with the lowest and highest availability. Weather downtime appears to have the greatest contribution to the total downtime for the lowest availability location, while repair time is the main contributor for the highest availability location.





(a) **(b)**

Figure 7 Production-based availability (%) around the focus area of the study and (b) contribution of downtime categories to the highest and lowest availability locations

Figure 8 illustrates the total O&M cost per produced MWh, revealing a more uniform distribution of unit cost in relation to the availability values across the different locations. This is due to a trade-off of higher power generation due to better wind speed profiles and higher O&M costs due to decreasing accessibility of vessels for maintenance operations. For example, a hypothetical wind farm installed at point [1.000°, 51.500°] appears to reach an availability level of 92.6% in return of high unit costs amounting to 24.5 £/MWh as a result of the poor wind speed profile resulting in low power production. Nevertheless, exceptions of this observation can be found, for example, in the areas positioned in the southern part of the specified region, where high availability together with relatively low unit costs can be observed. This observation can potentially lead to the conclusion that these regions can offer a good balance of availability versus costs. However, it has to be noted that other factors such as geotechnical conditions, environmental impact assessment studies and other parameters need to be taken into account before determining the suitability of a location for the installation of a wind farm (Mytilinou et al., 2018; Mytilinou and Kolios, 2019).

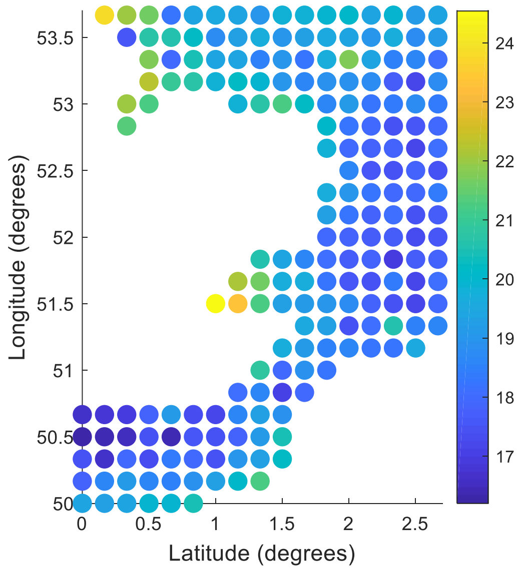


Figure 8 O&M cost per MWh around the focus area of the study

Finally, the expected total power production loss due to the wind farm downtime is plotted in Figure 9. Production loss reflects the total revenue loss due to downtime, as it is calculated by subtracting the power produced during uptime from the potential power produced both during uptime and downtime (wind speed profile of the location is also taken into consideration); it is therefore a parameter with a direct impact on the financial performance of the investment. The revenue loss plot was found to follow a similar to the availability plot pattern, with locations closer to shore indicating lower revenue potential losses due to the reduced downtime of the wind farm.

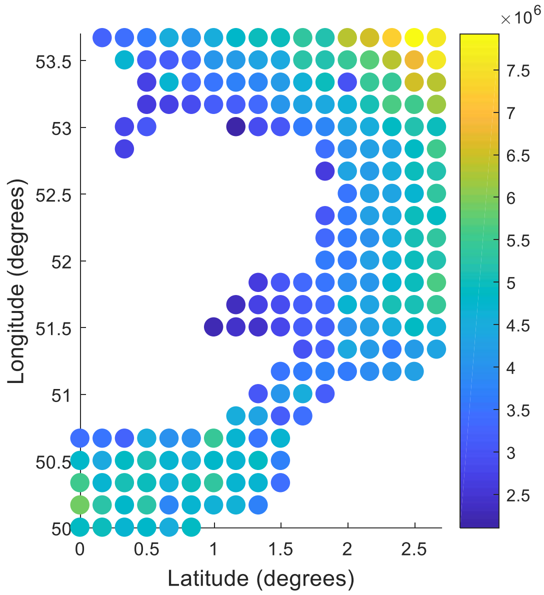


Figure 9 Production loss (in MWh) scatter plot of wind farm around the focus area of the study

4.2.3 Weather risk control policy options

Traditional insurance products available for renewable energy projects typically protect against natural disasters, such as storms, earthquakes and hurricanes (Grossi et al., 2005) as well as physical losses and damages to the plant/asset during the construction and operating phases (UNEP, 2004). Furthermore, academic literature on the effects of weather risks on offshore wind energy projects also focuses on analysing the effect of extreme weather events (Barabadi et al., 2016; Becerra et al., 2018; Lamraoui et al., 2014). However, risk management against the effect of seasonal fluctuations in climatic conditions, such as variation in wind speeds, temperature and wave height is becoming more relevant as investors are inclined to reduce their risk exposure. Weather risk hedging products are usually financial contracts which can be executed in the form of insurance or weather derivatives structured as swaps, futures and options that are based on a weather related index (Li, 2018); in the case of offshore wind, significant wave height and wind speed could be relevant weather related indices. The seller of the weather derivative bears the risk of potential financial losses as a result of the weather conditions in exchange of an upfront premium. If the predetermined limit of the index is surpassed, over a specified period, the project owner is compensated the downtime financial losses.

The index-based policy structure has the advantage of simplicity, although there may exist some ambiguity in terms of the actual financial impact caused by the exceedance of the specified threshold. In the case of offshore wind, for example, exceedance of the threshold of the significant wave height limit over a specified period of time may not necessarily lead to financial losses. On the contrary, power production loss due to downtime could be a risk index easier-to-translate into resulting revenue losses over a period of time, while relevant data can be retrieved by SCADA (Supervisory Control and Data Acquisition) systems installed in the wind farm.

Figure 10 illustrates the resulting power production losses due to the downtime on a monthly basis for the reference wind farm installed in the location [0.000^{o}, 50.334^{o}]. A threshold of 45,000 MWh over the period of a month was assumed, above which the buyer of the risk transfer product is compensated for the revenue loss corresponding to this threshold. The estimation of the premium should be based on the probability of exceedance of the specific limit. With a 5.9% monthly probability of exceedance, the risk of the investor is estimated (in terms of production losses) 45,000·5.9% = 2655MWh. Assuming a strike price of 100 £/MWh, the maximum premium that the buyer would be willing to pay is therefore £265,500 per month.

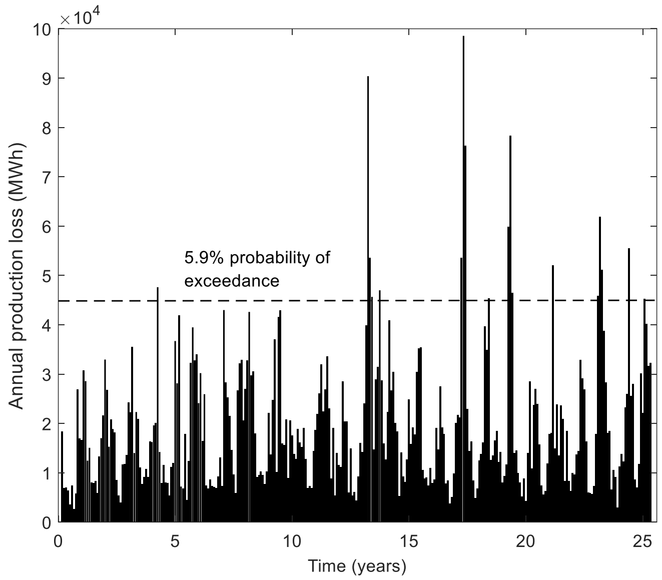


Figure 10 Monthly power production losses as a function of time for the location with coordinates (0.000°, 50.334°)

The exceedance probability (EP) curve is used by insurers to estimate the probable maximum loss (PML) for a portfolio of investments in a given period of time. The PML is a bespoke risk metric and is associated with a probability of exceedance reflecting the insurer's acceptable level of risk. As such, the insurer can use the EP curve to determine the magnitude of loss at the desired probability of exceedance level. In Figure 11, the monthly EP curve of the reference wind farm is demonstrated. The EP curve can also assist the distribution of losses between stakeholders. As such, the project owner would retain the first part of the loss (i.e. the deductibles), for example losses up to 45,000MWh, while the insurer covers monthly production losses occurring in excess of this amount.

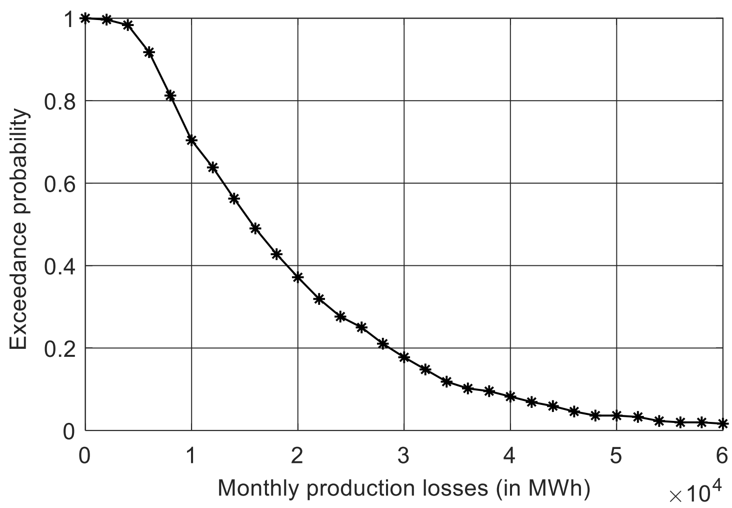


Figure 11 Exceedance probability curve

Setting the above threshold of monthly power production losses (i.e. 45,000 MWh) across all sets of coordinates of the designated region, the distribution of the exceedance probabilities is illustrated in Figure 12. For areas closer to the coast, the probability of exceedance does not surpass the level of 6%, while in areas further from shore probability reaches 18%. Comparing the scatter plot of probability of the production loss exceedance threshold with the production losses one (in Figure 9), it becomes evident that the amount of power production losses throughout the service life of the asset is not necessarily proportional to the entailed risk of surpassing a threshold set on a monthly or even annual basis. This map can provide a basis for screening which locations are likely to incur higher insurance premiums for weather related parametric risk control products.

Insurance policies are typically valid for a specified period of time defined in the insurance policy contract, varying from a few weeks to a number of years. It can, thus, be deduced that the magnitude of risk transferred to a third party greatly depends on the duration set by the contract. Specifically for offshore wind energy assets, the persistence of the weather conditions can be detrimental on the financial losses derived and by extension on the compensation required, since, depending on the terms of the contract, the policy may concern revenue losses incurred within the duration of a month (as it was assumed for the calculation of the probability of exceedance of the monthly production losses in the aforementioned application).

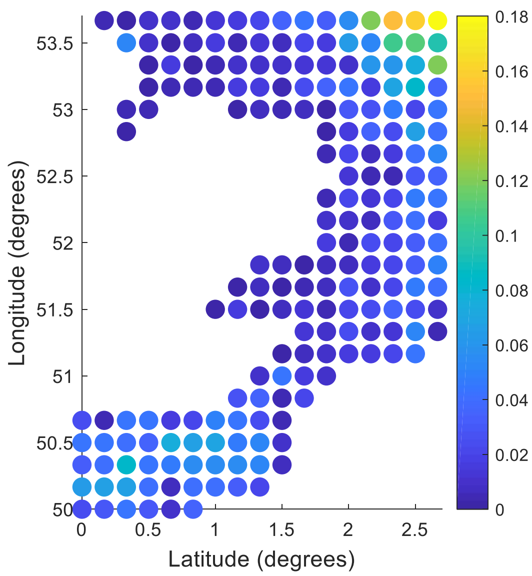


Figure 12 Probability of exceedance of monthly power production loss threshold (45,000 MWh/month)

5 Conclusions

There is a number of industries whose operations can be impacted by the varying weather conditions and offshore wind industry is certainly one of them. Although the traditional weather-related risk transfer products available are mainly employed to protect against catastrophic events, there is currently an increasing interest in hedging against seasonal weather fluctuation risks in order to minimise their impact on the financial performance of the investment. Protection against weather risk was originally included as a clause embedded in contracts for unforeseen weather conditions, but is now becoming a bespoke financial instrument to hedge the risk of the resulting financial losses, currently offered by big Insurance Companies and Brokers (Willis Towers Watson, 2018).

In this paper uncertainties present in the operational stage of offshore wind investments are investigated systematically with a view to inform risk control policies for hedging of the incurring losses. For the estimation of operational KPIs the latest databases of location-specific environmental conditions, failure rates, and required repair resources are integrated together with discrete time Markov chains for forecasting future sea states. The model is firstly applied to a reference wind farm installed in a specific location to test the applicability of the model and verify its results. Then, the model is applied to a set of locations in the south east coast of the UK to derive scatter plots of aforementioned KPIs, such as cost per MWh and power production losses, indicating the effect of weather and maintenance downtime throughout the O&M phase of the asset's lifecycle. Further to the calculation of power production losses, the probability of exceedance of a specified power production loss threshold was estimated across all locations of the south east coast, deriving insights regarding the distribution of the risk level of financial losses due to weather and maintenance downtime across the designated region.

It was observed that there is a trend for higher production-based availability levels in areas closer to the coast of the specified region, while the scatter plot of O&M cost per MWh demonstrated a more uniform pattern across the different locations indicating that there is a trade-off of higher power generation in locations further from shore due to better wind speed profiles and higher O&M costs, as a result of the decreasing accessibility of vessels for performing maintenance operations. Production losses distribution was found to follow a pattern similar to the availability one, with locations closer to shore displaying lower potential production losses due to the reduced downtime of the wind farm. Production losses can reflect the total revenue loss due to downtime. To this end, this variable was chosen as the most relevant parameter to demonstrate the financial risk induced by weather and maintenance downtime. It was highlighted that the amount of power production losses throughout the service life of the asset is not necessarily proportional to the entailed risk of surpassing a set threshold; rather, risk can be significantly affected by the applicability period of the policy.

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G. Multi-stage stochastic optimization framework for power generation system planning integrating hybrid uncertainty modelling

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Multi-stage stochastic optimization framework for power generation system planning integrating hybrid uncertainty modelling

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Abstract

In this paper, a multi-stage stochastic optimization (MSO) method is proposed for determining the medium to long term power generation mix under uncertain energy demand, fuel prices (coal, natural gas and oil) and, capital cost of renewable energy technologies. The uncertainty of future demand and capital cost reduction is modelled by means of a scenario-tree configuration, whereas the uncertainty of fuel prices is approached through Monte Carlo simulation. Global environmental concerns have rendered essential not only the satisfaction of the energy demand at the least cost but also the mitigation of the environmental impact of the power generation system. As such, renewable energy penetration, $CO_{2,eq}$ mitigation targets, and fuel diversity are imposed through a set of constraints to align the power generation mix in accordance to the sustainability targets. The model is, then, applied to the Indonesian power generation system context and results are derived for three cases: Least cost option, Policy Compliance option and Green Energy Policy option. The resulting optimum power generation mixes, discounted total cost, carbon emissions and renewable share are discussed for the planning horizon between 2016 and 2030.

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1 Introduction

World total electricity generation is expected to grow by 69% from 2012 to 2040 and make up almost a quarter of total energy consumption by 2040 [1]. On the other hand, resource depletion and environmental concerns have forced decision makers to aim not merely to satisfy the increasing demand at the least cost, but also to move towards more sustainable economic development. To this end, many countries have enacted environmental policies to regulate the greenhouse gas (GHG) emissions from power production units using fossil fuels. In 2017, renewable energy sources covered 40% of the increase in primary demand, while net additions of coal-fired plants are expected to reduce by 55% in the following 20-year horizon, in relation to additions taking place from 2000 up to 2017 [2].

Although renewable energy technologies can achieve a reduction in total GHG emissions from power production, their ability to satisfy demand largely depends on the renewable resource potential of the region. Intermittent renewables can provide a certain amount of electricity but are not effective as standalone technologies to provide baseload power. Power generation planning seeks to design the optimal power generation mix by optimizing a performance indicator (such as minimizing the energy system cost), while at the same time satisfying a set of conditions related, for example, to the security of supply, the limitation of resources, the energy diversity, the environmental impact as well as the renewable technology capacity factors and the evolution of their costs. It is, hence, a challenging undertaking requiring the examination of numerous, often interrelated, aspects.

Mathematical programming is an appropriate method for determining optimal electric power generation systems that will minimize the overall cost (or other objective functions) while satisfying a set of underlying conditions. A number of authors have undertaken studies related to the determination of the optimal energy mix at a national [3–8], regional [9–13] or even at building [14] level. Most studies use the minimization of the power generation system cost as the objective function, which most frequently includes the investment cost of new generating technology, the fuel price, the fixed and variable operating costs. Other costs considered in literature are: salvage and dismantling costs [13,15], emissions costs [16–19], cost of electricity not supplied [20–22], imports of fuel and electricity [12,17–19], cost of carbon capture and storage units [22], cost of transmission [12,23] and cost of storage [23, 25].

Conventional energy planning is performed based on a deterministic projection of demand, capital cost of different generation technologies, fuel price, etc., assuming that all variables are certain and remain unchanged throughout the planning horizon [12]. However, some of the future forecasts, such as demand growth, fuel price and renewable energy cost, are susceptible to change in the future, making the planning solution invalid when those variables deviate from the forecasted values [3].

Many works have been established to develop optimization models that incorporate uncertain inputs in the energy generation planning [7]. Multistage stochastic optimisation (MSO) method has been widely used to model the uncertainty of selected variables with specific probabilities by means of a multi-period scenario tree. The fundamental concept of MSO is recourse, allowing corrective actions to be implemented in each stage based on the corresponding uncertainty realized so far [10]. In the first stage, a decision has to be made “here and now” before perceiving uncertainty, then in the next stage the decision is made after realizing the uncertainty values [21,25]. For example, the energy mix for period $t+1$ can be decided only after realizing the energy demand at period t.

Li et al. formulated a multistage interval-stochastic energy model using integer linear programming for supporting electric power system planning under uncertainty of power demand [26]. Through a multistage stochastic nonlinear programming model, Thangavelu et al. suggested the inclusion of uncertainty in demand, fuel price and technology cost by assigning scenarios to each variable [3]. Krukanont and Tezuka considered the uncertainty of energy demands, plant operating availability and carbon tax rate in developing a two-stage stochastic linear programming optimization model to analyse the near-term Japanese energy system planning using real data [25]. Bakirtzis et al. summarized various planning models which incorporated uncertainties, and performed a scenario-based mixed-integer linear programming model to illustrate the effect of demand, fuel prices and CO_2 prices' uncertainties on planning decisions using real data from the Greek power system [27].

The probabilistic scenario tree and Monte Carlo simulation (MC) approach are two foremost approaches that have been used to represent uncertainty parameters in MSO problems. The former approximates continuous distribution into discrete scenarios and performs optimization at each realization of uncertain parameter weighted with the corresponding discrete probability [28]. The latter portrays input uncertainty by generating random scenarios based on continuous distribution, which can be determined from historical data or expert judgement [29]. Scenario trees have been widely used for structuring stochastic programming models in power generation system planning [3,10,14,26], due to their ability to discretize the vast number of possible outcomes of the uncertain variables [14]. The scenario-tree based stochastic programming framework is efficient when the optimization problem is convex and the number of decision stages is small [30]. Nevertheless, a number of scenario reduction techniques (such as backward reduction or forward selection) are available to deal with the rapidly growing number of scenarios in a multistage stochastic programming framework [31].

Some previous studies implemented MC simulation to model uncertainty of key parameters in the power generation mix [32]. As such, Tekiner et al. formulated a mixed integer linear program to minimize the total weighted three objective functions (total cost, CO_2 emissions and NO_x emissions) and used the MC simulation technique to produce 1,500 demand scenarios [33]. Betancourt-Torcat and Almansoori used the MC method to simulate uncertainty associated with natural gas price and developed a multi-period linear model to determine optimal power generation in the United Arab Emirates [28]. Min and Chung also applied the MC approach to integrate the uncertainty of power demand and fuel prices, and generated a linear model to solve South Korea’s long-term power generation mix problem [32]. Finally, Piao et al. used the MC technique to predict power demand and used it as input in a nonlinear stochastic optimization model for identifying strategies to improve air quality in Shanghai [34].

The present work proposes a multi-stage stochastic optimization model that determines the medium-to-long term optimal electricity generation mix, taking into consideration the uncertainty in electricity demand, capital cost reduction for renewables technologies and fuel prices along the planning horizon. In this work, the uncertainties are modelled through a hybrid method combining the scenario-based and the MC simulation approach. As such, the volatility of fuel prices (natural gas, oil and coal) was modelled through MC simulation process, while the associated uncertainty in electricity demand growth and capital cost reduction for renewable technologies was addressed by applying a finite number of possible weighted scenarios. Novelty of this work lies in developing a hybrid uncertainty modelling approach within the stochastic optimization framework, as well as in the use of updated input data used to perform the optimization of the Indonesian power generation mix. Furthermore, we compare results derived after formulating different probability density distributions (normal, uniform, Pert and Weibull) to model stochastic fuel prices through the MC simulation and we present results for a number of POs outlined in Section 5 to derive useful insights on the response of the system under different sets of constraints.

Based on data collected from online databases, official reports as well as communication with people from the Ministry of Energy and Mineral Resources of Indonesia, Indonesia’s power system portfolio is used as the input of the proposed model to derive optimal power generation mixes and additional capacity to be built in each period across a timeframe from 2016 to 2030 to satisfy electricity demand whilst fulfilling environmental concerns, renewable penetration and energy diversity targets in this case study.

Results of the case study could assist policy makers derive useful insights regarding optimal planning pathways towards sustainable power generation systems, taking into account uncertain inputs changing over the planning horizon.

The remainder of this paper is structured as follows: Section 2 defines the system of this study navigating through the proposed methodology, the uncertainty modelling and the specifications of the MSO method, Section 3 presents the mathematical formulation of the problem outlining its objective function and constraints. Next, in Section 4, the Indonesian energy context is presented, while Section 5 describes the results derived from the application of the MSO method to the baseline case and subsequently to a number of defined planning options. Then, in Section 6 results are further discussed and finally, Section 7 draws the main conclusions of this work.

2 Problem definition

2.1 Problem Statement

This study addresses the medium to long term power generation expansion planning (PGEP) problem of a country or region by determining the optimal combination of power production plants under uncertain electricity demand increase, capital cost reduction for renewable technologies and fuel prices for conventional technologies across the planning horizon. The method can be extended to incorporate other uncertainties; nevertheless, the ones chosen have been widely cited in literature as among the most impactful [3,10,35–38]. It should be also noted that adding more uncertain variables increases the number of scenarios and thus requires higher computational effort. Figure 1 illustrates a schematic representation of the proposed methodology. It includes the required input (deterministic and stochastic), objective function, set of constraints and the outputs.

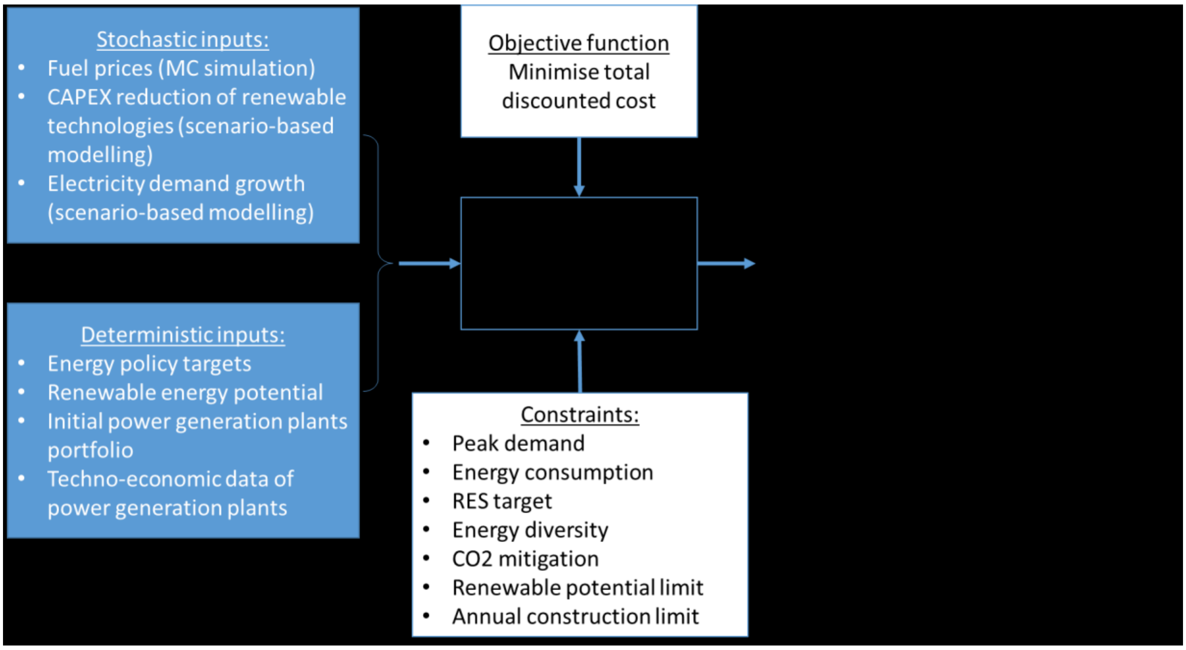

Figure 1 Schematic representation of the model

The planning horizon of the problem is divided into a set of time intervals (t). Each time interval represents a multiyear period. In this study, ten power generation technologies are considered as alternatives for the new power plants to be built including pulverized coal-fired (PCF), natural gas combined cycle (NGCC), diesel power, hydro power, geothermal, biomass, wind onshore, wind offshore, solar photovoltaic (PV) and concentrated solar (CSP) power plants.

The required installed capacity (RIC) is calculated by considering the peak demand (PD) and the reserve margin (RM) (in MW), while the net power production (P) represents the electricity generated by power generation facilities in one year (in GWh) after making an allowance for plant own power consumption (O) and transmission and distribution losses (L). Net power generation needs to meet the projected power consumption demand (CD). The model takes into account the capacity from current power generation facilities (EIC) and assumes that the power plants will be decommissioned once their service lifetime has been reached. Techno-economic input data of power plants used in the model include capital cost $(CAPEX)$, fixed operation and maintenance (O&M) cost (FOM), non-fuel variable O&M cost (VOM), fuel cost (FC) (which is subjected to uncertainty), carbon emission rate (C_{rate}), capacity factor (CF) and technical lifetime of the power plant (L_m) and were collected both through desktop research and through communication with people from the Ministry of Energy and Natural resources. The total installed capacity for each renewable technology $\left(IC_{\tau_{re}}\right)$ is also restrained by the renewable potential $\left(RE_{pot}\right)$ of the country. Additionally, new power plants to be built for each technology cannot exceed their annual construction limit (CL). The annual construction limit for each technology in a region or country varies depending on the availability of labor, area available for construction, and social and technological readiness for a particular technology. For the purposes of this study, a number of assumptions needed to be considered:

i. Learning curve effects are only applied to the onshore wind and solar PV power plants, whose capital cost is assumed to experience a declining rate through the course of the planning horizon, due to technological development. Capital costs of other technologies were assumed to retain their initial values and future costs were discounted to the present.
ii. The current work integrated the volatility of fuel price into the model for three types of fuels, including coal, natural gas and diesel, while biomass price was assumed to retain a mean value which (similarly to all technologies) is discounted throughout the planning horizon.
iii. The PV degradation rate is assumed to remain stable (at 0.8%/year [39]) throughout the lifetime of the solar PV power plant. Allowing for future survey and potential mapping, the renewable potential is expected to increase to a certain level each year (1% increase per year is assumed). This can be linked with the technological advancement which can allow further harvesting of the resource. Renewable technologies are assumed to have zero emissions.
iv. Although the capacity factor may vary throughout the year, the values have been assumed to remain constant.

v. In order to calculate the produced electricity (in MWh) from conventional energy power plants (coal, natural gas and petroleum-fired power plants), the following expression was used:

$$FR = \frac{HR}{HV} \quad \text{Eq. 1}$$

where, the amount of fuel consumed to generate 1 MWh (FR) is calculated as the power plant heat rate (HR) divided by the heating value of the fuel (HV) (Eq. 1). Table 1 includes the fuel consumption rates used as inputs in the model.

Table 2: Fuel consumption rate used in the model (Source: [40]**)**

Fuel type	Fuel consumption rate $(\boldsymbol{FR})$	
Coal	0.53	ton/MWh
Natural gas	8.9	MMBTU/MWh
Petroleum	1.81	barrel/MWh

vi. The total cost of power generation throughout the planning horizon is discounted to present value with a certain assumption of interest rate (r).

vii. The degradation rate of solar PV is included into the model to reflect the effect of degradation of the solar PV power plants on the generation output.

viii. Minimum share of a certain technology can be imposed by setting a minimum contribution of each technology to the energy mix (Min_{cap}). For example, to manage the risk of intermittency from renewable energy sources policy makers can set the share of coal and gas power at a certain minimum level.

ix. The sustainability criteria are fulfilled by means of: the carbon tax (C_{tax}) , which represents the external cost of environmental impact mitigation; the carbon emission limit (C_{target}) which bounds the amount of $CO_{2,eq}$ emission produced by the power generation sector in one year and the renewable energy penetration target (RE_{target}) represents the minimum share of power generated from renewable energy sources.

x. Fuel diversity is imposed within an acceptable range by means of enforcing a maximum proportion cap (Max_{cap}) for each technology. The maximum proportion cap can also be used as a tool to restrain an undesired technology option.

The following targets are aimed to be achieved:

i. Ensuring the future electricity demand will be met at the least cost, both in terms of required installed capacity and net power generation.
ii. Fulfilling the required renewable penetration target to promote a renewable contribution to the power generation mix.
iii. Restraining $CO_{2,eq}$ emissions within the target set by government regulations.
iv. Renewable energy new installed capacity is restrained by the annual construction limit and the resource potential of the region.
v. Complying with fuel diversity targets to manage risk associated with dependency on certain fuel sources or technologies.

Decision variables represent the new power plant installed capacities derived under varying technological, environmental and economic criteria. The optimization model determines the following key decisions at each time period:

i. Future optimal power generation mix.
ii. Renewable contribution to the power generation mix.
iii. Power generation cost structure breakdown (capital cost, fixed cost, variable cost, fuel cost and carbon cost) at present value.
iv. Power plant facilities that have reached their end of life (decommissioning plan).
v. Capacity expansion planning (new capacity to be built) for each type of power generation technology.
vi. Required capital cost for capacity expansion project (new power plant to be built).

vii. Fuel consumption required by power generation facilities in one year.
viii. Annual electricity production from each type of power generation technology.
ix. GHG emission from the power generation activities.

2.2 Uncertainty modelling

In the proposed model, future projection of uncertain variables is represented as a multi-stage scenario tree that grows with both scenario-based nodes and MC random generated nodes.

i) Demand: The uncertainty of peak demand and power consumption growth are represented by three scenario-based nodes (low, medium and high) with their assigned probability.
ii) Capital cost reduction for renewable technologies: Technology innovation is anticipated to gradually reduce the cost of energy of renewables. In this study, wind onshore and solar PV are considered to experience a decreasing rate in their capital cost. The uncertainty of the capital cost reduction rate for wind onshore and solar PV are represented by three scenario-based nodes (low, medium and high) with their assigned probability.
iii) Fuel Price: The volatility of fuel prices (coal, natural gas and diesel) is represented by n MC random generated nodes assumed to follow a normal probability distribution function for each fuel type. Normal distribution has been widely used in many stochastic problems [28,41]; nevertheless, other probability distribution functions were also tested in order to evaluate the effect of statistical uncertainty.

The study system covers a time horizon of 4 periods and 3 stages of 4, 5 and 5 years duration, respectively. Figure 2 demonstrates the multistage scenario tree that is developed by the three uncertainty variables (electricity demand, capital cost reduction and fuel price). Both the uncertainty of electricity demand and capital cost reduction are represented by three nodes: “Low”, “Medium” and “High” with assigned probability values 0.3, 0.5 and 0.2, respectively, as shown in Figure 2. Furthermore, each MC simulation sample is considered as a separate node with $1/n$ probability. A scenario (s) is a route from the root node to a leaf node and the probability of scenario s (p_s) equals the product of probability of occurrence realized from root node to leaf node. Hence, the probability of scenario s is the joint probabilities of all uncertain variables. The sum of corresponding joint probabilities of all scenarios is equal to 1. After reaching the leaf node at each stage, key decisions (installed capacity for each technology) from a set of n scenarios are averaged to provide the input value for the next node. Hence, in each stage, $n \cdot 3^{2 \cdot t}$ optimizations are performed, where n is the set of random fuel price MC sample, assumed to follow a normal probability distribution and t is the number of stage. Since fuel prices volatility is hard to model accurately by following a three-scenario-tree pattern, MC simulation was used to generate a random set of fuel prices based on their mean and standard deviation values of each technology's fuel price. It should be highlighted that increasing the size n of the MC generated samples can provide more robust results; however, it significantly increases the processing time. To identify the minimum sample size, a convergence study was implemented which indicated that results started to converge for $n = 150$.

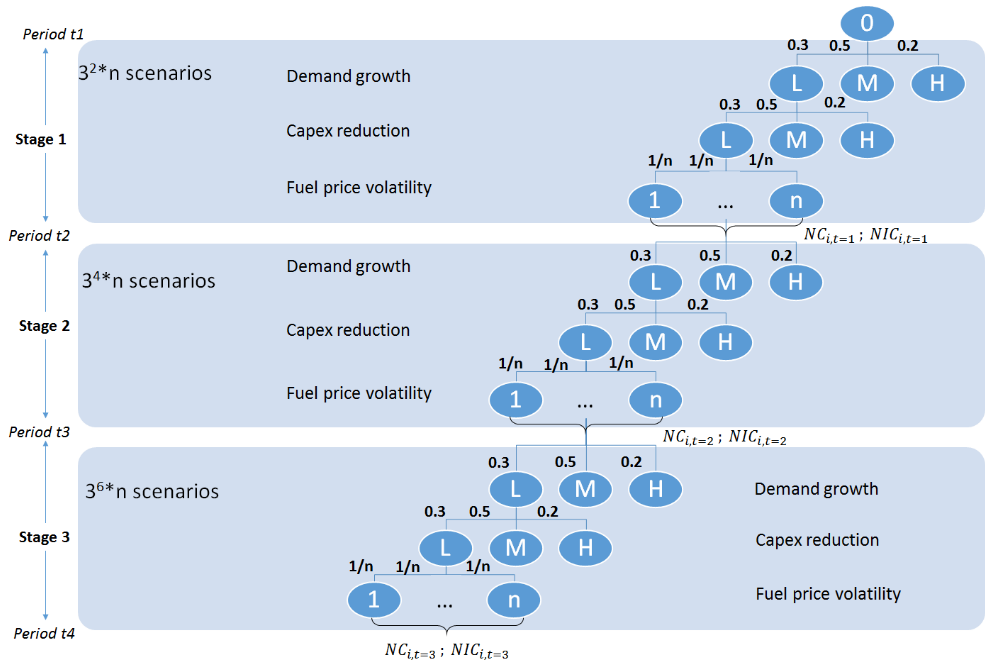

Figure 2: Uncertain inputs represented by scenario tree with assigned probabilities under the baseline scenario

As mentioned above, the model assumes a normal probability distribution function for the uncertainty modelling of fuel prices as shown in Figure 3. Nevertheless, results derived from using other probability distribution functions, namely uniform, PERT and Weibull (Figure 4) were also exported for the sake of comparison. The same set of MC fuel price samples is used for all branches of the scenario tree.

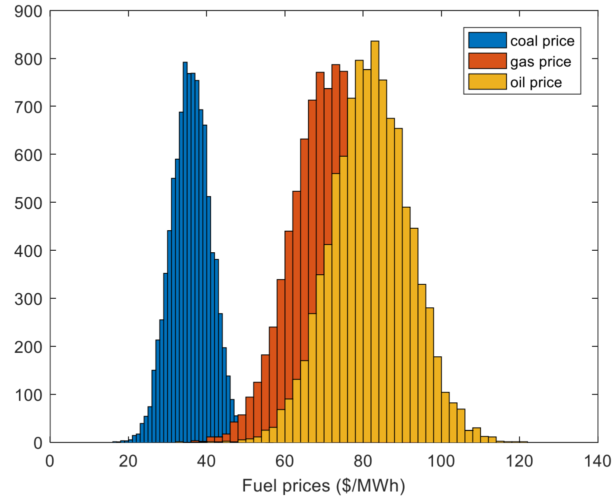

Figure 3 Normal probability distributions histogram of fuel prices of conventional technologies considered for the baseline scenario

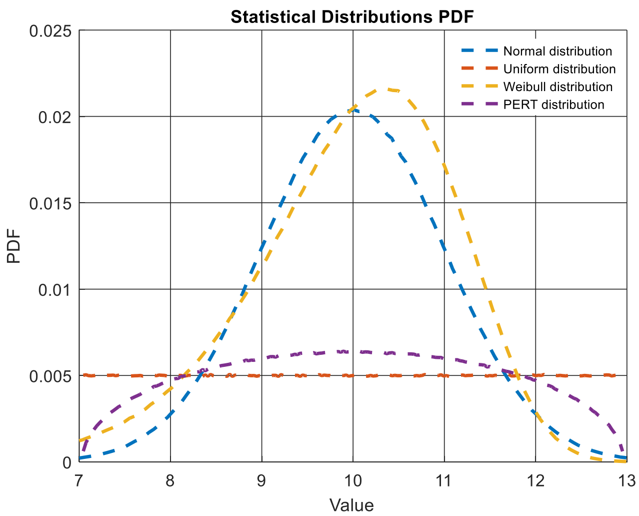

Figure 4 Normal, uniform, Weibull and PERT distribution plots

3 Mathematical formulation

3.1 Objective Function

The mathematical formulation of the optimization model is presented in this Section. In Appendix A, the nomenclature of the parameters and variables used throughout the paper is included. The objective function of the model (Eq. 2 – 18) is the minimization of the discounted total cost of the power generation mix, given as:

$$Min\, f = \sum_{\tau=1}^{10} (EC + NC)_{t,s}$$
$$\forall\, t = 1{:}3 \text{ and } s \in [s_D, s_C, s_F] \qquad \text{Eq. 2}$$

In equation (2), EC and NC are the annual power generation cost of existing and new power plant capacity, s refers to a specific combination of s_D, s_C and s_F values (energy demand scenario,s_D, capital cost reduction scenario of new onshore wind and solar power plants,s_C, and fuel price scenario, s_F) during the time period, t. Hence, the minimization of the objective function takes place for every combination of scenarios at each time period. The total cost consists of power generation costs from existing and new power plants, each comprising the annualized capital cost, the fixed and variable operating (O&M) costs, as well as the fuel and carbon costs.

Overnight capital cost is annualized over the lifetime of the plant, while other costs are calculated on a yearly basis. Fixed O&M cost represents the operation and maintenance costs that are not dependent on the activity of the power generation plant. In contrast, non-fuel variable O&M cost, fuel cost and carbon emissions vary according to the energy production of the plant. Solar PV and wind onshore technologies are subject to capital cost reduction over the planning horizon due to assumed technological advancements. It is assumed that, if the system requires capacity expansion at the beginning of a particular period, t, this expansion project has to be completed by the end of the previous period, t_p.

The electricity system costs of existing power plants consist of the annualized capital cost, ($EACP$), the fixed O&M cost, ($EFOM$), the non-fuel variable O&M cost, ($EVOM$), the fuel cost, (EFC) and the carbon emissions cost of existing power plants, (ECC).

$$EC_{t,s} = (EACP + EFOM + EVOM + EFC + ECC)_{t,s}$$

$$\forall\, t = 1{:}\,3 \;\text{ and } s \in [s_D, s_C, s_F] \qquad \text{Eq. 3}$$

where, the annualized capital cost of the existing power generation technology capacity is calculated based on the discount rate (r) and the technology life time (L_τ) by means of the following formula:

$$EACP_{t,s} = \left(\sum_{\tau=1}^{10} \left(EIC_{t,\tau} \cdot ECAPEX_{\tau,t_p} \right) \cdot \frac{r}{1-(1+r)^{-L_\tau}}\right)_{t,s} \qquad \text{Eq. 4}$$

$$\forall\, t = 1{:}\,3 \;\text{ and } s \in [s_D, s_C, s_F]$$

where, $\mathrm{EIC}_{t,\tau}$ stands for the technology's τ total installed capacity (MW) during the time period t and $\mathrm{ECAPEX}_{\tau,t_p}$ is the capital cost in period t_p. Accordingly, the fixed O&M cost is calculated as:

$$EFOM_{t,s} = \left(\sum_{\tau=1}^{10} (EIC_\tau \cdot FOM_\tau)\right)_{t,s} \qquad \text{Eq. 5}$$

$$\forall\, t = 1{:}\,3 \;\text{ and } s \in [s_D, s_C, s_F]$$

where, $\mathrm{EFOM}_{\,t,s}$ is the fixed O&M cost per kW of installed capacity of existing power plants calculated for each scenario and time period. The non-fuel variable O&M cost of existing power plants ($EVOM$) is estimated by the following equation:

$$EVOM_{t,s} = \left(\sum_{\tau=1}^{10} (EIC_\tau \cdot CF_\tau \cdot VOM_\tau \cdot 8760)\right)_{t,s} \qquad \text{Eq. 6}$$

$$\forall\ t = 1{:}\,3 \text{ and } s \in [s_D, s_C, s_F]$$

where, CF_τ is the capacity factor of the power generation technologies, and VOM_τ is the non-fuel variable O&M cost calculated per MWh of power generated. The fuel cost of existing fuel-powered energy plants (EFC) is calculated as:

$$EFC_{t,s} = \left(\sum_{\tau=1}^{3}\sum_{sf=1}^{3}\left(EIC_\tau \cdot CF_\tau \cdot\ 8760 \cdot FP_{\tau,sf} \cdot p_{sf}\right)\right)_{t,s} \qquad \text{Eq. 7}$$

$$\forall\ t = 1{:}\,3 \text{ and } s \in [s_D, s_C, s_F]$$

where, $FP_{t,sf}$ denotes the fuel price. Finally, the annual carbon cost of existing power plants, $ECC_{t,s}$ is estimated as follows:

$$ECC_{t,s} = \left(\sum_{\tau=1}^{3}\left(C_{emit_\tau} \cdot C_{tax_\tau}\right)\right)_{t,s} \qquad \text{Eq. 8}$$

$$\forall\ t = 1{:}\,3 \text{ and } s \in [s_D, s_C, s_F]$$

where, the mass of $CO_{2,eq}$ emitted per year is calculated as a function of the $CO_{2,eq}$ emission rate of power plant technology (C_{rate_τ}) by the following formula:

$$C_{emit_\tau} = EIC_\tau \cdot CF_\tau \cdot 8760 \cdot C_{rate_\tau} \qquad \text{Eq. 9}$$

Above equations are also applied for the new power generation plants. The electricity system cost of new power plants was estimated for every scenario and time period as:

$$NC_{t,s} = (NACP + NFOM + NVOM + NFC + NCC)_{t,s} \qquad \text{Eq. 10}$$

$$NACP_{t,s} = \left(\sum_{\tau=1}^{10}\left(\frac{r}{1-(1+r)^{-L_\tau}} \cdot NIC_\tau \cdot NCAPEX_\tau\right)\right)_{t,s} \qquad \text{Eq. 11}$$

$$NFOM_{t,s} = \left(\sum_{\tau=1}^{10}(NIC_\tau \cdot FOM_\tau)\right)_{t,s} \quad \text{Eq. 12}$$

$$NVOM_{t,s} = \left(\sum_{\tau=1}^{10}(NIC_\tau \cdot CF_\tau \cdot VOM_\tau \cdot 8760)\right)_{t,s} \quad \text{Eq. 13}$$

$$NFC_{t,s} = \left(\sum_{\tau=1}^{3}\sum_{sf=1}^{3}\left(NIC_\tau \cdot CF_\tau \cdot \ 8760 \cdot FP_{\tau,sf} \cdot p_{sf}\right)\right)_{t,s} \quad \text{Eq. 14}$$

$$NCC_{t,s} = \left(\sum_{\tau=1}^{3}\left(C_{emit_\tau} \cdot C_{tax_\tau}\right)\right)_{t,s} \quad \text{Eq. 15}$$

$$C_{emit_\tau} = NIC_\tau \cdot CF_\tau \cdot 8760 \cdot C_{rate_\tau}$$
$$\forall\, t = 1{:}3 \text{ and } s \in [s_D, s_C, s_F] \quad \text{Eq. 16}$$

The proposed optimization model was developed using the constrained solver fmincon of MATLAB R2017a optimization toolbox, which is based on sequential quadratic programming [42].

3.2 Constraints

Besides minimizing the cost, the model considers the following constraints to satisfy energy security, renewable penetration, fuel diversity and carbon emission reduction targets.

3.2.1 Electricity Peak Demand

This constraint ensures the total installed capacity could satisfy the peak demand (PD) for all scenarios and time periods. Reserve margin is taken into account as a buffer to protect against system breakdowns or sudden upsurges in electricity demand. It is defined as the difference between the (required) installed capacity (RIC) and the peak demand divided by the peak demand [43,44]. Electricity demand is driven by population growth, economic development and various other factors. However, extensive electricity demand estimation is not the focus of the current work. The following constraints ensure that the installed capacity of existing power plants plus the installed capacity of new power plants are sufficient to meet the expected peak demand plus the reserve margin.

$$\left(\sum_{\tau=1}^{10}(IC_\tau)\right)_{t,s} = (EIC + NIC)_{t,s} \qquad \text{Eq. 17}$$

$$\left(\sum_{\tau=1}^{10}(RIC_\tau)\right)_{t,s} = PD_{t,s} \cdot (1 + RM) \qquad \text{Eq. 18}$$

$$(IC)_{t,s} \geq (RIC)_{t,s}$$

$$\forall\, t = 1{:}3 \text{ and } s \in [s_D, s_C, s_F] \qquad \text{Eq. 19}$$

3.2.2 Electricity Consumption Demand

This constraint guarantees the electricity generated by power generation facilities (P_τ) exceeds the projected power consumption (CD) after taking into consideration the plant's own use of electricity (O), as well as the transmission and distribution losses (L).

$$\left(\sum_{\tau=1}^{10} P_\tau \cdot \big(1 - (\,O + L)\big)\right)_{t,s} \geq \left(\sum_{s_D=1}^{3}\left(p_{s_D} \cdot CD\right)\right)_{t,s} \qquad \text{Eq. 20}$$

$$\forall\, t = 1{:}3 \text{ and } s \in [s_D, s_C, s_F]$$

3.2.3 Renewable Contribution Target

This constraint gives explicit control to set a minimum renewable energy share in power generation mix to boost renewable energy penetration. This constraint that can be varied across the different time periods, with targets set at more ambitious levels in the course of time. As explained in the Nomenclature in Appendix A, τ

denotes the type of technology, with $\tau = 1{:}3$ representing the conventional technologies and $\tau = 4{:}10$ the renewable energy technologies.

$$\left(\frac{\sum_{\tau=4}^{10}(EIC_\tau \cdot CF_\tau) + \sum_{\tau=4}^{10}(NIC_\tau \cdot CF_\tau)}{\sum_{\tau=1}^{10}(EIC_\tau \cdot CF_\tau) + \sum_{\tau=1}^{10}(NIC_\tau \cdot CF_\tau)}\right)_{s,t} \geq \ RE_{target_t} \qquad \text{Eq. 21}$$

$$\forall\, t = 1{:}3 \ \text{ and } s \in [s_D, s_C, s_F]$$

3.2.4 Minimum Proportion Constraint

This constraint defines the minimum contribution of each technology in the power generation mix for each period of time ($Min_{cap_{t,\tau}}$). It is useful to ensure the more preferred technology is at a certain minimum level. For example, to manage the risk of intermittency from renewable energy sources, policy makers can set the share of coal and gas power at a certain minimum level. This constraint is included through the following expression:

$$\left(\frac{EIC_\tau \cdot CF_\tau + NIC_\tau \cdot CF_\tau}{\sum_{\tau=1}^{10}(EIC_\tau \cdot CF_\tau) + \sum_{\tau=1}^{10}(NIC_\tau \cdot CF_\tau)}\right)_{t,s} \geq \ Min_{cap_{t,\tau}} \qquad \text{Eq. 22}$$

$$\forall\, t = 1{:}3,\ \tau = 1{:}10 \ \text{ and } s \in [s_D, s_C, s_F]$$

3.2.5 Maximum Proportion Constraint

By imposing a maximum proportion constraint, for example on the more cost efficient power generation technologies, the model imposes the introduction of other technologies in the power generation mix in order to cover the energy demand, rendering the power generation mix more diverse. Fuel diversity can be enforced by policy makers to maintain the dependency of each technology or fuel source within an allowable range by means of setting the maximum proportion cap ($Max_{cap_{t,\tau}}$) for each technology, τ, at a particular time period, t. Grid stability should also be taken into account. The fact that most renewable energy technologies cannot be dispatched when required, as they strongly depend on weather conditions, prevents them from being a reliable base-load solution over a long term period. As such, through this constraint the total electricity production from renewable technologies can be set not to exceed a maximum proportion of the total electricity demand. The maximum proportion cap can also be used as a tool to restrain an undesired technology option. A different maximum proportion cap can be applied to each technology and time period.

$$\left(\frac{EIC_\tau \cdot CF_\tau + NIC_\tau \cdot CF_\tau}{\sum_{\tau=1}^{10}(EIC_\tau \cdot CF_\tau) + \sum_{\tau=1}^{10}(NIC_\tau \cdot CF_\tau)}\right)_{t,s} \leq Max_{cap_{t,\tau}} \qquad \text{Eq. 23}$$

$$\forall\, t = 1{:}3\,,\ \tau = 1{:}10 \text{ and } s \in [s_D, s_C, s_F]$$

3.2.6 $CO_{2,eq}$ Emission Limit

This constraint limits the allowable amount of $CO_{2,eq}$ emissions produced from fossil-fuel generation facilities. The introduction of the $CO_{2,eq}$ limit controls the introduction of fossil-fuel plants and forces the inclusion of renewable technologies to the power generation mix so as to satisfy the rest of the demand. Different limits can apply at each planning period.

$$\left(\sum_{\tau=1}^{10}\left(IC_\tau \cdot CF_\tau \cdot 8760 \cdot C_{rate_\tau}\right)\right)_{t,s} \leq C_{target_t} \qquad \text{Eq. 24}$$

$$\forall\, t = 1{:}3 \text{ and } s \in [s_D, s_C, s_F]$$

3.2.7 Renewable Potential Limit

The renewable potential expresses the theoretical upper limit of the amount of energy that can be produced from renewable sources over a particular geographic region as estimated by surveys undertaken by experts [16]. This constraint is imposed on renewable technologies to make sure the energy derived from renewable sources is within the potential capacity of that region or country.

$$EIC_{t,\tau} + NIC_{t,\tau} \leq RE_{pot_{t,\tau}} \qquad \text{Eq. 25}$$

$$\forall\ t = 1{:}3,\ \tau \in [4{:}10]$$

In this study, the maximum potential (RE_{pot}) for hydro, geothermal, biomass, onshore wind, offshore wind, solar PV and solar CSP are summarised in Table 4.

3.2.8 Annual Construction Limit

This constraint determines the annual construction upper limit for renewable energy plants, which is subject to the availability of labour, manufacturing capacity, area available for construction, social readiness for a particular technology and other factors. The construction limit remains unchanged across the different time periods.

$$NIC_{\tau,t,s}\ \leq\ CL_{\tau}$$

$$\forall\ t = 1{:}3,\ \tau \in [4{:}10] \text{ and } s \in [s_D, s_C, s_F] \qquad \text{Eq. 26}$$

3.2.9 Non-negative constraint

By this constraint, it is assured that only non-negative new rated capacities can be accepted for every scenario, time period and technology in the solution.

$$NIC_{\tau,t,s}\ \geq\ 0$$

$$\forall\ t,\ \ s \in [s_D, s_C, s_F] \text{ and }\ \tau\ = 1{:}10 \qquad \text{Eq. 27}$$

4 Application to the Indonesian power generation system

In this study, Indonesia’s power system’s portfolio is used as input for the proposed model. Indonesia's prominence is highlighted by its population of 255 million people (fourth largest in the world) in 2016 [45] and its considerable potential of fossil-fuel and renewable resources. Globally, Indonesia is the largest coal exporter and fourth largest coal producer. The country has an estimated 28 billion tons of coal reserves (accounting for 3.1% of total global reserves [46]). It is the world's tenth largest producer of natural gas and the seventh largest exporter of liquefied natural gas (LNG) [47].

Indonesia is the largest economy in Southeast Asia and has achieved steady, high growth rates over the last 15 years. Its energy consumption is predicted to grow rapidly as a result of population growth, rapid urbanisation and rising living standards [47]. Therefore, satisfying demand growth and ensuring the sustainability of energy supplies is one of key pillars of Indonesia's economy. In 2016, Indonesia had approximately 59.6 GW installed power plant capacity, generating 290 TWh of electricity [45]. Electricity peak load was estimated to reach 32,204 MW in 2017 [48]. Energy mix is currently comprised by coal (54.69%), gas (25.89%), oil (6.97%) and renewables (12.45%) [49]. The Indonesian government seeks to reduce the dependency on fossil fuel by increasing the renewable energy contribution to the power sector by at least 25% by 2030 [50]. Additionally, according to the 2014 National Energy Policy (the "2014 NEP") of Indonesia, renewable energy should reach at least the 23% of the power generation mix by 2025, while in 2050 the target is to increase renewables share to at least 31% [51]. As a contingency to the high share of renewable energy in the country's mix, PLN (the company responsible for the majority of Indonesia's energy production) will be required to use another 5.1 GW of gas-fired power plants to meet the resilience requirements of the power generation system [52]. The forecasted power demand growth and base fuel price assumption data were obtained from the National Electricity General Plan (RUKN) draft in 2015. RUKN also specifically sets the minimum reserve margin target (set to 35%), as well as the assumption on own use and transmission losses of the power system in Indonesia (9.48% according to [48]). The carbon emission reduction target was set to 26% from the Business As Usual (BAU) value in 2030, as specified in Presidential Decree No. 61 of 2011 on the National Action Plan for Reducing Emissions of Greenhouse Gases in efforts to enforce environmental impact mitigation [53]. The summary of Indonesia's 2015 initial fleet capacity by generation technology can be found in Table 2.

Table 23. Indonesia's power generation portfolio in 2015 (Source: [54]**)**

Generation technology	Capacity (in MW)
Coal-fired	25,697
Natural gas-fired	17,964
Diesel power	6,394
Hydropower	5,342
Geothermal	1,435
Biomass	86
Wind Onshore	1
Solar PV	11
Total	56,932

Furthermore, the detailed techno-economic data used as input in the present case study and their references are shown in Table 3. Each technology is characterised by a capacity factor. The capacity factor is defined as the ratio of the actual electricity output during a certain amount of time to the maximum potential electrical output during this period.

The proposed model and the case study did not consider nuclear energy as the choice of power generation technologies because the utilization of nuclear energy in Indonesia will be considered only following the optimal utilization of new energy sources (such as hydrogen, coal bed methane, liquefied coal and coal gasification) and renewable energy. Assuming the potential of coal, gas and renewable energy is large enough, the use of nuclear energy was considered to be the last option. However, if despite the optimal utilization of new energy and renewable energy sources, the renewable energy share in total energy consumption still could not achieve a minimum 23% target by 2025, then nuclear energy will be considered as an option to fulfil the target [50]. As carbon tax has not been implemented in Indonesia yet, external cost is excluded in the cost of electricity generation for this study, while the imports and exports of electricity are not taken into account in this case study as the amount of power exchange with neighbouring countries is not significant. The annual construction limits of the renewable energy generation technologies were estimated on the basis of historic annual installed capacities of each technology as well as the renewable potential (summarized in Table 3). Under the business-as-usual (BAU) scenario, carbon emissions from the power sector are projected to reach 750 million tons in 2020, 1000 million tons in 2025 and 1250 million tons in 2030 [55].

Table 3. Techno-economic data of power plants

Technology	Capacity factor[a]	Lifetime[a]	Capital cost[a]	Fixed O&M cost[a]	Variable O&M cost[b]	Fuel cost (mean value)[f]	$CO_{2,eq}$ emission rate[a]	Annual construction limit	Renewable potential[c]
	%	years	$/kW	$/kW/year	$/MWh	-	$tCO_{2,eq}/MWh$	MW/year	MW
Coal (PCF)	0.70	30	1,500	31.0	3.5	51 $/ton	1.09	-	-
Gas (NGCC)	0.70	30	950	17.1	5	8.02 $/MMBTU	0.6	-	-
Diesel	0.70	30	700	11	6	45 $/barrel	0.8	-	-
Hydro	0.40	40	2,411	14.7	3.5	-	0	1600	75,670
Geothermal	0.75	30	2,687[d]	116	6	-	0	1000	28,910
Biomass	0.80	20	1,600	108	4	-	0	1300	32,654
Wind Onshore	0.28	30	1,800[e]	10.25	1	-	0	1000	60,600
Wind Offshore	0.35	25	6,331	60	3	-	0	50	
Solar PV	0.16	25	3,300[e]	21	2	-	0	8500	207,800
Solar CSP	0.20	20	4,168	69	4	-	0	30	

[a] Techno-economic data derived from the average value of various sources: [1,3,16,28,37,38,56–61]; [b]Source: [61]; [c]Source: [45,62]; [d]Source: [63]; [e]Initial capital cost value at the beginning of planning horizon;
[f]Source: [40]

5 Results

The case study performed capacity expansion planning with 2016 as the base year and three planning stages at years 2020, 2025 and 2035. The stochastic optimization model minimizes the total expected cost of the power generation mix for all three planning stages by considering all possible input scenarios. The proposed model was initially applied to determine the optimal power generation mix under a baseline case. Accordingly, the model was applied under three representative cases calling for: the “Least cost option”, the “Policy Compliance option” and the “Green Energy Policy option”.

5.1 Baseline case

Under the baseline case, existing targets for renewable energy contribution were considered as input to the model (minimum increase of 16% by 2020, 23% by 2025, and 31% in 2050), the maximum $CO_{2,eq}$ emissions limit was set according to the BAU scenario for each planning period (presented in Section 4.1), while the allowable contribution of each technology was set to 45% for all technologies. This limit was picked on the basis that coal should not exceed the 2015 quotas.

The optimised stochastic power generation mix for all leaf nodes run for planning period 2025 is shown in Figure 5 and it includes coal 20.0–45.0%,natural gas 9.0–32.0%, oil 3.5–17.5%, hydro 9.0-12.5%, geothermal 8.8–12.3%, biomass 2.3-11.9% and onshore wind 2.7–4.1%, offshore wind 0%-0.14% and solar PV 0%-8.0%. It has to be noted that results shown in this figure do not depict the likelihood of occurrence of each scenario. To identify the weighted mean proportion of power generation produced from each technology, τ, during time period, t, each observation is multiplied by the probability of occurrence of its originating scenario s_k (where k is a specific combination of s_D, s_C and s_F scenarios) and the products are, then, summed up. For instance, the weighted mean proportion of power generation derived from technology τ_1 is calculated as:

$$\bar{x}_{\tau_1} = \sum_{k=1}^{K} \left(p_{s_1} x_{\tau_1,s_1} + p_{s_2} x_{\tau_1,s_2} + \cdots + p_{s_k} x_{\tau_1,s_k} \right) \qquad \text{Eq. 28}$$

In Figure 6, the optimised stochastic power generation mix across the whole simulation period is illustrated. Total weighted mean power installed capacity was calculated 72.2 GW in the 2020 baseline case, increasing to 166 GW in 2030 due to the growing energy demand. Outliers have been removed from the box plot representation, while the weighted mean proportions of the different technologies in the power generation mix are denoted by a red asterisk. The central red mark in the whisker charts represents the median, while the bottom and top edges of the blue boxes indicate the 25th and 75th percentiles, respectively. The black whiskers cover the non-outliers that represent the most extreme data points. Constraints imposing the renewable technologies contribution, as well as lower carbon emission levels appear to enforce the decrease of fossil-fuels-based technologies over time. In fact, coal, NG and oil installed capacities are reduced by 11%, 45% and 34% from 2020 to 2030 time periods, while hydro, geothermal, biomass and onshore wind are increased by 58%, 117% and 112%, respectively (as shown in Figure 7). Furthermore, new weighted installed capacity was estimated 24.3 GW in 2020, 51.8 GW in 2025 and 80.5 GW in 2030, weighted RES share was 35% in year 2030, $CO_{2,eq}$ emissions were 570 million tons and weighted total discounted cost was calculated $ 471 billion. The model failed to find an optimum solution for around 5% of the total uncertainty scenarios, meaning that not all constraints could be satisfied under these scenarios. Results illustrated here were, thus, cleansed and their probabilities were readjusted to sum up to one.

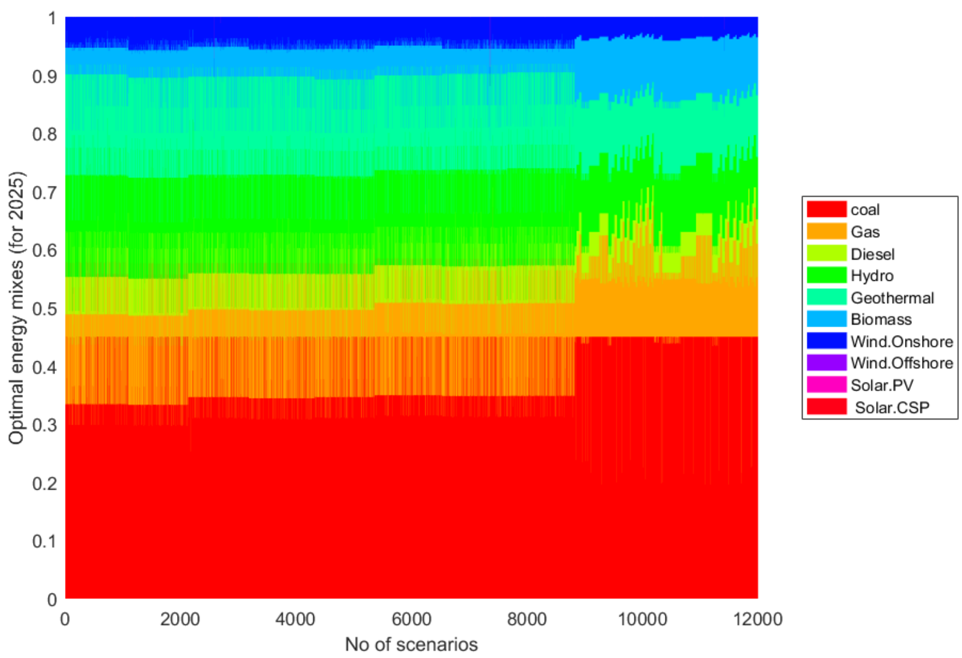

Figure 5 Power generation mix across different scenarios (for year 2025)

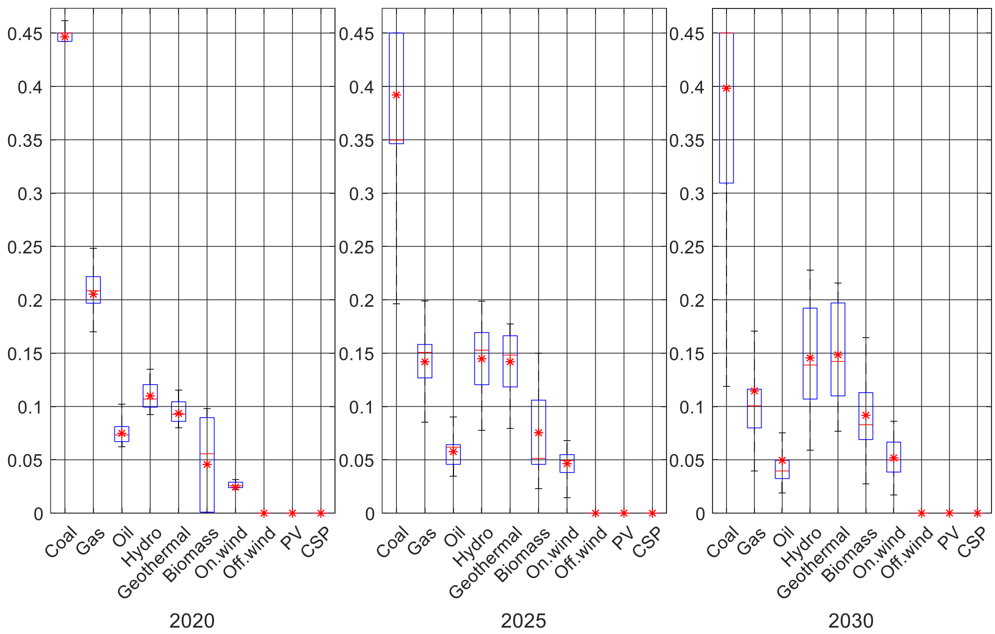

Figure 6 Optimised stochastic power generation mix throughout the simulation period under the Baseline Case

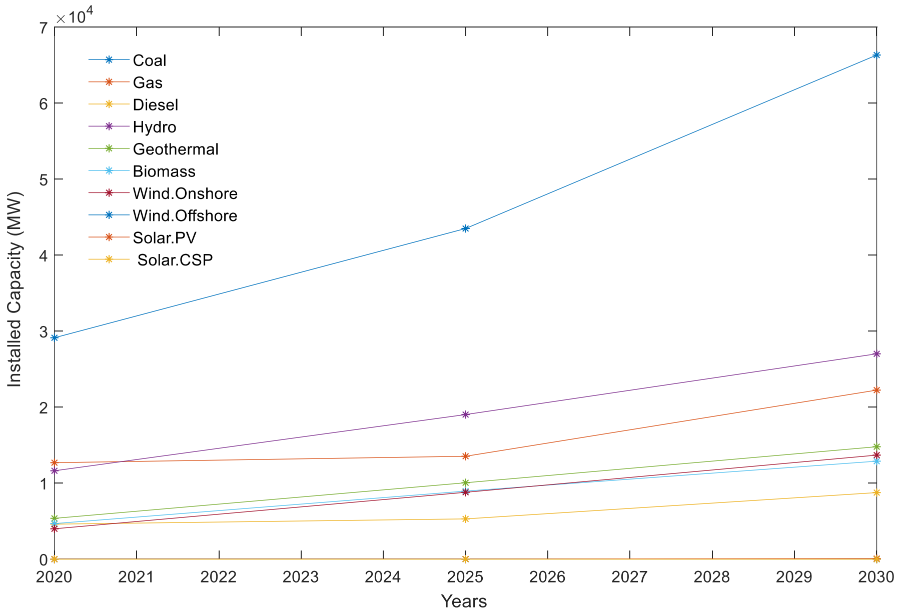

Figure 7 Weighted average installed capacity under the baseline case

Above results were derived under the assumption that the MC sample of fuel prices follow a normal distribution. In Figure 8, stochastic power generation mixes for the 2030 planning period, under the assumption of uniform, PERT and Weibull probability distributions, are shown. The equivalent PERT, Weibull and uniform distributions were based on fitting the baseline normal distribution. Generally, results appear not to deviate substantially in relation to normal distribution, and slight deviations can be observed mostly for Weibull distribution predicting 4% less coal, 8% less NG and 13% more oil share in relation to the baseline case.

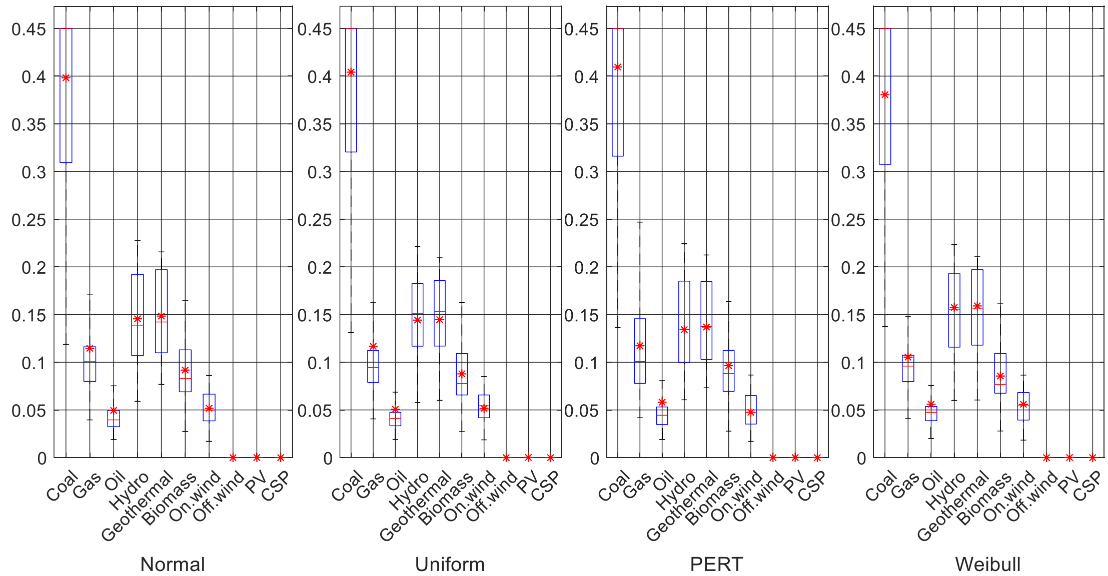

Figure 8 Optimal power generation mix under the 3 different probability distributions for 2030

5.2 Modelling of Planning Options (POs)

The proposed model was, then, applied to determine the optimal power generation mix for three Planning Options (POs): Least cost, Policy compliance and Green Energy Policy option. Different sets of constraints were imposed for each option and are summarised in Table 4.

The least cost PO focuses only on minimizing the cost of the power generation system, while no carbon emissions limit, renewable contribution and fuel diversity targets are in place. The policy compliance option imposes the renewable energy penetration targets, $CO_{2,eq}$ emission limits and required coal and natural gas quotas prescribed by the Indonesian's National Energy Policy (NEP). The Low Carbon Energy option enforces stricter renewable energy penetration targets and

$CO_{2,eq}$ emission limits. It should be noted that the power generation mix is based on the total power generation of the installed technologies.

Table 4. Set of constraints for each PO

Constraint	Baseline case	Least cost option	Policy Compliance option [a]	Green Energy Policy option
Peak demand	√	√	√	√
Consumption demand	√	√	√	√
Renewable potential limit	√	√	√	√
Annual construction limit	√	√	√	√
Minimum proportion	x	x	Coal: 30% in 2025 29% in 2030 NG: 22% in 2025	x
Maximum proportion	45% for each technology	x	Oil: 25% in 2025 24% in 2030 Rest of technologies: 45%	45% for each technology
Renewable penetration target	16% in 2020 23% in 2025 25% in 2030	x	16% in 2020 23% in 2025 25% in 2030	24% in 2020 35% in 2025 38% in 2030
$CO_{2,eq}$ emission limit	750 m ton in 2020 1000 m ton in 2025 1250 m ton in 2030 of $CO_{2,eq}$/year	x	26% $CO_{2,eq}$ reduction in relation to 2020, 2025 and 2030 BAU	30% reduction in relation to 2020, 2025 and 2030 Baseline case
Carbon pricing	x	x	x	$ 30 /metric ton of $CO_{2,eq}$

[a] Source: [45,50]

5.2.1 Least Cost option

The power generation mix of the Least Cost option is dominated by coal power, since there is no imposed carbon emission restriction or renewable penetration target. Even though the renewable penetration in this option is not as high and varied as in other options, it can still fulfil the 25% renewable penetration target for 2030, due to the high contribution of the relatively low cost hydropower, as well as the contribution of geothermal, biomass and onshore wind power plants.

According to the results, overall power generation in 2030 will rely heavily on the three most cost efficient technologies: coal (57.1%), geothermal (13.2%) and hydropower (13.1%). The rest of the power generation originates from gas (5.9%), onshore wind (4.6%), biomass (3.2%) and diesel power (2.9%). Cost efficiency accounts both for the total cost of the technology integrating the capital, fixed operational, variable operational and fuel cost, as well as for the total lifetime duration and the capacity factor of each technology. As can be seen from Figure 9, to satisfy the increasing demand at the least cost, coal installed capacity will keep growing rapidly throughout the planning horizon. On the other hand, natural gas and diesel consumption experience a decreasing trend as their contribution is slowly superseded by coal and hydropower.

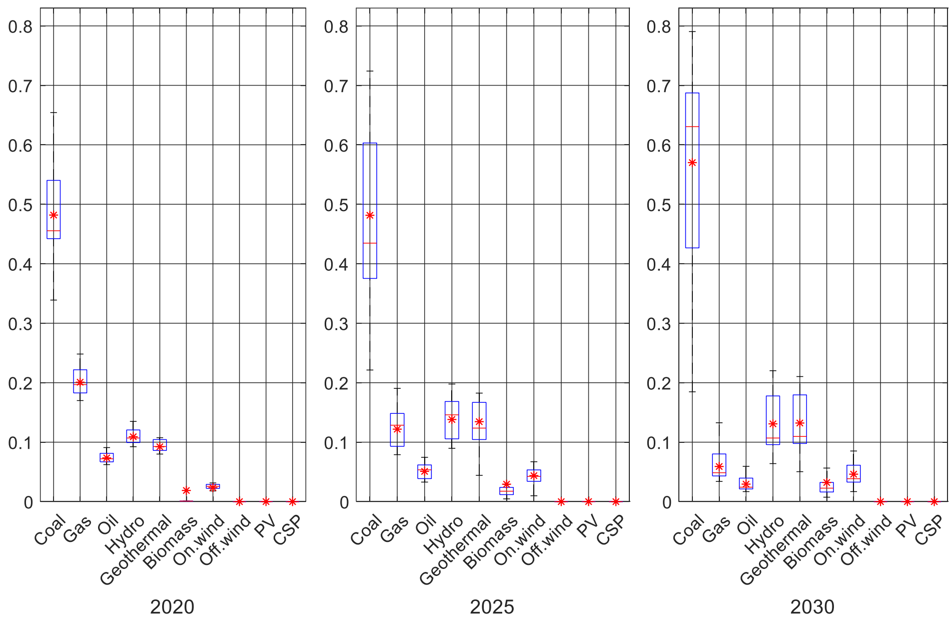

Figure 9. Power generation mix for Least cost option

5.2.2 Policy Compliance option

This option encompasses the stochastic power generation mix optimization, based on the Indonesian government's policy targets for the power generation sector, as detailed in Table 4. The set of constraints considered for this option include a minimum gas utilization in the power sector of 22% (in 2025) to promote domestic use of natural gas. Coal share is also imposed a minimum limit of 30%

by 2025, while oil share is set to reach a maximum percentage of 25% by 2025. Figure 10 shows that the power generation system will be dominated by coal, hydro and natural gas-fired power plants. While coal and hydro are proposed by the model due to their low cost characteristics, expansion of natural gas capacity is mainly driven by the minimum proportion limit imposed by the policy. However, coal power growth is limited up to a certain level that satisfies the $CO_{2,eq}$ reduction and RES penetration targets. Further, according to the model output, hydro, geothermal and onshore wind will fill the gap in 2030 to satisfy the increasing power demand. As the capital cost for onshore wind is expected to decrease over the planning horizon, the weighted average onshore wind energy production starts to grow from 3% in 2020 to 5.5% in 2030, according to the model.

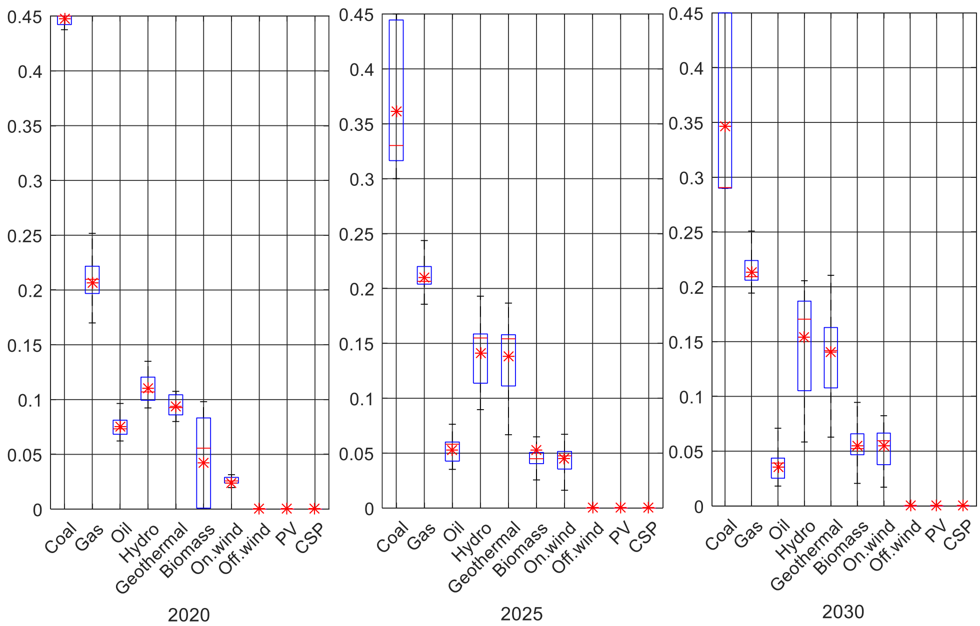

Figure 10. Power generation mix for policy compliance option

5.2.3 Green Energy Policy option

The Green Energy Policy option aims to investigate the effect of enforcing progressively stricter targets for the RE penetration (reaching 38% minimum RE share in 2030) and mitigation of environmental impact on the power generation mix, throughout the planning period. To this end, a hypothetical carbon pricing was also introduced as a policy for reducing emissions and drive investments into cleaner power generation technologies. Since, no carbon pricing policy is currently in effect in Indonesia, this study assumes an average price of $30/metric ton of $CO_{2,eq}$, which is comparable to other studies in literature [38,64,65]. No constraints on the diversity of the power generation mix were added. As shown in Figure 11, the power generation mix is again most likely to be dominated by coal as the cheapest option, while the gas-fired power generation technology appears to be the second most preferred solution under this set of constraints. Both technologies, however, demonstrate a decreasing trend from 2020 to 2030, due to the green energy targets and carbon reduction policies imposed. In fact, the weighted average power generation from coal-fired power plants was calculated approximately 43% of the power generation mix in 2020, which was reduced to 37.5% in 2030, while NG was reduced from 21% to 15%, respectively, according to the model. A similar pattern is followed by oil-fired power plants, which is reduced from 7.5% in 2020 to 4.5% in 2030. Hydro and geothermal power plants are again the preferred solutions for covering the largest part of the RES penetration target, while an increasing biomass capacity addition can be observed, along with a slight increase in the share of onshore wind and solar PV installed capacity.

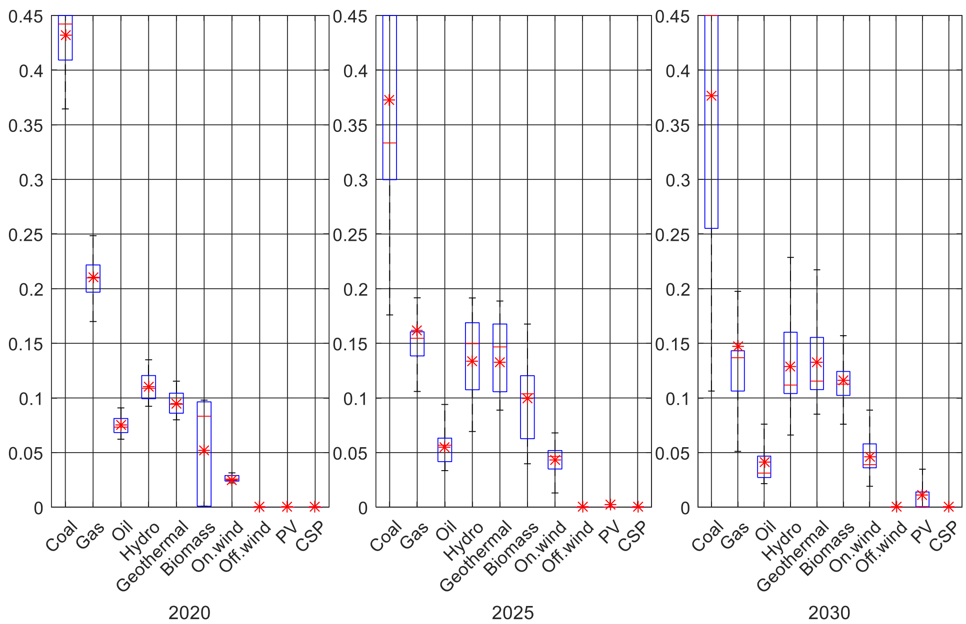

Figure 11. Energy mix for Green Energy Policy option

6 Discussion

Figure 12 integrates the values of renewable energy share, discounted total cost, $CO_{2,eq}$ emissions and total new installed capacity of renewable energy technologies under the different POs considered. As such, it can be observed that the Least cost option offers the lowest total discounted cost at the expense of higher $CO_{2,eq}$ emissions, as compared to the baseline case and the other options examined. In fact, during the planning period 2030, total weighted discounted cost is projected to amount to $ 446 billion, i.e. 5% lower, while $CO_{2,eq}$ emissions are 28% higher (i.e. 732 million ton) than the baseline case. This PO is also characterized by the lowest weighted new installed capacity and total contribution of renewables in the power generation mix when compared to the rest of the POs examined, reaching a weighted average of around 27% share during the planning period 2025, fulfilling the currently existing target of 23% RES share in the power generation mix. Although this option comes with the lowest cost, the power generation mix appears to be less diverse; for example, in year 2030 the individual shares of technologies, with the exception of coal, remain at relatively low levels (weighted values of the rest technologies are below 15%). This can potentially jeopardise the security of the power generation system, since alternative technologies that can provide peak power, such as NG-fired power plants have relatively small shares in the power generation mix. Peaking generation plants, such as the fast start and flexible gas-fired power plants are required to satisfy changes in peak demand and network congestions, which may be caused by the increasing integration of intermittent renewable energy in the network, challenging the power generation system security. Indeed, it is estimated that every 8 MW of wind generation installed, requires approximately 1 MW of new peaking power plant [66]. However, the present model does not take into account the ability of NG fired power plants at demand tracking. It should also be noted that intermittency only applies to specific renewable energy technologies, i.e. the solar PV and the onshore/offshore wind power plants, while geothermal and biomass technologies, which appear to be present in the

Indonesian power generation mix, can be predictable in terms of their output (i.e. dispatchable sources).

As far as the Policy Compliance PO is concerned, it is indicated that the total discounted cost will be higher than the Baseline and the Least cost option, i.e. $ 487.5 billion for year 2030, due to the minimum 24% share of gas-fired plants constraint enforced by the Government. Nevertheless, this PO offers better environmental impact mitigation, as it limits the $CO_{2,eq}$ emissions to 592 million ton of $CO_{2,eq}$ per year, achieving the 26% $CO_{2,eq}$ reduction target for 2030. The RES contribution achieved by this option reaches a weighted mean value of 31%, which is higher than the Least cost option but lower than the Green Energy Policy option. The decreasing trend in power generation from diesel power is a result of the high cost of diesel fuel, as well as the policy target to limit the diesel power up to a maximum 1% in 2030 with the aim to minimize the utilization of expensive imported oil.

The optimal total weighted discounted cost under the Green energy policy option was estimated $592.7 billion, ranking this option as the most expensive among all other options, potentially due to the higher amount of new installed capacity of renewables, needed to satisfy the more ambitious environmental impact mitigation targets. Increasing costs were greatly attributed to the introduction of the carbon pricing policy. Additionally, under this option, the weighted RES share equals to 39% and the expected $CO_{2,eq}$ emissions amount to 514 million tons per year during the 2030 time period. The higher RES penetration targets, the carbon pricing policy and the more ambitious $CO_{2,eq}$ emissions reduction targets resulted in an improved environmental performance of the power generation system, which, however, incurred higher cost to the power generation system.

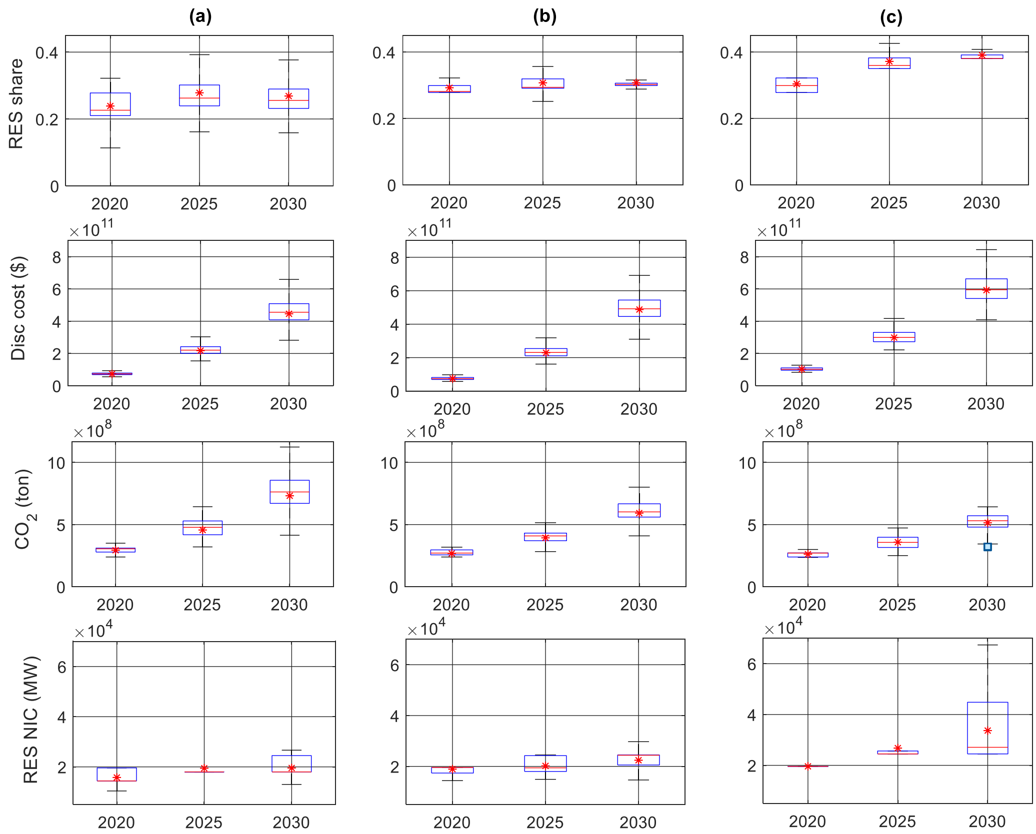

Figure 12. Renewable energy contribution proportion, total discounted cost, $CO_{2,eq}$ emissions and Renewable energy sources (RES) New Installed Capacity (NIC) of technologies for the: (a) Least cost option, (b) Policy compliance option and (c) Green energy policy option

7 Conclusions

In this paper, a multi-stage stochastic optimisation model was developed to optimize future power generation mix of a region or country by minimizing the total discounted cost, whilst also considering a number of constraints related to the peak and consumption demand, renewable energy potential limit, renewable energy penetration targets, annual construction limit, fuel diversity, $CO_{2,eq}$ emission targets and carbon pricing policy. The model took into account the uncertainty of three variables, including the demand of electricity, the future reduction of capital cost of renewable technologies (due to learning curve effects), and the volatility of coal, natural gas and diesel prices. Uncertainty in energy demand and declining capital cost of solar PV and onshore wind was simulated by means of a scenario-tree approach, while the volatility of fuel prices was simulated through Monte Carlo simulation assuming a normal probability distribution.

Indonesia's power system has been used as a case study to test the applicability of the proposed model by means of a baseline case. The model was, then, applied to determine the optimal power generation mix for three planning options: Least Cost, Policy Compliance and Green Energy Policy option.

Across all cases simulated, coal appeared to play a dominant role in the development of power generation system in Indonesia within the next 13 years, as a result of its relatively low construction and operation cost. The results indicated that to achieve the sustainability target set by the policy, Indonesia needs a major expansion in renewable-based power generation capacity to meet the future demand as the conventional fossil-based power generation is capped up to a certain level to meet the $CO_{2,eq}$ reduction target. This will be a significant challenge as the required installed capacity of renewable generation is much higher than the current installed capacity for each renewable technology. On the one hand, enhancing the renewable energy and environmental impact mitigation targets can increase the RES share in the energy mix to the expense of a higher total power generation system cost. On the other hand, a cheaper power generation mix could potentially be achieved (which will potentially also satisfy the RES penetration target); however, imposing no diversity constraints might jeopardise the security of the power generation system. A more secure power generation system can be achieved by diversifying the generation capacities and accommodating fast start and flexible gas-fired power plants. However, the share of power generated from coal and natural gas combined has to be kept below approximately 60% in 2030 to achieve more ambitious environmental impact mitigation targets as the ones assumed under the Green energy policy option. This maximum limit can be increased by shifting from coal to natural gas generation at the expense of higher power generation system cost. Gas-fired generation can, thus, be used as a contingency technology, in order to approach the $CO_{2,eq}$ emission targets, while at the same time offer higher protection against the intermittency of renewable-based power generation and hence support the integration of wind and solar technologies.

The developed model could be a useful tool for decision makers to assist in quantitative analysis and to provide a better understanding in power generation system planning. The results generated by the model could be improved by supplying more accurate data, such as comprehensive remaining technical life data of the existing power generation facilities and annual construction limit for each renewable energy technology that has been assessed further. The methodology developed in this study could also be used in other problems where the optimal solution is highly dependent on the stochasticity of key related variables.

Appendix

Table 4 – List of symbols

C_{rate_τ}	$CO_{2,eq}$ emission rate of power plant technology (ton $CO_{2,eq}$/MWh)
p_{s_D}	Probability of energy demand scenario
p_{s_c}	Probability of capital cost reduction scenario
p_{s_f}	Probability of fuel cost volatility scenario
CF_τ	Capacity factor of power plant technology (%)
CL_T	Annual construction limit for each technology (in MW/year)
C_{emit}	$CO_{2,eq}$ emitted per year (ton of $CO_{2,eq}$/year)
C_{target}	$CO_{2,eq}$ emission limit (ton of $CO_{2,eq}$/year)
C_{tax}	Carbon tax (\$/ton of $CO_{2,eq}$)

L_t	Technical life (in years)
$RE_{pot_{t,T}}$	Renewable potential limit (in MW)
RE_{target_t}	Renewable penetration target in energy mix (%)
s_C	Capital cost reduction scenario of new onshore wind and solar power plants
s_D	Energy demand scenario
s_F	Coal, gas and oil fuel price scenario
CD	Power consumption demand (in MWh)
$EACP$	Annualized capital cost of existing power plants ($/year)
EC	Power generation cost of existing power plants ($/year)
$ECAPEX$	Capital factor of existing power plants ($/kW)
ECC	Carbon cost of existing power plants ($/year)
EFC	Fuel cost of existing power plants ($/year)
$EFOM$	Fixed O&M cost of existing power plants ($/year)
EIC	Installed capacity of existing power plants (MW)
$EVOM$	Non-fuel variable O&M cost of existing power plants ($/year)
FOM	Fixed O&M cost ($/kW)
FP	Fuel price ($/MWh)
FR	Fuel consumption rate (ton/MWh; MSCF/MWh; barrel/MWh)
HR	Power plant heat rate (Btu/kWh)
HV	Average heating value of fuel (Btu/ton; Btu/ft^3; Btu/barrel)
IC	Total installed capacity (MW)
L	Transmission and distribution losses (%)

Max_{cap}	Maximum proportion in energy mix / diversity (%)
Min_{cap}	Minimum proportion in energy mix (%)
$NACP$	Annualized capital cost of new power plants ($/year)
NC	Power generation cost of new power plants ($/year)
$NCAPEX$	Capital factor of new power plants ($/kW)
NCC	Carbon cost of new power plants ($/year)
NFC	Fuel cost of new power plants ($/year)
$NFOM$	Fixed O&M cost of new power plants ($/year)
NIC	Installed capacity of new power plants (MW)
$NVOM$	Non-fuel variable O&M cost of new power plants ($/year)
O	Own use (%)
P	Net power production (in GWh)
PD	Peak demand (in MW)
RIC	Required installed capacity (in MW)
RM	Supply reserve margin (%)
VOM	Non-fuel variable O&M cost ($/MWh)
f	Total power generation cost discounted to present value
r	Interest rate (%)
s	Scenario (path in scenario tree)
t	Time intervals or period
τ	Power generation technology including coal (denoted as “1”), natural gas (“2”), oil (“3”), hydro (“4”), geothermal (“5”), biomass (“6”), onshore wind (“7”), offshore wind (“8”), solar PV (“9”) and solar CSP (“10”)

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APPENDICES

Appendix A - Design implications towards inspection reduction of large-scale structures

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Design implications towards inspection reduction of large scale structures

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Abstract

Operational management is a key contributor in life cycle costs, especially for large scale assets which are in most times complex in structural hierarchy and with a large nominal service life. Decisions on the operational management may concern the number of inspections or maintenance strategies which may allow full utilization of structural capacity or sacrifice residual life in order to avoid an unscheduled intervention. Design of such assets is often governed by design standards which offer the designer the flexibility to take certain decisions that may affect the CAPEX to OPEX ratio such as that of building a more robust structure which may eliminate the need for costly inspection operations. This paper is investigating this approach, taking the example of offshore wind turbine support structures as the reference case, and examines the relevant provisions of the DNV-Os-J101 Standard with respect to the design implications that such a decision may have to the overall life-cycle cost of the structure. Assessment of the structural properties under different design conditions is evaluated through a combination of detailed cost model and an iterative optimization algorithm. The approach which is followed and documented, can be applicable to other complex structural systems for decision making through evaluation of service life costs.

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Keywords: offshore wind energy, monopile, design optimisation, material safety factors, inspection and maintenance, cost model, genetic algorithm

1. Introduction

Complexity of structural systems, introduce a variety of factors that a designer should take into account during the design stage of the project which could in any way affect subsequent stages of the service life of an asset. Energy assets are in most cases characterized by increased complexity and hence decisions over their design and operation becomes even more demanding. Offshore wind energy structures is a representative example of this phenomenon, varying significantly from similar applications, such as those of the offshore oil and gas industry, in the sense that they are deployed in arrays of several units (this number can reach or exceed 100) hence the requirements in mass production, should be designed to accept higher risks due to their unmanned operation in normal conditions and the fact that they refer to a marginal business were profits are limited and highly uncertain. In particular, as of July 2016, 3,344 units were installed and grid connected across Europe, at an average distance to shore of 42 km and 25 meters of deployment depth, accounting of 11.5 GW of total capacity [1] with ambitious targets for the foreseeable future (18 GW to be deployed by 2020) [2].

In this paper we consider the example of the frequency of inspection and maintenance of offshore wind support structures, usually determined by Industrial Standards such as the DNV-RP-J101 [3], recommending fixed intervals between consecutive inspections and outlining the design structural requirements of the wind farm turbines. Since certification is essential for an offshore wind farm to be eligible for insurance, it is of paramount importance for the wind turbines to acquire the certification needed through compliance to the underpinning standards. Although standards are in general very prescriptive, they often allow designer the flexibility to change the length of the inspection intervals by modifying the design of the substructure. As such, the designer can overdesign the support structure through higher material factors in order to expand the inspection intervals yielding significant inspection and potential maintenance cost gains. As a consequence, increasing the material factor of the structure is expected to

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have an effect on the material volume of steel and therefore on the construction cost of the support structure.

This paper investigates the effect of material safety factors on fatigue design of offshore wind turbine monopiles and quantifies the cost implications associated with each case. Results of this work highlight the fact that design elements of offshore wind farms should be based on strategic decisions affecting the levels of CAPEX and OPEX over the lifecycle of an offshore wind farm.

Nomenclature

CAPEX	Capital expenditures
CVI	Close visual inspection
GVI	General visual inspection
OPEX	Operating expenditures
ROV	Remotely Operated Vehicle

2. Inspection of offshore wind turbines

According to DNV-OS-J101 (Chapter 13) [3] periodical inspections should be performed during the design life of the offshore wind farm in the following components:

- wind turbines,
- structural system above water,
- structural system below water,
- submerged power cables.

The present paper focuses on the inspection of the structural system below water. Costs of subsea structural surveys represent around 1% of the total maintenance costs according to a report compiled by Garrad & Hassan [4]. Nevertheless, the high level of expenditure devoted for such investments render their limitation a rather important business.

Typical offshore subsea survey components for the inspection of the structure for the periodical inspections consist of the general visual inspection (GVI) and the close visual inspection (CVI) usually carried out through a Remotely Operated Vehicle (ROV).

One of the main issues of calendar-based maintenance of the subsea structural components is the determination of the interval between consecutive inspections. According to [3] inspection for fatigue cracks should take place at least every five years. However, the frequency of inspections may be waived according to the design philosophy that has been used for the structural components in question. As such, when the fatigue design of the component has been performed by using safety factors corresponding to a condition of no access for inspection operations, the inspections on the specific part could be eliminated. When, however, material factors are smaller, more regular inspections need to be performed. The Guidance note of the DNV-Os-J101 Standard with regards to inspections for fatigue cracks (section 13.3.7.2) recommends that the interval between consecutive inspections can be expressed in relation to the material safety factor γ_m as:

$$\text{Inspection interval} = \text{Calculated fatigue life} \cdot \gamma_m{}^5/1.25^5 \quad (1)$$

Therefore,

- when γ_m=1.25, inspections for fatigue cracks can be fully eliminated,
- when γ_m=1.15, inspections for fatigue cracks are needed every 13 years,
- when γ_m=1.0, inspections for fatigue cracks are needed every 7 years.

It becomes, thus, evident that overdesigning a monopile substructure could potentially reduce calendar-based maintenance costs. However, increasing the material factor would result in a higher volume of the steel quantity used for the construction of the substructure with a subsequent increase in the manufacturing and transportation costs.

3. Development of lifecycle cost model

In order to estimate the effect of the different design configurations on the cost of energy, a lifecycle cost model was developed.

Existing literature on the lifecycle costs of an offshore wind farm indicates that the cost drivers fall into the 5 main phases of the offshore wind farm's life (as in [5-7]), characterized by different operating conditions and cost structures:

1. Development and consenting (D&C)
2. Production and acquisition (P&A)
3. Installation and commissioning (I&C)
4. Operation and maintenance (O&M)
5. Decommissioning and disposal (D&D)

Above cost categories are further broken down into their constituent elements, and accordingly a database is built with the related cost elements.

The cost of energy can be calculated by the following equation:

$$\mathrm{LCOE} = \frac{\text{Sum of lifetime discounted generation costs (£)}}{\text{Sum of discounted lifetime energy output (MWh)}} =$$

$$\mathrm{LCOE} = \frac{\sum_{t=1}^{n} \frac{\mathrm{CAPEX_t + OPEX_t + D}}{(1+\mathrm{WACC})^t}}{\sum_{t=1}^{n} \frac{\mathrm{NET_t}}{(1+\mathrm{WACC})^t}} \quad (2)$$

Where $\mathrm{CAPEX_t}$ is the capital costs in the year t, $\mathrm{OPEX_t}$: operations and maintenance costs, D: decommissioning costs, $\mathrm{NET_t}$: net electricity production in the year t, WACC: weighted average cost of capital.

It is noted that the calculation of total lifetime expenses is based on discounting annual financial flows, taking into consideration the time value of money.

The cost model aims at capturing the impact of applying a different design philosophy by using varying safety factors to the structure on the CAPEX and OPEX. Therefore, the cost components that are explicitly impacted by the design of the monopile are: (a) the cost of monopile steel mass, fabrication, transportation and installation, and (b) the subsurface inspection costs for fatigue cracks. To this end, these are the elements, which are further investigated within the context of this paper.

The following assumptions were applied for setting up the model with regards to the above parameters:

(a) The cost of the monopile (CM_t) during the production and acquisition stage derives from the sum of fabrication (CoF_{monop}) and material cost (CoM_{monop}):

$$\mathrm{CM}_{P\&A} = \mathrm{CoM}_{monop} + \mathrm{CoF}_{monop} \quad (3)$$

The cost of monopile material is calculated by the following equation:

$$\mathrm{CoM}_{monop} = \mathrm{SQ}_{monop} \cdot \mathrm{SP} \quad (4)$$

Where SQ is the steel quantity for the monopiles, SP is the steel price per ton. Cost of fabrication is empirically assumed to be priced twice the cost of the volume of steel required.

$$\mathrm{CoF}_{monop} = 2 \cdot \mathrm{CoM}_{monop} \quad (5)$$

$\mathrm{CM}_{P\&A}$ is added to the cost of installation of the monopile carried out during the installation phase CM_{I}. It was assumed that a high-capacity jack-up vessel needs to be hired for the transportation and installation of the monopiles. The vessel's capacity was assumed to be 5 monopiles with a mobilization time of 3 days. Table 1 displays representative installation vessel day rates in relation to their crane capacity [8].

(b) Sub-surface inspection costs ($\mathrm{CM}_{I\&C}$) are assumed to be carried out by a diving support vessel chartered on the spot market. Cost components of inspections of the structural system below water are summarized in Table 2. The rest of the model's parameters were kept stable across the cases investigated.

Table 1 Approximate day-rates, in thousands £(Source: [8])

Vessel daily rates (thousands £)	Jack-up vessel crane capacity (tones)
192.6	1,200
147.3	1,000
102.0	800

Table 2 Typical inspection costs for structural system below water (Source: [9])

Survey type	Mob, £	Demod, £	Vessel day rate, £/day	Reports, etc.
Structural: GVI/CVI	120,000	60,000	25,000	10,000-15,000

4. A framework for design optimisation of offshore wind support structures

A structural optimisation model based on coupled FEA (finite element analysis) and GA (genetic algorithm) is used to determine the thickness distributions of monopiles.

4.1 Parametric FEA model of offshore wind turbine monopiles

A parametric FEA model of offshore wind turbine monopiles was established using ANSYS, which is a widely used finite element (FE) software. The parametric FEA model enables the design parameters of wind turbine monopiles to be easily modified to create various monopile models. The 3D geometry model and FEA mesh are depicted in Figs. 1 and 2, respectively.

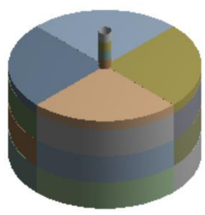

Figure 1 3D geometry models

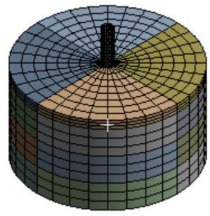

Figure 2 FEA mesh

The flowchart of the parametric model of wind turbine monopiles is presented in Fig. 3.

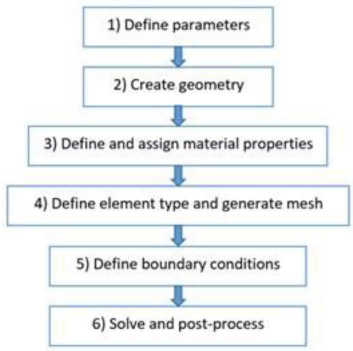

Figure 3 Flowchart of the parametric FEA model for offshore wind turbine monopiles

4.2 Genetic algorithm

GA is a widely used search heuristic that mimics the process of natural selection. Due to its capable of handling large number of design variables and avoiding being trapped in local optima, GA has been employed in complex problems and has proven to be robust for practical engineering application [10], wind turbine composite blades [11] and OWT related studies [12,13]. In GA, a population of individuals (also referred to candidate solutions) to an optimisation problem is iteratively evolved toward better solutions. Each individual contains a set of attributes (such as its chromosomes and genotype) which can be mutated and altered. The evolution generally begins with a population of random individuals, and it progresses iteratively. The population in each iteration is called a generation, in which the fitness of each individual is evaluated. The value of the objective function in the optimisation problem being solved is generally taken as the fitness. The individuals having higher fitness are stochastically selected from the current population, and the genome of each individual is then modified (such as mutated and recombined) to form a new generation, which is then utilised in the next iteration. The GA generally terminates when either the number of generations reaches the maximum value or the current population achieves a satisfactory fitness level.

GA searches for optimal solutions through an iterative way, which is summarised below:

1. Define optimisation objectives, design variables and constraints: The optimisation objectives, design variables and constraints are defined at the first step of GA.
2. Initialise population: Initial population (i.e. initial candidate solutions) is randomly generated in this step.
3. Generate a new population: In this step, a new population is created through mutation and crossover.
4. Design point update: In this step, the design points in the new population are updated.
5. Convergence validation: The optimisation converges when convergence criteria have been reached. If the convergence criteria have not yet been reached, the optimisation is not converged and the evolutionary process of GA proceeds to the next step.
6. Stopping criteria validation: If the iteration number exceeds the maximum number of iterations, the evolutionary process is then terminated without having reached convergence. Otherwise, the algorithm returns to Step 3 to generate a new population.

The above Steps 3 to 6 are repeated until the optimisation has converged or the stopping criterion has been reached.

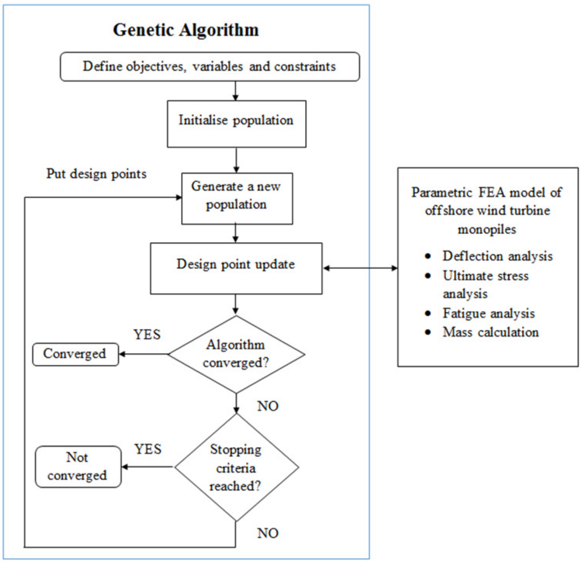

Figure 4 Flowchart of the optimisation model

5. Case study

5.1. Presentation of the case study

In this section the aforementioned methodology is applied to a 500MW offshore wind farm, consisting of 83 turbines. There are numerous studies that have investigated an OWF of 500MW (for example in [4], [6, 14, 15]), allowing for the comparison of results. The wind farm design parameters of the cost model consider a distance to O&M port of 40km, average mean wind speed at 100m above mean sea level 9m/s, fixed monopile foundation type, water depth 20m, 25 years of asset life, nameplate capacity of 6MW and construction duration 5 years. Table 3 presents the distribution of cash flows during the five lifecycle stages of the wind farm at a 30 year period, including 5 years of construction. This includes 5 years of building up the wind farm and 25 years of operation. The parameters that remain stable in the cost structure of the wind farm were adopted by literature sources such as [14] and [15] mostly for the CAPEX and decommissioning components (D&C, P&A, I&C, D&D), while [4] and [9] provided input for calculating the maintenance costs (O&M). The aggregated costs of constant parameters are illustrated in Most of them are presented in Table 4.

Table 3 Distribution of cash flow for the five economic evaluation stages (Source: [14, 16])

	Investment year								
	0	1	2	3	4	5	6–9	10–29	30
	Operational year								
	−4	−3	−2	−1	0	1	2–5	6–24	25
Stage	Weighted investment distribution over the years								
D&C	34%	2%	2%	21.5%	40%	0.5%	0%	0%	0%
P&A	0%	0.1%	16.3%	37.3%	43.4%	3%	0%	0%	0%
I&C	0%	1.65%	1.66%	32.5%	61.4%	2.8%	0%	0%	0%
O&M	0%	0%	0%	0%	0%	0%	0%	100%	0%
D&D	0%	0%	0%	0%	0%	0%	0%	0%	100%

Table 4 Constant cost elements (Source: [14])

Lifecycle stage	Cost element	Costs (£million)
D&C	Project management	41.7
	Legal authorization	16.5
	Surveys	18.9
	Engineering	1.1
	Contingencies	124.6
P&A	Wind turbines	420.3
	Power transmission system	156.5
	Monitoring system	2.5
I&C	Port	14.7
	Installation of the components	265.8-$CM_{I\&C}$
	Commissioning	0.2
	Insurance	20.8
O&M	Onshore logistics, Workboats, Aviation, Crane barge services, etc.	Costs considered according to [4],[9].
D&D	Port preparation	20.9
	Removal operation	188.2
	Waste management	-13.9
	Site clearance	3.6
	Post-decommissioning monitoring	3.6

5.2. Geometry of the monopile

The monopile used in this study has an outer diameter of 6m and an overall length of 55m, consisting of eleven 5m-length segments with varied thicknesses. 35m of the monopile are embedded into the soil, and the remaining 20m covers the distance from seabed level up to the sea surface. Table 5 presents the initial dimensions of the monopile.

Table 5 Dimensions of monopile (bottom-up)

Segments	Outer diameter (m)	Length (m)
Seg1-11	6	5

5.3. Loading conditions

The design of the monopile considers both ultimate and fatigue load cases. For the ultimate load case, the extreme sea condition (i.e. 50-year extreme wind condition combined with extreme significant wave height) is taken as the critical ultimate load case. For the fatigue load case, both wind and wave fatigue loads for the normal operation of offshore wind turbine monopiles are considered. Table 6 lists the ultimate loads under extreme sea condition, and Table 7 presents the fatigue loads. The aerodynamic loads in Table 6 are taken from [17] for WindPACT 5MW wind turbine (making the assumption that a 6 MW will in practice undergo similar loading conditions), which is a reference wind turbine designed by NREL (National Renewable Energy Laboratory).
The wind turbine weight (including the tower head weight (480,076 kg), additional weight at transition connection (5,000 kg) and tower weight (539,000 kg)) with a value of 1,024,076 kg (10,035,945N = 1,024,076kg*9.8m/s^2) is taken into account by adding a point load on the monopile top. For the ultimate load case, a load safety factor of 1.35 is applied to aerodynamic, wave and current loads. For the fatigue analysis, D curve in seawater with cathodic protection is chosen as the fatigue design curve.

Table 6 Ultimate loads under extreme sea condition

Item	Aerodynamic loads [17]	Wave loads	Current loads
F_x (kN)	1,057	677	348
M_y (kN-m)	135,000	-	-

Table 7 Fatigue loads (Note: subscript *f* denotes fatigue loads)

Item	Aerodynamic loads [17]	Wave loads
$F_{x,f}$ (kN)	197	210
$M_{y,f}$ (kN-m)	29,874	-

6. Results

Three values of material safety factors are considered (i.e. 1, 1.15 and 1.25). The obtained thickness distribution of the monopile is presented in Table 8.

Table 8 Thickness distribution of the monopile

Segment ID	**Thickness [m]**		
	Case A	Case B	Case C
1~7	0.074	0.083	0.089
8	0.060	0.067	0.077
9	0.054	0.055	0.067
10	0.052	0.053	0.056
11	0.045	0.051	0.052

The mass of the monopile, the mass increase in relation to the reference case, along with the resulting CAPEX to OPEX ratio and LCOE values under the different cases are presented in Table 9.

Table 9 Results of the analysis

Inspection scheme	**Base case A: Every 7 years**	**Case B: Every 13 years**	**Case C: No inspections**
Mass of the monopile (kg)	535,230	592,500	642,420
Mass of monopile and tower (kg)	89,161	93,915	98,058
Mass increase (%)	0	6.5	12.2
CAPEX to (annual) OPEX ratio	$\frac{\mathbf{1,235}}{\mathbf{86.0}} = \mathbf{14.36}$	$\frac{\mathbf{1,244.8}}{\mathbf{85.8}} = \mathbf{14.51}$	$\frac{\mathbf{1,253.4}}{\mathbf{85.7}} = \mathbf{14.62}$
LCOE (£/MWh)	120.44	120.95	121.42

According to the derived results, despite the decrease in OPEX due to the wider fixed inspection intervals, employing higher material factors in the monopile structure is expected to increase the total cost of energy. Nevertheless, it is worthwhile noting that the cost model analysis is quite sensitive to a number of parameters, as outlined by literature [15], [6], and results are highly depended on the variability of these parameters, e.g. the discount rate, the O&M costs, the support structure cost, etc. The steel prices, which in the present analysis play an important role in the determination of the cost of energy under the different cases, for example are quite volatile and fluctuate considerably among countries as well as across different grades of steel, quality and transport options [6]. In the present analysis a base price of £690 per ton of bulk steel was assumed. Fig.5 shows that in order to breakeven the cost of energy between monopile designs with material factors 1 and 1.15 (when all other variables remain constant) the steel price needs to amount £100/ton; while the breakeven steel price for worth switching from 1 to 1.25 material factor is £80/ton.

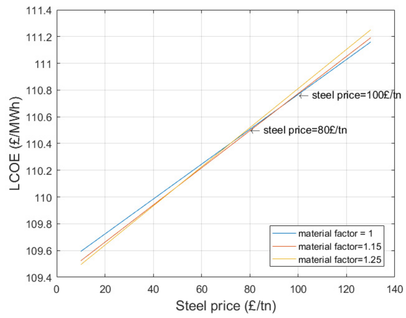

Figure 5 Breakeven points of steel prices resulting in equal costs of energy under different material factors

7. Discussion

This study investigates the potential of design Standards provisions towards shifting the balance between OPEX and CAPEX. As it is expected, designing more conservative substructures is likely to increase the cost of energy; however, one has to take into account a number of market-related factors (which could be potentially incorporated in a more extensive cost model), before a final conclusion can be made. The supply chain of the offshore wind industry is currently being developed, hence pricing for lifting and transportation operations are likely to be reduced. Further, optimization and automation of manufacturing processes for monopiles are expected to reduce overall CAPEX, making the more conservative designs more attractive.

A different perspective suggests that more conservative designs could ultimately enable the consideration of the life extension of the asset, practice that has been extensively observed in oil and gas infrastructure with examples of assets which have doubled their nominal service life. Nevertheless, the financial impact of extending the fatigue life has to be evaluated by taking into consideration the additional revenues that would accrue from the additional energy production as well as the extra operating costs that are added. Moving towards deeper waters and considering XL monopiles, the exercise needs to be updated as both volume of material as well as extend of inspection will bear further complexities. On a similar logic and as the maturity of the industry increases, a new generation of smarter assets is expected to be developed, adopting 'smarter' concepts such as structural health monitoring for system prognostics. With consistent information about the performance of the assets, which can allow timely investigation of deviation of normal operation, the requirement for more conservative designs is alleviated and hence designs can be informed accordingly, once again affecting the CAPEX to OPEX ratio. The authors are currently investigating the cost/benefit balance of such design decisions in parallel studies.

8. Conclusions

The present study investigates the impact that different monopile designs can have, based on relevant provisions of design standards, on the life cycle costs of an offshore wind farm by developing a structural optimisation model based on FEA (finite element analysis) and GA (genetic algorithm) to determine the optimized thickness distributions under different material safety factors, coupled with a cost model which enables to detect the effect of above design elements on the capital and inspection and maintenance costs and, as a result, on the levelised cost of energy of the technology.

Application of the method on a hypothetical 6 MW offshore wind turbine, draws the following useful conclusions:

- Despite the decrease in OPEX, employing higher material factors in-line with the provisions of design standards, is expected to increase the total cost of energy.
- Variability of key design parameters, e.g. the discount rate, the O&M costs, the support structure cost, etc. may highly affect the confidence of the assessment.
- The optimization algorithm and cost model that have been developed are found to be sufficiently robust and can be employed for the evaluation of similar design variations, i.e. optimizing thickness to diameter ratio, piling length, longitudinal stiffeners consideration, consideration of integrity monitoring etc., towards reducing the LCOE.

It becomes apparent from the present study that the design options can have cost implications which need to be evaluated throughout the service life of the asset, in order to adequately support decisions.

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Appendix B - Stochastic Prediction of Offshore Wind Farm LCOE through an Integrated Cost Model

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Stochastic Prediction of Offshore Wind Farm LCOE through an Integrated Cost Model

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Abstract

Common deterministic cost of energy models applied in offshore wind energy installations usually disregard the effect of uncertainty of key input variables – associated with OPEX, CAPEX, energy generation and other financial variables – on the calculation of levelized cost of electricity (LCOE). The present study aims at expanding a deterministic cost of energy model to systematically account for stochastic inputs. To this end, Monte Carlo simulations are performed to derive the joint probability distributions of LCOE, allowing for the estimation of probabilities of exceeding set thresholds of LCOE, determining certain confidence intervals. The results of this study stress the importance of appropriate statistical modelling of stochastic variables in order to reduce modelling uncertainties and contribute to a better informed decision making in renewable energy investments.

Peer-review under responsibility of the scientific committee of the 3rd International Conference on Energy and Environment Research.

Keywords: *Offshore wind farm; probabilistic cost model; Monte Carlo simulation, levelised cost of electricity, stochastic inputs*

1. Introduction

Sources of uncertainty affecting investment decisions for offshore wind energy projects, can be found in the amount of capital, operating, decommissioning and financing costs, as well as in technical aspects, such as the wind farm availability, aerodynamic, electrical array and other losses. Considering the continuous progress in the sector,

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these input variables are continuously updated, while they also vary significantly across different regions and water depths. These input variables can be, thus, better defined within a range and a probabilistic analysis can be employed, in order to derive probabilities of obtaining a certain amount of cost of energy.

A common measure to evaluate the life-cycle costs of generation of an energy project, as well as to compare different generation technologies is the levelized cost of electricity (LCOE), accounting for the installed capital cost, the annual operating expenses, as well as the annual energy production [1,2]. This metric allows to calculate the per unit of electricity generated cost, expressed in £/MWh. The contribution of the present study lies in the amplification of a deterministic cost of energy model of a representative offshore wind farm (OWF) [3] with the incorporation of uncertainty in key input parameters to derive representative ranges of LCOE values.

2. Costs of offshore wind farms

2.1. Capital and operating costs of an offshore wind farm

Capital expenditure comprises costs for building and commissioning of the plant, such as costs associated with the project development and consenting up to financial investment decision (FID), material and labor costs for the turbine, support structure, tower, foundations, array cables, installation, transmission build and insurance during the construction phase. Capital costs in the offshore wind energy industry have been increasing over the last decade owing to a number of reasons: installations in deeper waters and farther from shore bearing increased construction and installation costs, rise in turbine prices due to design improvements ensuring higher reliability levels (as a result of the higher awareness of technical risks), constraints in port and vessel availability, changes in global and national macroeconomic drivers, such as labor, increasing prices of commodities and energy and fluctuations in exchange rates impacting the capital cost structure. CAPEX values range across a number of sources as illustrated in Fig. 1a.

Operation and maintenance (O&M) costs account for ongoing costs needed to operate and maintain the plant. OPEX usually consists of fixed costs that do not depend on the plant uptime and variable costs that depend on the time the plant operates. Operations mostly represent activities associated to high level management of the plant, such as remote and environmental monitoring, administration, marketing, insurance, payment of the rent and other back office activities. Maintenance is the task that bears most of the effort, cost and risk, consisting of preventative (costs of proactive repairs based on condition monitoring systems) and corrective maintenance tasks (involving costs for reactive repair or replacement of equipment). A number of recent publications (Fig. 1b) have attempted to estimate ranges of operating costs for offshore wind installations either based on historical data of installed projects, or through publically available data and direct surveys of project developers [4, 5].

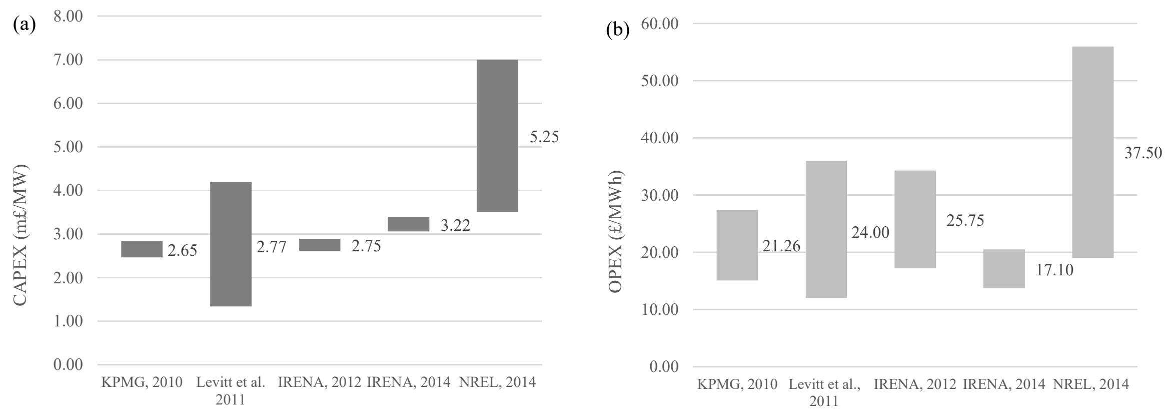

Fig. 1. (a) Range and average values of capital costs (£m/MW) in existing literature compiled and converted to 2015 £ currency; (b) Range and average values of operating costs (£/MWh) in existing literature compiled and converted to 2015 £ currency (Sources:[4–8])

3. Development of a cost model for offshore wind farms through life costing

3.1. Breakdown of cost model of the offshore wind farm

The breakdown and structure of the cost model have been adopted from the "Simple Levelised Cost of Energy Model" developed in the context of DECC Offshore Wind Programme [9]. The use of a broadly available simple cost model can increase the consistency and transparency of the calculations, considering that the purpose of the paper was not to provide a detailed cost model of an offshore wind energy investment; but, rather, to indicate how assessment and results would change if the deterministic analysis is expanded to take into account systematically the stochasticity of some uncertain financial and technical variables. The CAPEX and OPEX components of the OWF are depicted in Fig. 2.

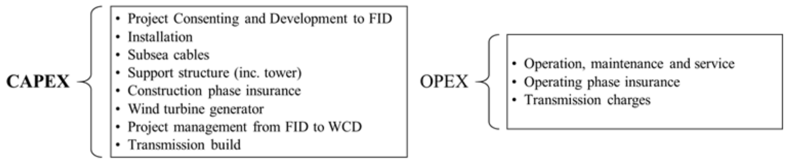

Fig. 2. OPEX and CAPEX break down (Source:[9])

3.2. Stochastic expansion – A Monte Carlo simulation approach

The deterministic cost model developed was expanded with the view to include stochastic parameters and to derive probabilities of exceeding set thresholds of the output variables at the same time assigning confidence intervals to the reported results. Towards this direction, the parameters of the cost model were divided into stochastic variables, design parameters and output variables.

Stochastic are the variables whose values are subject to variations and cannot be approximated with a deterministic value. Stochastic variables are assigned probability density functions (PDF) defining the frequency of occurrence of a value within a range. Evidently, not all parameters of the model are useful for a probabilistic analysis. Design parameters are the ones that need to be determined by the designer of the offshore wind installation and hence whose values cannot be approximated by a PDF. For the investigated case study, the wind farm design parameters are listed in Section 4.

In the present cost analysis, the variables that were considered as stochastic were: the CAPEX components, the operational expenses, the gross load factor, the wind farm availability, the aerodynamic array losses, the electrical array losses, other losses, the decommissioning cost as well as the discount rate. While the design parameters of the problem were the asset life, the type of the monopile, the capacity of the wind farm and the construction duration (years). Finally, LCOE was set as the output variable.

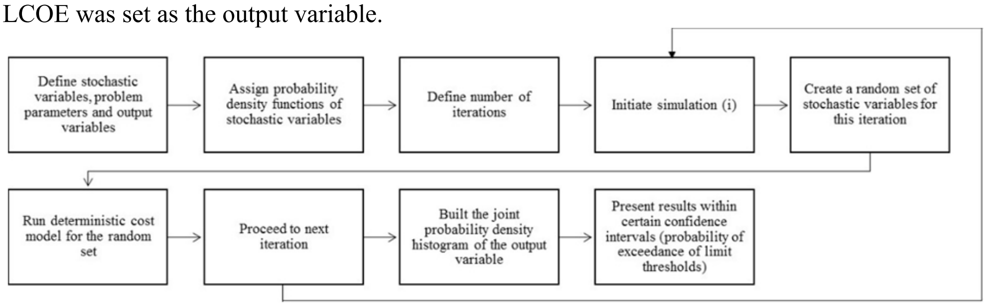

Fig. 3. Description of the simulation process

The proposed methodology (Fig. 3) has been modelled in Microsoft Excel, using Monte Carlo simulations to generate stochastic inputs, which are then undertaken in the @RISK extension.

4. Stochastic evaluation of LCOE through accumulated industry databases

4.1. Case study description, definition of stochastic variables, design parameters and output variables

The case study employed was based on the design (problem) parameters of a simple LCOE model developed by BVGA (as mentioned earlier) allowing for comparison against a base case scenario OWF with deterministic values. As such, the case study concerns an OWF of 500MW installed capacity, representing a typical UK Round 2 site installation (ranging from 65MW- 900MW). The wind farm design parameters of the cost model consider a distance to O&M port of 40km, average mean wind speed at 100m above mean sea level 9m/s, fixed monopile foundation type, 20 years of asset life, nameplate capacity of 6MW and construction duration to be 5 years.

As far as the unknown input variables are concerned, in the absence of detailed statistical data, accumulated data from different sources of literature were sought and their impact on LCOE was investigated with a view to highlight the importance of appropriate statistical modelling of stochastic variables in order to reduce modelling uncertainties. To stochastically model the uncertain variables, the CAPEX and OPEX ranges identified in literature (Fig. 1a and 1b) were used to estimate the coefficients of variation, in order to observe the impact of variation on the accuracy of results. In the case that real data are available through operators' experience, the same process could be adopted, following distribution fitting of the real data or estimates with determined confidence levels.

4.2. Determination of probability density functions of stochastic variables

Initially, the ranges of values from literature were considered to follow a normal probability distribution. Based on this assumption, and for given minimum, maximum and mean data values for operating and capital costs (retrieved from literature), the standard deviations and hence the coefficient of variation values were estimated as shown in Table 1. It should be noted that non-normal distributions can accommodate relevant set of data.

Table 1. Standard deviation (σ) and coefficient of variation values (COV) derived from literature sources illustrated in Fig. 1a and 1b

	Capital costs (million £/MW)		Operating costs (£/MWh)	
	σ_CAPEX	COV	σ_OPEX	COV
KPMG, 2010	0.12	0.04	3.76	0.18
Levitt et al. 2011	0.87	0.32	7.30	0.30
IRENA, 2012	0.09	0.03	5.20	0.20
IRENA, 2014	0.10	0.03	2.07	0.12
NREL, 2014	1.07	0.20	11.20	0.30

The coefficient of variation values of capital and operating costs (summarized in Table 2) were used to estimate the standard deviations for each of the OPEX and CAPEX elements of the DECC cost model, respectively. The mean values, μ of the stochastic variables (adopted from the DECC cost model) are shown in the left side of Table 2. The rest of the unknown input variables (associated with energy generation and financial variables) were also approximated through normal distributions and standard deviations of 10% over their mean values.

4.3. Results

The base case deterministic LCOE value using the mean values of the unknown variables as listed in Table 2 was found to be 116.3£/MWh. Accordingly, the stochastic cost modelling was performed for the five (5) sets of standard deviations calculated in Section 4.2 through Monte Carlo simulation (MCS). Fig. 4 illustrates the generated joint probability distributions of LCOE values derived for all five (5) sets of data, while in Table 3 the resulting summary statistics are presented. LCOE1 calculation corresponds to data retrieved from KPMG (2010); LCOE2 to data from IRENA (2011) and so on (as shown in Table 3).

Table 2. Mean values and standard deviations of the stochastic variables (mean values are adopted from DECC cost model)

CAPEX: (£000s/MW)	μ
Project Consenting and Development to FID	160
Project management from FID to WCD	37
Construction phase insurance	41
Turbine (exc. Tower)	1117
Support structure (incl. tower)	467
Array cables	81
Installation	271
Transmission build	429
Construction contingency	244
OPEX: (£000s/MW/yr)	
Operation, maintenance and service	67
Operating phase insurance	15
Transmission charges	10

Energy generation	
Gross load factor (%)	Normal (μ=52.1%, σ=5.21%)
Wind farm availability (%)	Normal (μ =95.4%, 4.8%)
Aerodynamic array losses (%)	Normal (μ =9.0%, 0.09%)
Electrical array losses (%)	Normal (μ =1.0%, 0.1%)
Other losses (%)	Normal (μ =4.6%, 0.46%)
Decommissioning cost (£)	Normal (μ= 247000, σ=24700)
Financial variables	
Discount rate (%)	Normal (μ=8.9%, σ=0.89%)

Table 3. Summary statistics derived from the five (5) different data sets

(£/MWh)	LCOE 1	LCOE 2	LCOE 3	LCOE 4	LCOE 5
Input source	KPMG, 2010	Levitt et al. 2011	IRENA, 2012	IRENA, 2014	NREL, 2014
Min value	72.74	49.28	71.26	67.12	70.89
Max value	216.25	228.33	203.72	210.24	214.79
μ	117.91	117.92	117.93	117.92	117.92
σ	15.65	21.22	15.83	16.14	16.07

Unsurprisingly, the LCOE probability distribution associated with the highest COV is characterized by the highest standard deviation; hence, the highest variation in the results. Among the cases that were considered above, the one with the highest standard deviation is LCOE2 with σ=21.22 £/MWh (Table 3), represented in Fig. 4 by the dark grey coloured histogram. Conversely, the probability distribution with the steepest probability of occurrence peak and the lowest standard deviation (σ=15.65 £/MWh) corresponds to LCOE1 (light grey colour), which demonstrates a considerable concentration of results around the mean LCOE value. Fig. 4 illustrates the frequency histograms of the output variable (LCOE) with figures for the highest and lowest scatter datasets. In fact, for the lower scatter dataset (LCOE1), the 5% and 95% percentiles are presented with LCOE values of 94.7 and 145.7 £/MWh, respectively. For the latter values of LCOE, the corresponding percentiles for the highest scatter dataset (LCOE2) are 12.5% and 90.2%. Probability distributions of LCOE with intermediate scatter datasets are also included in Fig. 4 (i.e. LCOE 3, 4 and 5).

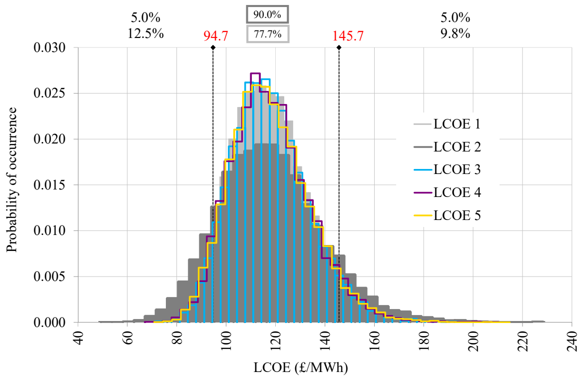

Fig. 4. Probability distributions of LCOE values for different sets of stochastic input variables (percentiles for two extreme scatter datasets)

4.4. Sensitivity analysis

The stochastic cost modelling was followed by a sensitivity analysis in order to investigate the impact of the unknown input parameters on the LCOE mean value. The baseline mean value was calculated around 117.9 £/MWh following the stochastic expansion of the cost model.

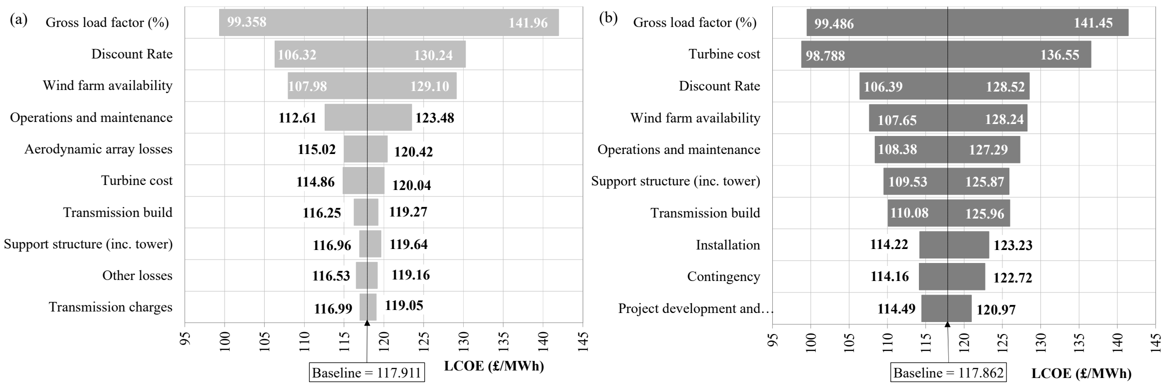

Fig. 5. Tornado diagram for (a) LCOE1 (lowest scatter dataset); (b) LCOE2 (highest scatter dataset)

Tornado diagrams for the lowest and highest scatter datasets are presented in Fig. 5a and 5b, respectively. As shown, the sensitivity of LCOE to the problem variables changes when different variabilities of stochastic parameters are considered. For instance, when wider ranges (higher scatter dataset) in turbine cost, O&M and support structure costs are considered, they appear to have a higher impact on LCOE than in the case of the lowest scatter dataset. Additionally, a few parameters such as installation, contingency and project consenting and development costs that are found to have considerable impact in the highest scatter dataset case, they are not as impactful on the LCOE for the lowest scatter dataset.

5. Conclusions

The LCOE models of renewable energy technologies are usually deterministic, generating results under specific conditions and assumptions. Nevertheless, some of the input parameters are uncertain or may change over time; hence, they should be better defined in a range. Examples are the different components of capital and operating costs, the discount rates as well as technical parameters such as the capacity factor. A probabilistic analysis intends to account for these uncertainties and to quantify their influence on the cost of energy. This study has extended a deterministic cost model to account for uncertainties associated with investing in an OWF.

Results illustrate that appropriate statistical modelling can significantly influence accuracy in prediction of LCOE. The proposed methodology suggests the application of probabilistic methods such as Monte Carlo simulation for the systematic modelling of uncertainties towards a better informed decision making framework in renewable energy investments. The framework developed for the extension of the deterministic method to account for stochastic inputs, can be further applied to other cost models and similar engineering problems.

Acknowledgements

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Appendix C - Effect of electricity market price uncertainty modelling on the profitability assessment of offshore wind energy through an integrated lifecycle techno-economic model

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Effect of electricity market price uncertainty modelling on the profitability assessment of offshore wind energy through an integrated lifecycle techno-economic model

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Abstract. According to the Contracts for Difference (CfD) scheme introduced to support the deployment of offshore wind installations, an electricity generation party is paid the difference between a constant “strike price” (determined be means of a competitive auction) and the average UK market electricity price for every MWh of power output produced. The scheme lasts for 15 years, after which the electricity output is sold on the average market price. To this end, estimating the long term profitability of the investment greatly depends on the forecasted market prices. This paper presents the simulation results of future electricity prices based on three different simulation methods, namely: the Geometric Brownian motion (GBM), the Autoregressive Integrated Moving average (ARIMA) and a model combining Mean-Reversion and Jump-Diffusion (MRJD) processes. A number of simulation paths are generated for a time horizon of 10 years and they are introduced to a fully integrated techno-economic model developed by the authors. As a result, joint probability distributions of the NPV derived from the three different methods are presented. This study is relevant to investors and policy makers to check the viability of an investment and to predict its stochastic temporal return profile.

1. Introduction

Offshore wind energy has been rapidly expanding in Europe during the last decade. According to WindEurope annual offshore wind statistics, there are currently 92 wind farms in operation across European countries (4,149 grid-connected wind turbines) [1] with UK accounting for 43% and Germany for 28% of all grid-connected turbines.

In the United Kingdom, there is currently a transition from the Renewables Obligation (RO) scheme to the Contracts for Difference (CfD) scheme, introduced by the recent Electricity Market Reform (EMR). The CfD scheme is a private law contract between a producer and the Low Carbon Contracts Company (LCCC), a government-owned company. An electricity generation party with CfD is paid the difference between a constant “strike price” and the average UK market electricity price (“reference price"). The Generator sells electricity under a Power purchase agreement to a licensed supplier or trader at an agreed reference market price. If the reference price is higher than the strike price, the generation party has to pay back the difference to the LCCC. The bottom line is that company always gets the strike price for the electricity generated. The scheme lasts for 15 years (while the expected lifetime of an OW energy asset is 25 years), after which the electricity output is sold on the average UK electricity market price, hence imposing uncertainty to the revenues yielded by the investment after the 15th year of operation [2]. As such, the forecasting of electricity prices becomes pertinent towards estimating future returns of the offshore wind energy project as well as, the overall profitability of the investment.

This work aims to stochastically assess the impact of volatile market electricity prices on the profitability assessment of offshore wind farms. We develop and formalize a process for more detailed modelling of the future economic cash flow of an offshore wind farm by employing a tested lifecycle techno-economic model which accommodates the uncertainty modelling of electricity prices through employing different forecasting methods in order to test how these can affect the Net Present Value (NPV) distribution analysis of the wind farm. A stochastic cost modelling of the economic profitability is finally derived.

2. Lifecycle techno-economic model

The methodological framework of the techno-economic model is illustrated in Figure 1. The main components of the life cycle cost of a fixed OW farm are the following: (i) the CAPEX module, which includes development and consenting (D&C), production and acquisition (P&A), installation and commissioning (I&C), and decommissioning and disposal (D&D) costs, (ii) the general site characteristics module with details on the weather conditions, site water depth, distance from port, vessels, cost of personnel etc., (iii) the FinEx module with parameters related to the financing expenditures, namely the Weighted Average Cost of Capital (WACC), inflation rate, equity and debt ratio, etc., (iv) the OPEX module, which considers reliability data from literature, cost of personnel, materials, vessels and related maintenance processes, which will provide availability and O&M cost estimates pertinent for the cost analysis and (v) the Revenue model, which considers the net power generation, the strike prices (according to the CfD scheme), and the market electricity price. A detailed description of the model can be found in [3].

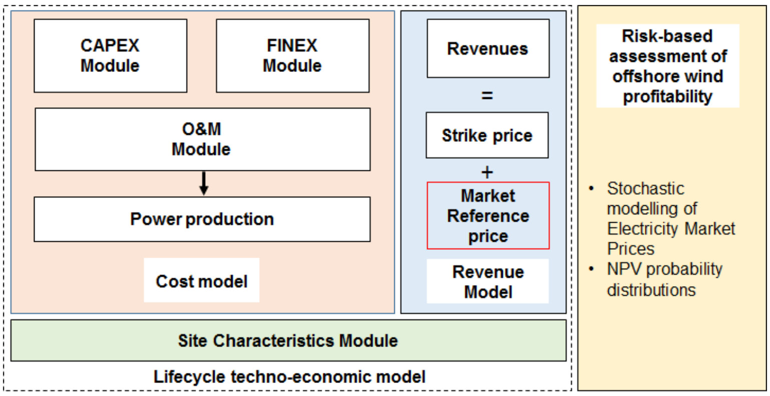


Figure 1 Illustration of integrated techno-economic lifecycle model

3. Modelling & Simulation of future wholesale electricity prices

This section looks at the forecasting methods that were employed to model electricity market prices, towards incorporating the uncertainty and variability in the cash flow model of the analysis. The modelling of market electricity prices has been carried out by numerous authors in literature [4–6], highlighting the advantages and disadvantages of each technique and applying them in various contexts. Time series techniques are usually based on extrapolating a set of historic observations to predict their behavior in the future. In [5], electricity price forecast techniques are categorized into: multi-agent, fundamental methods, reduced-form models, statistical approaches and computational intelligence techniques. Statistical methods, including autoregressive models forecast the future value of a time series by applying a mathematical correlation of the previous values with the current values. The ARIMA time series model and the Geometric Brownian motion are among the most cited forecasting techniques [4,7,8]. However, statistical methods cannot capture sufficiently the presence of spikes in the dataset, especially for price-only models, but also for models using fundamental variables. Mean-reverting jump-diffusion (MRJD) processes are more appropriate to reproduce patterns of spikes and reversion to a long term mean level [9].

In this study we have tested above forecasting techniques to identify the effect of uncertainty modelling in electric market prices on the profitability of an offshore wind investment. Daily historical data of electricity market prices (found in [10]) were used to stochastically model the future revenues of the investment.

3.1. Geometric Brownian motion

Financial time series are most commonly based on stochastic differential equations (SDEs) which are the most general descriptions of continuously evolving random variables. Geometric Brownian motion is the simplest and most common financial time series model, according to which the logarithm of the randomly varying quantity follows a Brownian motion with drift.

Brownian motion (also called Wiener process) with drift parameter μ and volatility σ is a kind of Markov stochastic process $\boldsymbol{W} = \{X_t: t \in [0, \infty)\}$ of the form:

$$X_t = \mu t + \sigma W_t \tag{1}$$

The generalised form of the Geometric Brownian motion (GBM) process is specified through a stochastic differential equation (SDE) of the form [11]:

$$\frac{dS_t}{S(t)} = \mu dt + \sigma d\mathrm{W}(\mathrm{t}) \tag{2}$$

where, S(t) denotes the price of the electricity at time t, μ represents the drift parameter, σ the volatility of the electricity prices and W is the standard Brownian motion.

The Wiener process satisfies the following properties: a) The process starts from 0 $X_0 = 0$ (with probability 1), b) $\boldsymbol{W}$ has Gaussian increments, i.e. for $h \geq 0, X_{t+h} - X_t$ is normaly distributed with $\mu = 0$ and variance σ (same distribution as X_h), c) $\boldsymbol{W}$ has independent increments; that is, for $t_1, t_2, .., t_n \in [0, \infty)$ with $t_1 < t_2 <, .., < t_n$, the random variables $X_{t_1}, X_{t_2} - X_{t_1}, \dots, X_{t_n} - X_{t_n - 1}$ are independent, d) X_t has a normal distribution with mean t_n , e) $\boldsymbol{W}$ has continuous paths, namely with probability 1, X_t is continuous on $[0, \infty)$.

Using Itô's lemma and integrating over time, the relationship between an initial value S_t and a later value S_{t+T}:

$$S_{t+T} = S_t \cdot \exp\left[\left(\mu - \frac{\sigma^2}{2}\right)T + \sigma W_t\right] \tag{3}$$

Above equation is the GBM model. This process has the advantage that it always remains positive and it can represent the characteristics of many variables.

3.2. Mean-reverting jump-diffusion (MRJD) process

The jump-diffusion model can be expressed by the following general stochastic differential equation for the increment of the electricity price (after removing seasonality and trend from the dataset):

$$dX_t = \mu(X_t, t) + \sigma(X_t, t)dW_t + dq(X_t, t) \tag{4}$$

Where, dW_t represent the increments of a standard Wiener process (i.e. Brownian motion) and $dq(X_t, t)$ are the increments of a jump process.

When there is a high electricity demand, more expensive power generation technologies need to be brought online to cover the electricity load. During these periods, electricity prices exhibit jumps. In general, spot electricity prices are characterised by high volatility, seasonal cycles and occasional spikes. In mean-reverting jump-diffusion processes, the drift term $\mu(X_t, t)$ can force reversion to long term mean levels. The Ornstein-Uhlenbeck process, which is the most applied mean-reversion process (initially introduced in finance to model interest rate dynamics [12]), is expressed as:

$$dX_t = (\alpha - \beta X_t)dt + \sigma dW_t \tag{5}$$

Where, β the mean-reversion speed and $\frac{\alpha}{\beta}$ is the long term mean reversion level.

3.3. *Autoregressive Integrated Moving Average (ARIMA)*

ARIMA or Box-Jenkins model [13] is a statistical method standing for autoregressive (AR) integrated (I) moving average (MA) and it is a generalisation of the Autoregressive Moving Average model (ARMA), where "I" (standing for Integrated) is a differencing step that is used to remove trend or seasonality from the time series. ARIMA models use standard notation of ARIMA (p,d,q) and (P,D,Q) for their seasonal counterparts. In power systems applications, ARIMA models have been used for load forecasting [14,15], with good results, as well as to model and forecast day-ahead electricity prices [16,17] and weekly prices [18]. ARIMA method was deemed appropriate for this study considering the ability of the method to take into account the seasonal trend of the dataset of electricity prices.

- The Autoregressive part (p) specifies which previous values from the data series are used to predict the current values or else the number of autoregressive orders.
- The Difference part (d) specifies the order of differencing of the time series before the application of the model. To apply the ARIMA model, the dataset is required to be stationary; if not, a transformation of the series to the stationary form needs to take place. Differencing is one of the simplest ways to achieve this. Box and Jenkins (1976) introduced a model that contains not only the autoregressive and moving average parts, but also the differencing part [19].
- The moving average part (q) specifies the order of moving average orders in the model, namely how the mean values deviation of the previous time series are used to predict the current values.

As such, the mathematical formulation of the ARIMA(p,d,q) model can be described using a lag operator notation (defined as $L^i X_t = X_{t-i}$) as follows:

$$\varphi(L)(1 - L)^d X_t = c + \theta(L)\varepsilon_t \tag{6}$$

where, X_t is the price at time t, c a constant term, d the differencing order, ε_t is the random error at time t; further, $\varphi(L)$ are the parameters of the AR model formulated as:

$$\varphi(L) = 1 - \varphi_1 L - \cdots - \varphi_p L^p \tag{7}$$

where, p refers to the autoregressive terms, while $\theta(L)$ are the parameters of the MA(q) model expressed as:

$$\theta(L) = 1 + \theta_1 L + \ldots + \theta_q L^q \tag{8}$$

where q refers to the moving average terms [13].

4. Simulation of future electricity prices

4.1. Electricity price prediction under the different methods

Monthly and daily data of the wholesale electricity prices were collected from different sources [10,20] to compile a dataset starting from March 2003 to December 2017. The dataset (178 observations) was divided into two parts, the first consisting of 118 observations, which was used to build the model and the second of 60 observations for testing the model.

After determining the input parameters for the best-fitting ARIMA model (through Expert Modeler of SPSS) as well as the respective inputs for the Geometric Brownian motion, and the Mean-Reversion and Jump-Diffusion (MRJD) processes using historic monthly electricity prices, we, accordingly, simulated 1,000 sample paths, 10 years into the future. Figure 2 illustrates the simulation results of future electricity prices with the MRJD model from 2017 to 2027.

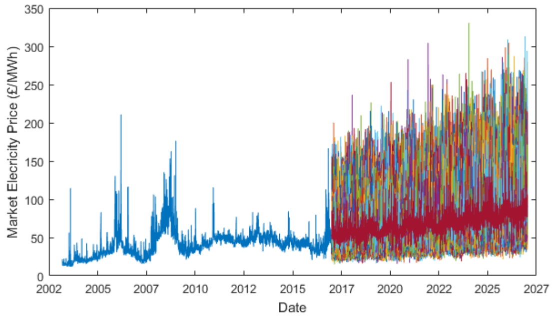


Figure 2 Simulation of future electricity prices with the MRJD model

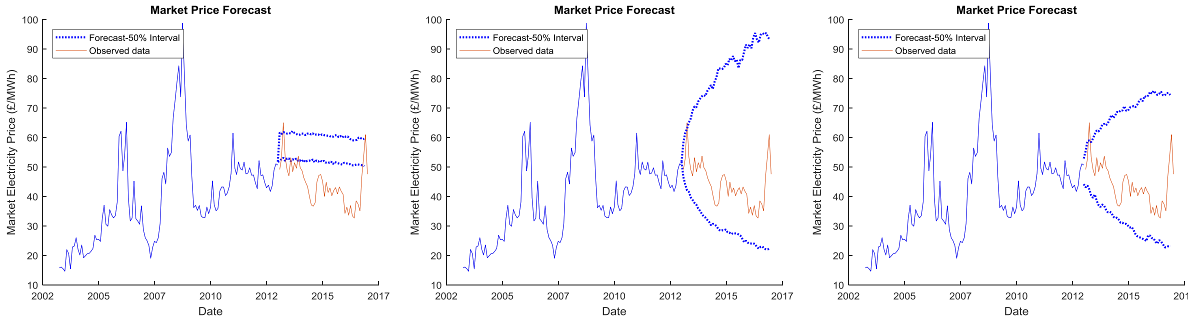
4.2. Validation of methods

In Figures 3(a)-(c), the 50% upper and lower confidence limits of the resulting model for the first part of the dataset, as well as the observed data for 2015-2017 (2nd part of the dataset) are illustrated for the 3 different forecasting methods. The mean absolute percentage errors and the percentage errors between the observed data and the forecasted values for the four testing years are summarized in Table 1. ARIMA was deemed to have the lowest Mean Absolute Percentage Error in comparison to the other 3 methods namely 14.8%, indicating a relatively better fitness of the ARIMA model to the dataset, followed by the MRJD and the GBM models. MAPE is a measure of prediction accuracy of the forecasting method and is calculated as follows:

$$MAPE = \frac{100\%}{n} \sum_{t=1}^{n} \left| \frac{F_t - A_t}{A_t} \right| \tag{9}$$

Table 1 Validation of methods

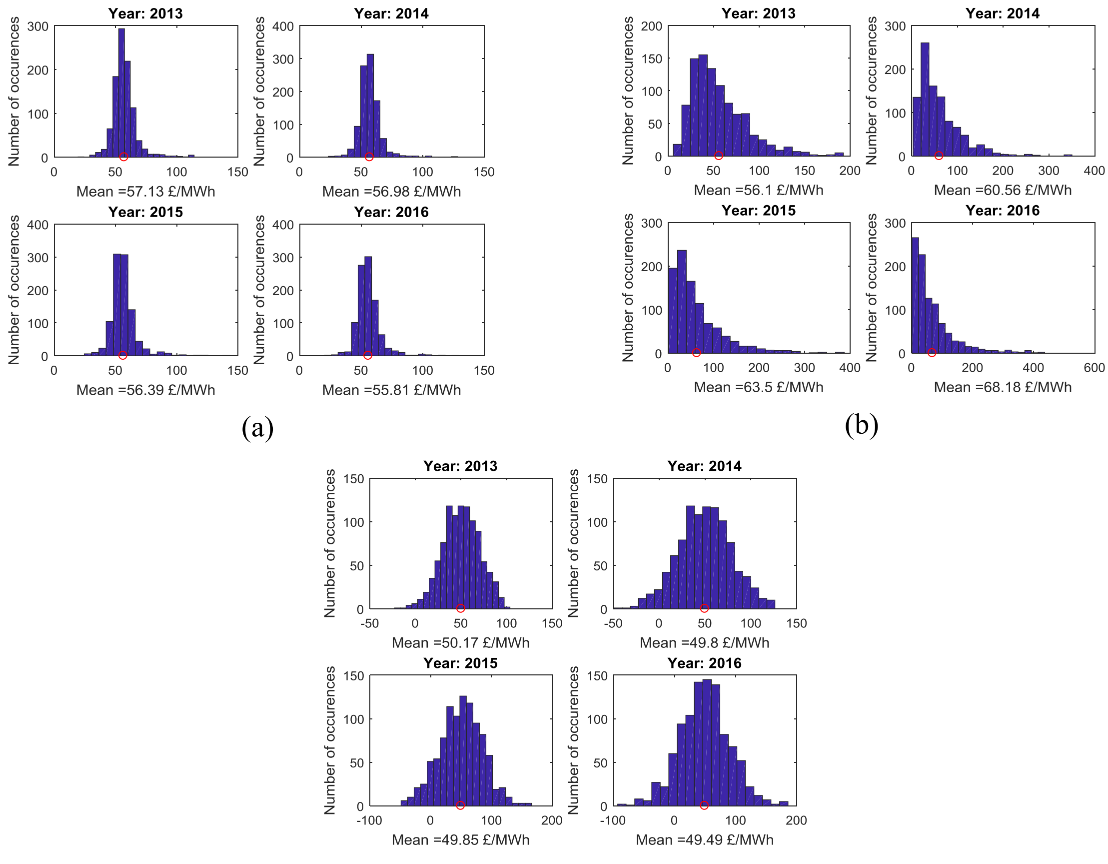
	Error (%)				Mean Absolute Percentage Error (MAPE)
	2013	2014	2015	2016	
GBM	12.6%	44.8%	63.9%	70.7%	48%
ARIMA	-3.3%	14.4%	21.2%	20.4%	14.8%
MRJD	10.0%	30.8%	37.1%	35.7%	28.4%



(a) (b) (c)

Figure 3 Test cases for electricity prices forecasting: (a) MRJD, (b) GBM, (c) ARIMA

The variability of the simulated electricity prices can be illustrated in Figures 4(a)-(c). It can be observed that MRJD method demonstrates a lower variability probably due to the drift term which forces reversion to long term mean levels (Figure 4(b)). The ARIMA model has the greatest variability as shown in Figure 4(c), probably due to the complex correlations between the previous values with the current values, leading to diverse paths per each simulation. Finally, as far as GBM is concerned, a positively skewed distribution (Figure 4(c)) with a long tail towards higher electricity prices was compiled from the 1,000 simulated paths.



(a) (b)

(c)

Figure 4 Probability distributions of electricity prices test cases: (a) MRJD, (b) GBM, (c) ARIMA

5. Results

5.1. Case study

Having modelled electricity market prices on a monthly basis, the stochastic modeling, based on distribution of economic outcomes of the investment, is performed. The case study that is used for the application of the method consists of a 504MW capacity wind farm located in the North Sea region, 36km away from shore. Weather data (3-hourly data over a 3-year period) were retrieved from BTM ARGOSS [21] for modelling the operational phase of the asset. The specifications of the wind farm investment are included in Table 2.

Table 2 Base case wind farm investment specifications

Wind farm characteristics		Values
Wind farm	Total wind farm capacity, P_{WT}	504 MW
	Projected operational life of the wind farm, n	25 years
	Construction years, T_{constr}	5 years
	Number of turbines, n_{WT}	140
General Site characteristics	Distance to port, D	36 km
	Water depth, WD	26 m
Wind turbine	Rotor diameter, d	107 m
	Hub height, h	77.5 m
	Pile diameter, D_{pile}	6 m
	Rated power	3.60 MW
	Cut-in speed	4 m/s
	Cut-out speed	25 m/s
Economic parameters	WACC	8.81%
	Corporate tax	17%
	Depreciation rate	18%
	Debt share	70%
	Equity share	30%
	Return on equity	15.8%
	Interest rate on debt	7%
	Inflation rate	2.5%
	Strike price	140 £/MWh

Wholesale electricity prices were retrieved from the BEIS 2016 Updated Energy & Emissions Projections [22] for the base case investigated. The total CAPEX was estimated £1.67 billion, annual OPEX £56.6 million, NPV=£174.1 million at a real discount rate of 6.15%, while the LCOE=108.9 £/MWh. The results indicate that P&A costs have the highest contribution to the LCOE value, accounting for 46%, while O&M costs correspond to 30% of the total cost. A breakdown of the costs per Phase of the wind farm under the baseline case is illustrated in Figure 5.

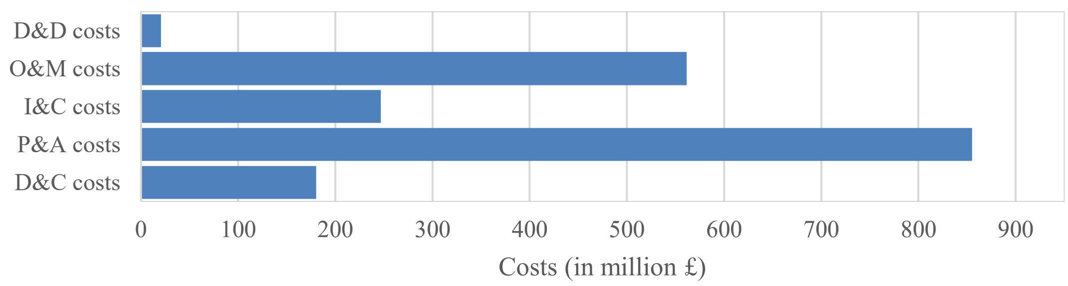
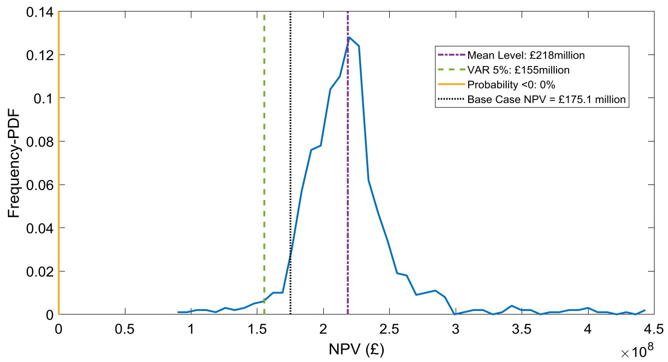


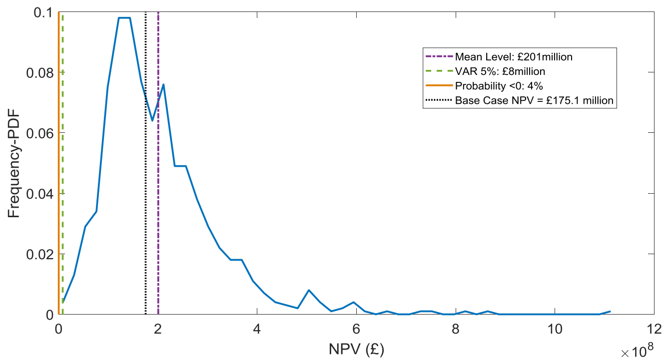
Figure 5 Deterministic lifecycle costs breakdown

5.2. Net Present Value Stochastic Analysis

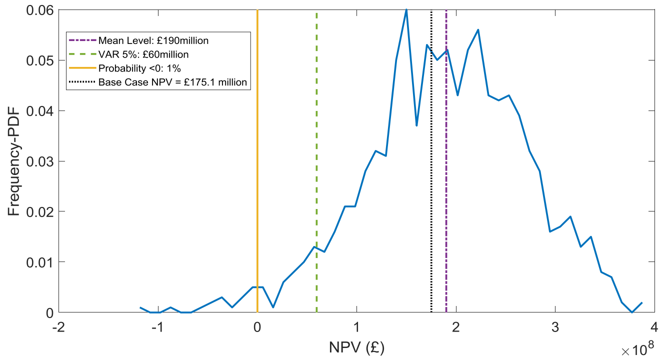
The joint probability distributions of the NPV derived from the three different methods are plotted in Fig. 6(a)-(c). The assumptions considered for the calculation of the probability distribution curves are the same as the ones compiled in Table 2. The Value at Risk (VaR) is a traditional risk measure approximating the probability that the value of an asset or portfolio will drop below a particular value over a specified confidence level and in the context of a planning horizon. VaR is always specified with a given confidence level α. As such, as shown in Figure 6(a), the NPV of the investment has a VaR 5% of £155million denoting that there is 95% probability that NPV will exceed £155million.
It can, thus, be inferred from the illustrated probability distributions that GBM method has the lowest VaR 5% = £8million, while the MRJD method yields a probability of zero for a negative NPV, as well as the highest mean NPV in comparison to the other three methods. The mean NPV derived from the ARIMA method indicated the closest proximity to the deterministic base case NPV.
As far as the shape of the probability distributions is concerned, following a similar pattern on the electricity prices scatter of data, the resulting NPVs demonstrate a positively skewed normal distribution with a medium variability, when a GBM is employed, implying non-linear relationships between stochastic electricity prices and NPV output. MRJD-derived curve has a low variability, again as a result of the existing drift term, while the opposite applies to ARIMA model which returns a NPV distribution with a high variability.



(a)



(b)



(c)

Figure 6 NPV probability distributions: (a) MRJD, (b) GBM, (c) ARIMA

6. Conclusions

In the UK context, following the 15-year period of the CfD scheme, offshore wind generators are obliged to sell their produced electricity on the electricity spot prices; hence, becoming subject to the risk of volatile and uncertain financial cash inflows. To this end, detailed and accurate assessment of expected returns during the post-CfD scheme becomes pertinent towards understanding the real cost and opportunity of investing in new or existing operational wind farms. Such an assessment could facilitate fair valuation of assets, supporting relevant investment/divestment decisions. To identify the best forecasting method for modelling the energy market prices, one has to determine the scope of the analysis. The present paper focuses on stochastically calculating the long-term electricity market prices and estimate the stochastic profitability of the offshore wind energy investment beyond the expiration of the CfD strike price support mechanism.

Statistical methods, such as the Autoregressive Moving Average, have a strong underlying mathematical and statistical theory, accommodating temporal correlations between past observations and current prices; as such, they can attach some physical interpretation to their components. Nevertheless, they are often criticized for their limited ability to capture nonlinear behaviour of electricity prices and they have been reported to perform better for short-term predictions (i.e. forecasts from a few minutes up to a few days ahead) [5]. They can, however, capture the seasonality that electricity prices exhibit on a daily, weekly and seasonal level basis. MRJD are considered to give a simplified picture of the price dynamics and are not expected to provide accurate results on an hourly basis, but rather recover main characteristics of the electricity prices at a daily time scale; thus, they may be considered as appropriate for longer term forecasting, requiring as input only the prior data of a time series to generalize the forecast. Among the methods tested, ARIMA demonstrated the lowest Mean Absolute Percentage Error in the validation cases, denoting a better long-term forecasting capability, which is relevant to service life financial appraisal of offshore wind energy investments.

Other available methods, such as Computational Intelligence techniques can also be considered as more relevant for long term forecasting since they can produce more accurate results, handling complexity and non-linearity. Nevertheless, their application usually requires a larger dataset (in comparison to the price-only models) of fundamental drivers, including the system forecasted demand, weather related data, fuel costs, etc.

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