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Offshore wind power system economic evaluation framework under aleatory and epistemic uncertainty

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HIGHLIGHTS

- Systems exploiting renewable energy sources are deeply affected by uncertainty and variability
- Deterministic analysis may lead to inaccurate decisions and underestimating inherent risk.
- A framework for economic performance assessment of offshore wind power systems is proposed
- Comprehensive set of uncertainties is considered (correlations, resources availability, energy price, failures).
- The approach allows a thorough and realistic assessment.

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ABSTRACT

Design and assessment of energy systems is affected by many sources of uncertainty and variability determining their technical and economic performances. This is even more relevant in systems exploiting renewable energy sources, given the intrinsic uncertainty in their availability. In this case, traditional design and evaluation methods based on deterministic analysis assuming average nominal values of involved parameters may lead to inaccurate decisions and underestimating inherent risk. Software tools for evaluating investment in renewable power systems are widespread, but uncertainty is often only included in the form of simple sensitivity analysis, changing one-element at time, thus failing to give a complete picture of uncertainty propagation effects. Some contributions on the economic evaluation of renewable energy systems under uncertainty are available in the literature, but only a few sources of uncertainty are considered. As a contribution to filling this gap, in this work, a framework for economic performance assessment of offshore wind power systems considering the effects of both epistemic and aleatory uncertainty is proposed by simultaneously considering the uncertainty of the correlations used to model the system, the variability of resource availability and energy sale price as well as the impact of failures and major disruptive events. The approach allows a thorough and realistic assessment of uncertainty propagation on the profitability of the investment, and is demonstrated in an accompanying application example.

1. Introduction

Exploitation of renewable energy sources is a fundamental aspect in the decarbonization and energy transition strategies enforced to counteract climate change and secure energy supply. While wind energy is a mature technology, offshore wind power systems are experiencing a notable growth both in the development on novel technical solutions and in the global installed power base. Offshore wind power plants have several advantages over their land-based counterparts, especially considering the higher available wind speeds owing to the absence of terrain obstacles, the lack of land consumption, and the lower visual impact, which allows wider acceptance from the public opinion. Nevertheless, offshore wind power plants are penalized by higher installation and operational costs owing to logistic issues, to the necessity of transferring on land the produced energy, and the severity of the operating environment causing much higher maintenance expenses.

However, renewable energy systems are subject to several sources of

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Nomenclature

Symbol [Unit] Caption
A [−] Availability
AMM [€/y] Depreciation charge
AP [MWh/y] Annual produced energy
CF [€/y] Cash flow
C_t [€/h] Hourly cost of technichans
c_p [−] Power coefficient
CV [−] Coefficient of variation
$E[x]$ [−] Expected value of x
EP [€/MWh] Hourly electricity price
HP [MW] Hourly produced energy
I_0 [€] Investment cost
L [€/y] Loan instalment
NPP [MW] Nominal produced power
NPV [€] Net Present Value
N_t [−] Number of required technicians
$O\&M$ [€/y] Managing and preventive maintenance cost
OC [€/y] Operating cost
P [W] Power
$P(x)$ [−] Occurrence probability of x
q [−] Share interest debt
R [€/y] Revenue
RC [€] Restoration cost
ReC [€] Repair cost
RT [h] Recovery time
S [m2] Swept area
T [€/y] Taxes
U [m/s] Wind speed
$V0$ [€] Debt
VaR [−] Value at risk
$WACC$ [−] Weighted average cost of capital
WS [m/s] Wind speed
Y [−] Plant years life

Subsctipts
Symbol Caption
y Year
h Hour

Greek symbols
Symbol [Unit] Caption
σ [€] Standard deviation
ρ [kg/m^3] Air density
η_g [−] Generator efficiency
η_{gb} [−] Gearbox efficiency
η_{pe} [−] Power electronic efficiency

uncertainty, both epistemic (i.e. caused by a lack of knowledge, but theoretically reducible) and aleatory (i.e. caused by random phenomena and intrinsically not reducible) which impact on system profitability and generate technical and economic performances variability resulting investment risk and financial risk [4]. This could even be hedged by new financing instruments [44] but requires a through consideration during the design, planning and assessment phases.

In wind power systems, uncertainty does not only arise from imprecise turbine design relationships and from variability of wind speed and sales price of produced energy, but also from downtime and costs deriving from random failure of internal components [13,29,66] as well as from disruptive external events deriving by natural hazards and man-made events (i.e. ships collision, rogue waves, earthquakes, etc.) which threat to destroy the entire system truncating its useful life.

However, as discussed at length in section 2, while previous literature focused on analysing specific uncertainty issues of wind power systems, such as wind speed of energy price forecasting [32,41,42,49] an overall model incorporating and integrating all variability sources [45,82] is still lacking. Moreover, available economic assessment models for wind power plants, either on-land and offshore usually only allow a deterministic analysis of a sensitivity analysis by changing the value of variables one at a time. When random variation of parameters is included, it is usually made considering the economic effect of just a few variables, thus preventing a comprehensive assessment of the effect of uncertainties on the investment profitability and risk.

In this paper, in order to give a contribution to fill this gap, a new general method for risk analysis and economic performance assessment of renewable energy system, and in particular offshore wind power plants, is proposed. This methodology simultaneously considers the main sources of epistemic and aleatory uncertainty, allowing to estimate the net present value probability distribution and some associated risk measures. The developed approach can be useful for more detailed and risk aware assessment of offshore wind power investments providing a useful decision-making tool for designers, managers, and investors. In our opinion the novelty of this contribution lies in three main aspects.

Firstly, to the best of our knowledge, there are no papers focusing on the economic evaluation of offshore power systems under uncertainty. Secondly, in literature some articles focus on the power system evaluation under uncertainty, considering only aleatory uncertainty of wind speed (renewable energy load) or few other variables. This paper considers the random uncertainty related to wind source availability, of the economic market scenarios as well as impact of random failures and disruptive events. Finally, this framework includes epistemic uncertainty related to the non-perfect ability of mathematical model to represent the system and the epistemic uncertainty of the characteristic of the system (e.g., power curve, gear box efficiencies, etc.).

The paper is organized as follows. Firstly, a literature review is carried out to assess the state of the art in economic evaluation and uncertainty propagation in (offshore) wind power systems. A general framework to assess the economic performance of renewable energy systems under uncertainty is presented. Next, a detailed model focused on offshore wind power systems is developed. Subsequently, a case study is presented in order to show the capabilities of the model and demonstrate the importance of considering uncertainty during the economic performance assessment of offshore wind power systems. Discussion of model limitations and perspectives for future work conclude the paper.

2. Literature review

Historically, the technical feasibility and economic viability of energy power plants have been assessed resorting to deterministic analysis assuming average and nominal values of input parameters. To account for uncertainty a sensitivity analysis is often made. While sophisticated global sensitivity analysis techniques are available (i.e. Sobol method), these are computationally intensive. As a consequence, one aften finds simplified analyses where the value of one parameter at a time is changed and the resulting impact of the chosen performance measure is observed. As a step further, Monte Carlo analysis techniques have been often used to generate random scenarios. This can be performed by simultaneously changing around the mean in a random manner multiple variables value, or, in more sophisticated cases, by reproducing specific structure (by means of marginal characteristics and dependence properties). As an alternative a substantially deterministic analysis can be performed accompanying by a dynamic analyses factoring in the random uncertainty of some relevant time-dependent parameters such

Table 1
Comparison of wind energy systems uncertainty modelling in the literature.

References	Type of model (Technical/ Economic)	Uncertainty modelling			
		Energy price	Wind speed	Technical model	Failures
[61]	Yes/Yes	No	No	No	No
[51]	Yes/Yes	No	No	No	No
([15]; [17])	Yes/Yes	No	Yes	No	No
[20]	Yes/No	No	Yes	No	No
[67]	Yes/No	No	Yes	No	No
[49]	Yes/No	No	Yes	Wind Power forecasting	No
[68]	Yes/No	No	Yes	Power Curve	No
[58]	Yes/No	No	Yes	Manufacturing tolerance and insect contamination	No
[41]	Yes/Yes	Yes	Yes	No	No
[63]	Yes/Yes	Yes	Yes	Power Curve	No
([47]; [69]; [74])	Yes/No	No	No	No	Yes
([32]; [76])	Yes/Yes	No	Yes	No	No
([8]; [77])	Yes/No	No	Yes	No	Yes
[54]	Yes/No	No	No	No	Yes
[3]	Yes/No	No	Yes	Wake effect, internal wind farm collector system, unavailability of wind turbine	No
This work	Yes/Yes	Yes	Yes	See Table 2	Yes

as electricity market price evolution and wind speed changes. However, the above approaches neglect a thorough analysis of uncertainty propagation issues of all variables resulting in erroneous performance estimation and lacking risk assessment.

In recent years, some authors have begun to study the problem of uncertainty in renewable energy systems. In traditional and renewable energy systems, short and long term decisions have to be made under conditions of uncertainty, thus methods for modelling uncertainty in decision-making under uncertainty in energy sector have been reviewed [70]. Since energy supply and demand are strongly affected by uncertainty, an optimization strategy was proposed for the operating schedule [36]. A multi-criteria decision-making problem under uncertainty was developed to select the most appropriate renewable energy system at a specific site [1]. A generic stochastic simulation-optimization framework to deploying financially viable systems has been proposed [63]. This framework includes the uncertainty of energy sources and model elements, but does not directly consider failures, disruptive events, financial risk, and fiscal policy risk. The failures and maintenance uncertainty greatly affects the economic performance of the system, so a method focusing on modelling the uncertainty of reliability costs and failures has been proposed [23].

In wind power sector, the most studied type of uncertainty is aleatory uncertainty. In fact, the majority of papers available in literature focuses on wind speed and power forecasting.

One of the most widely used approaches for wind speed prediction consists in the construction of a Weibull probability density function from historical wind speed data [2,10,25,32,42,62,65,75]. Probabilistic forecasting methods are also used to identify the most suitable type of predictive distribution [71], demonstrating the maturity of this research field. The use of Markov chain in short-term prediction has also been explored in order to reduce restricted assumptions on wind speed probability distribution [12]. Other works has focused on the forecasting wind power produced by incorporating the temporal and spatial dependence structure [26] or adopting other solutions, which are reviewed elsewhere [84].

Another source of aleatory uncertainty, in economic evaluation of renewable power plants, stems from the electricity sale price. The energy price can be analysed as a stochastic process by employing ARIMA [22,37], ARMA and ARMAX [79] models.

Table 1 compares how uncertainty has been accounted for in the relevant literature. Excluded from the table are articles focusing only on energy price prediction [9,18,22,31,38,40,43,48,79,80] and wind speed prediction [11,24,56] not applied to a wind system.

Note that authors of papers [41] and of [61] use commercial software, respectively EViews and RETScreen, to conduct their analysis. Although the most popular methods for dealing with uncertainty, especially epistemic uncertainty, are Monte Carlo sampling from a predefined probability density function and, especially for aleatory uncertainty, stochastic models, the above works deal with stated sources of uncertainty by different methods, e.g. using Markov chains and ARIMA and SARIMA methods for aleatory uncertainty. With the exception of this work, only three papers in the table above include failures and none assesses economic performances of wind turbine. Considering the epistemic uncertainty of relations and effectiveness of the WT model, only four papers include these sources of uncertainty but not failures.

There are several computer tools, some purely deterministic, others considering uncertainty, for analysing the integration of renewable energies in various energy systems. [28] was developed for the technical and financial analysis and optimisation of thermal generation, renewable generation and energy storage systems, but it is a deterministic tool and only admits sensitivity analysis. Hybrid Optimisation of Multiple Energy Resources [33] is another tool that can simulate different system solutions and admits optimisation and sensitivity analysis. The availability and load of the energy resource can be generated synthetically taking variability into account, or time series can be imported by the user. Scheduled maintenance activities can be defined, but random failures cannot be included in the analysis. Grid outages can be scheduled or random. Disruptive events can be considered, but they can occur at most once a year and their duration and start date are constant, which can only be randomised during the sensitivity analysis. The change in loads, prices and costs is only considered with a percentage change from one year to the next. [60] provides both sensitivity and risk analysis. The risk analysis is performed for the financial feasibility indicator selected by the user, but only using the Monte Carlo simulation. The user obtains the probability distribution of the selected indicator, but only a small number of key input parameters can be changed. Moreover, component efficiency, system life cycle and other important sources of epistemic uncertainty are not included. The random uncertainty of failures and disturbance events is neglected. Finally, SAM [72] is designed to facilitate decision-making in the renewable energy sector. It can perform parametric analysis, exceedance probability analysis and stochastic analysis. With stochastic analysis, it is possible to include uncertainty by estimating the effect of variability of inputs on an output variable by using Latin hypercube sampling. The shortcoming of this tool is its inability to include changes in the primary source over the years, random failures and other sources of uncertainty that change during the life cycle years. Therefore, it calculates the energy produced using coefficients to consider system availability, ageing of components and other losses. In this way, not only failures are neglected, but also disruptive events.

Overall, to the best of our knowledge, a general framework for evaluating the economic performance of renewable energy systems which simultaneously includes all sources of uncertainty is still lacking, and this work is the only one that consider a wide range of uncertainty sources to evaluate economic performances of offshore wind energy systems.

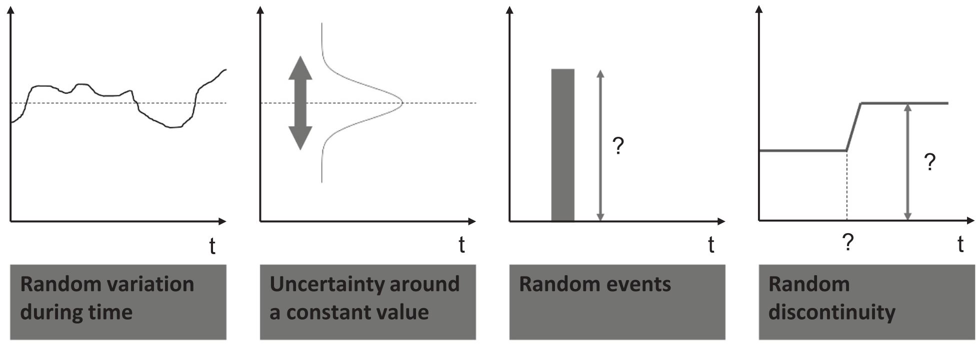

Fig. 1. Classification of variables affected by uncertainty.

Table 2
Considered sources of uncertainties.

Variable	Uncertainty nature	Variability type	Modelling approach
Bank interest rate	E	II	Monte Carlo sampling from predefined pdf
Investment cost	E	II	"
Plant nominal life	E	II	"
Self interest rate	E	II	"
Power coefficient	E	II	"
Gear box efficiency	E	II	"
Generator efficiency curve	E	II	Monte Carlo sampling from predefined pdf centered on nominal performance curve
Power electronic efficiency curve	E	II	"
Number of required technicians for system restoring	E	II	"
Repair costs	E	II	"
Disruptive external events	A	III	Monte Carlo sampling from hazard curve and random generation of failure severity level from fragility curve
Components failures	A	III	Monte Carlo sampling of Time to failure pdf and Monte Carlo sampling of time to repair pdf
Wind speed	A	I	Markov chain
Electricity price	A	I	ARIMA time series

3. Modelling framework for uncertainty propagation

In general, uncertainty is classified as either epistemic, i.e. caused by a lack of knowledge, but theoretically reducible, and aleatory, i.e. caused by random phenomena and intrinsically not reducible.

For renewable energy systems, and specifically offshore ones, nine families of uncertainty sources can be identified.

- Input uncertain variables, such as the availability and intensity of energy sources, represented by stochastic processes.
- External random events, such as disruptive events, for example earthquakes, ships or iceberg collisions, storms and rogue waves etc.
- Internal parameters epistemic uncertainty, such as the uncertainty related to components efficiencies values or to the inaccurate values given by the relationships used to design the system.
- Internal random events, for example components failures.
- Financial risk, that is settled, e.g., in cost of debt or, in general, in cost of capital.
- Tax risk, arising from changes in tax policies of countries.
- Social risk, for example resistance of population to the construction of a plant, or the change in environmental laws and energy policies of governments, which might allow support for renewable energy production.
- Market risk, i.e. the risk associated with changes in the selling price of energy or changes in the value of demand.

On the other hand, uncertain variables can be classified according to their nature in the manner shown in Fig. 1, where we recognize:

- Type I variability, typical of variables changing randomly their value over time. This behaviour can be modelled for instance by time series and random processes and in case of wind power systems could be represented by change over time of wind speed and direction or the variation of electricity sales price.
- Type II variability, typical of variables assuming an unknown value which is described according to a predefined probability density function: this can be represented by the uncertainty of interest rate or the value of efficiency of a conversion system.
- Type III variability, represented by random occurrence of point events of either know or unknown intensity. This is represented by internal equipment failures or external natural events likely to cause a major disruption to system operations. In this case random processes too can be used for modelling purposes.
- Type IV variability, represented by a random discontinuity where one or more variables occur a random step change in value at a random time. This situation is representative of economic, political and regulatory scenario variations during system life.

As far as wind energy systems are concerned, Lee and Fields [45] provide a comprehensive list of specific sources of variability and literature contribution addressing each source.

In this work we include the sources of uncertainty indicated in Table 2, where is indicated the affected variable, its variability type, the nature of uncertainty (Epistemic, E, or aleatory, A), as well as the adopted modelling approach.

Overall, the proposed general framework for economic performance assessment of renewable energy system, considering both random and epistemic uncertainty is schematically shown in Fig. 2.

The sources of uncertainty stated above are the inputs to the technical, reliability (i.e., the probability that a product will properly operate for a design life under the specified environmental or operating conditions [81]) and economical model and are used to assess the risk of the investment. As well known, risk refers to uncertainty of outcome, of actions and events and it represents uncertainty about and severity of the outcomes of an activity [6].

The technical model consists of mathematical formulations representing the system and the relationships used to assess its power output considering the wind variability, the wind turbine conversion efficiency. The reliability model is used to assess the availability of the system and determine production interruption periods caused by internal and external failure events. The economic model is used to evaluate costs,

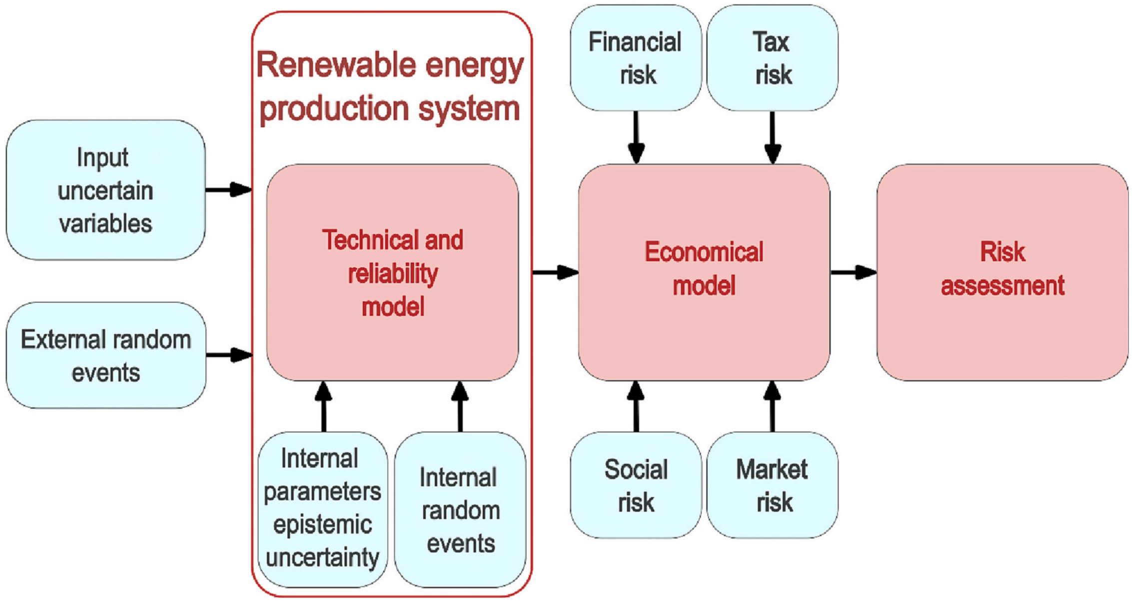

Fig. 2. Proposed general framework for economic performance evaluation of renewable energy system.

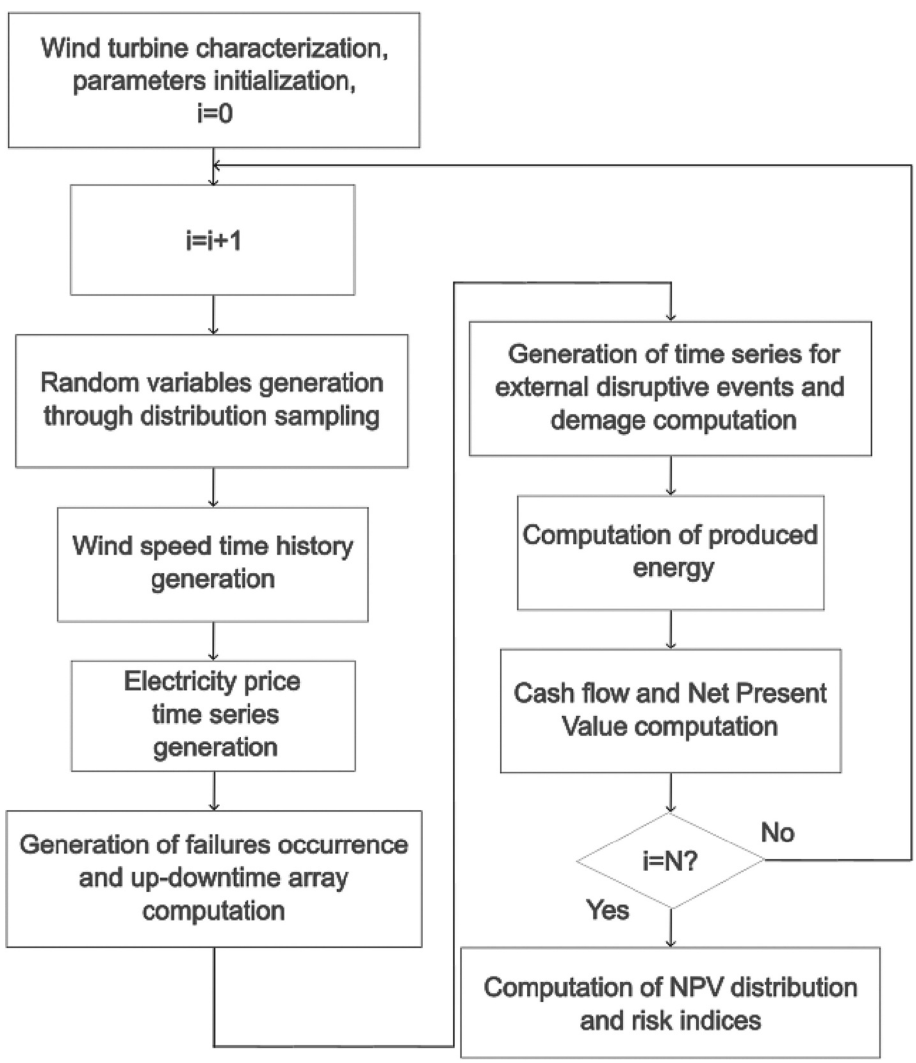

Fig. 3. Flowchart of the framework adapted for offshore wind power systems.

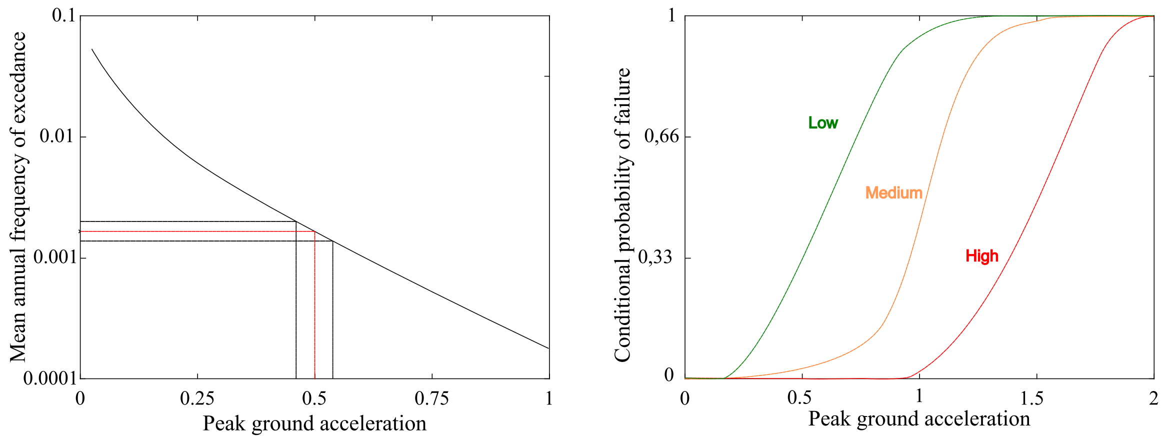

Fig. 4. Example of hazard curve discretization and example of fragility curves.

revenues and thus the required performance indicators of the economic result.

The model is conceived with a modular blocks structure, so that the specific manner to model the variables uncertainties can be changes in order to utilize the one better suiting to specific situations, and new modules can be added to model additional uncertainties.

Market risk is described by the electricity price variability. An ARIMA model is adopted, as motivated in Section 3.4. Given that in long-term analysis, the electricity price could change seriously under different scenarios, a trend parameter is included in the model to increases or decreases the price of a fixed or random percentage every year. Financial risk, such as interest rate variability, is simulated by Monte Carlo sampling from predefined probability density function.

The random discontinuities of social risk and tax risk are neglected for the most part in this work because they require a scenario analysis module which is planned as a future work. The uncertainty of plant life duration is accounted for by Monte Carlo sampling from predefined probability distribution.

The flowchart in Fig. 3 shows the logical sequence of the computational procedure in the proposed framework. Basically a Monte Carlo analysis approach is adopted where a sequence of random instances of the system life is simulated through a predefined number of iterations. At first a wind turbine and location is chosen. Environmental data are gathered and the turbine technical characteristics are input to the program data set. The number of runs, the expected life years of the system, and all other constant input data are declared, and the simulation is started. In each iteration the value of variables subjected to epistemic uncertainty is generated by sampling the corresponding probability distributions. Then, for each year, the hourly time series of wind speed and electricity prices, as well as the calendar or randomly occurring components faults (Section 3.2), are generated through simulation of the corresponding stochastic processes. This allows to compute the net annual energy production. Subsequently, the annual cash flows are computed resorting to the economic model, and the Net Present Value (NPV) is computed. After the predetermined number of runs is terminated the resulting set of NPV values are used to build the NPV frequency distribution histogram.

At the end, risk is assessed with three risk indicators:

- the NPV Coefficient of Variation $CV = \sigma[NPV] / E[NPV]$;
- the probability that $NPV < 0$;
- the probability of obtaining the economic loss indicated by investor-specified Value-at-Risk (*VaR*). This is the probability of obtaining a *NPV* value lower than the *VaR*.

For computational purposes the algorithm is based on four data vectors updated in each iteration. The adopted vectors *WS*, *EP*, *NPP*, *SV* represent respectively, over the system life span, the annual sequence of wind speed, electricity price, net produced power and system state with a time discretization chosen by the user. In this work a 1-h time discretization is adopted. The state vector values are the instantaneous system binary state variable $d_{yh} = 1$ or 0 representing whether the system is up or down according to failures and the subsequent restoration downtime. The *y* subscript represents the simulated year and h the current hour within the year. The same subscripts notation is also used to denote elements of *EP* and *WS* and *NPP* elements.

3.1. Disruptive events generation

With the term "disruptive events" we refer to external natural events (i.e. earthquakes, storms, rogue waves, impact with icebergs etc.), or even man-made events, such as terrorism acts or collisions with ships, which could impact on the wind turbine structure causing a damage. The sensitivity of a wind turbine structural integrity to natural hazard depends on the type of platform. For instance monopile and tripod foundations, being bottom-supported, may be affected by earthquakes, while floating structures would remain unaffected.

This modelling framework is suitable for various wind turbine support structures. e.g. spar buoy, tension leg platform, semi-submersible platform, monopile or tripod structure. Monopile and tripod foundations are fixed and limited to shallow water (i.e. <50 m) but they are widespread [5], while floating structures are used for deep water.

This means that a library of disruptive events models should be built and included in the simulation according to the site and the considered support structure. To develop the library of external disruptive events is outside the scope of this paper, and a model for earthquakes is only described here. We assume that a hazard curve (Fig. 4) is available to describe the annual probability of a seismic event occurring at a specific site in relation to its magnitude, expressed in terms of peak ground acceleration (PGA).

According to Huang et al. [34], to calculate the date of the event and its magnitude, the hazard curve is discretized into a user-defined number of magnitude classes. For each magnitude value, the annual probability of occurrence is thus obtained. Since each different magnitude class occurs at a fixed constant rate, the distribution the time between events is exponentially distributed. Monte Carlo sampling is used to determine the time to next event, and added to the current event date. The procedure is repeated until the end of plant life is reached, and the process is replicated over all magnitude classes in order to obtain a list of events dates and their magnitudes.

In order to estimate the damage the system suffers after each event, fragility curves are used [34]. Given the magnitude of the event (e.g. PGA), the fragility curve provides the probability of exceeding a predetermined damage state, i.e. failure modes. The limit seismic load before failure occurs is a random variable log-normally distributed, and the system will fail if its seismic capacity is less than or equal to the ground motion level corresponding to the chosen intensity measure. The cumulative density function of the probability of exceeding a fixed damage state (cdf_f) conditional on a PGA is given by (1):

$$cdf_{f(PGA)} = \Phi\left(\frac{1}{\beta} ln \frac{PGA}{\mu}\right) \quad (1)$$

where Φ is the standard normal cumulative distribution, μ the mean of the distribution and equal to $a{\cdot}PGA{\cdot}b$, a and b being experimentally derived constants, and β the standard deviation of the distribution.

Fragility curves are available in the literature for many pairs of damage states components, systems and plants, but they can also be constructed using simulation procedures (e.g. Finite Elements Simulation). With regard to bottom-fixed offshore wind power plants, fragility curves are available for monopile [19,46,55] and jacket foundations [78] subjected to seismic loading, combination of aerodynamic and seismic loads [7,83] and hurricane and seismic load [52], as well as electrical grid damages [27,64]. While [7,52] refer to land-based wind turbines, their results are easily applied to bottom-fixed offshore wind systems.

Three different damage levels are considered here, namely low, medium, and high. Each damage level is associated with a specific time to repair and cost, which is a percentage of the investment. The highest damage level is associated with a destructive damage, i.e. the interruption of plant life and the impossibility of restoring it. If the probability distributions of repair time and cost are known, it is possible to consider their uncertainty using Monte Carlo sampling.

For the determination of the damage level, a random number between 0 and 1 is sampled for each event, starting from the highest damage level, and arriving at the lowest. If the random number is less or equal to the cdf_f value associated to the PGA of the event, damage occurs. If the random number is greater than the cdf_f value, it is compared with another damage level until all occurrences of damage states are verified. If the random number is greater than all cdf_f values, the event does not lead to a fault.

The disruptive events that do not lead to a failure are neglected, while the others are included in the list of failures with their date, time to repair and cost.

At the end of this procedure, the output is a list containing the occurrence date, down time and expected cost of all disruptive events that will occur in the current run.

3.2. Components failures

It is assumed that the wind turbine system can be decomposed into the following components or subassemblies [73]: pitch and hydraulic system, generator, gearbox, blades, grease/oil/cooling liquid substitution, electrical components, contractor/circuit breaker, controls, safety, sensors, pumps/motor, hub, heaters/coolers, yaw system, tower/structure, power supply/converter, service, transformer and other. Each component or subassembly has three different failure modes which determine a minor repair, a major repair, or a replacement. The components are considered in series, so when a single element fail, the whole system fails and production stops. Each failure mode of each component is associated to a specific mean failure rate, time to repair and expected restoration cost (i.e. material replacement cost, subsequently utilized to compute the repair cost).

For each j-th component an overall constant failure rate λ_j is known as well as the frequency distribution f_i of the three i-th failure modes.

The algorithm to generate the failures events list includes the following steps:

1. The actual failure rate of each component failure mode is computed as $l_k = l_j\ f_i$. As failures occur at a constant rate, the distribution of their time to failure (*TTF*) will be exponential. All subsequent failures of the same type will occur after a certain random *TTF*, calculated from the last time the same type of failure occurred. The *TTF* is to be considered as a net time, i.e. excluding plant shutdowns due to further failure types occurring in the meantime. The different failure types, being conceptually independent of each other, will not affect the timing of the failure sequence of the other categories.
2. For each of the fault types, generate a *TTF* sequence by repeatedly randomly sampling its distribution. In practice, having extracted a random number $R \in [0,1]$, the m-th TTF of the k-th fault type will be $TTF_{km} = -\lambda_k \ln(R)$.
3. Repeat the procedure until the sum of the TTF_{km} generated for the fault type considered is at least equal to the nominal life of the installation, so as to generate a random sequence of faults of the same type covering the entire life of the installation.
4. For each k-th fault type, the theoretical date of occurrence of the m-th fault (assuming a zero time to repair, *TTR*) will be equal to the sum of all previous *TTF*s (TTF_{km}) times m ranging from 1 to m-1.
5. Repeat steps 2 to 4 for each type of failure, obtaining as many independent sequences of timed failures.
6. Combine the obtained sequences into a single sequence by sorting the faults by increasing date. This would be the timetable in which the various faults would hypothetically occur if repairs were instantaneous or occurred in negligible time.
7. Starting with the first fault in the sequence, add the random *TTR* generated for the repair of the fault under consideration to the current dates of all subsequent faults. The number of required technicians for the repair is sampled from a standard distribution centred in the mean number of required technicians and with a user given standard deviation. The restoration cost is sampled from a triangular distribution centred in the mean value of the restoration cost and with minimum and maximum value a percentage of the mean value (e.g. 90% and 110%). The repair cost is calculated multiplying hourly cost of the technicians, the number of required technicians, and restoring time and adding the cost of materials (Eq. (4)).
8. Repeat step 7 sequentially for all scheduled faults, updating the attempted occurrence date of all subsequent faults each time. This gradual shift allows the net *TTF* value of each fault to be maintained with respect to the previous occurrence of the same type of fault, net of interruptions for the repair of other faults occurring in the meantime. When the date of failures following the current one, as a result of this forward shift sequence, becomes greater than the nominal life of the system, these failures will be ignored because they will not occur.
9. When even for the penultimate fault in the sequence the *TTR* has been added (and thus the date of the next fault has slipped) the actual occurrence date of all faults is obtained.

The time-phased lists of external disruptive events and components failures are then merged, in order to obtain a global list containing all events and occurrence dates, ordered over time, their time to repair, the required number of technicians for the repair and their restoration cost over the entire plant life.

If the disruptive event date falls in a down-time period, the fault restoration process is interrupted and the system restoration from the disruptive event starts. The event date of the failures following a disruptive event are shifted as explained in the above algorithm, while the event date of a disruptive event remains unchanged.

At the end of the events generation procedure, the entire system life span is subdivided into unit time intervals Dt (here Dt = 1 h). For each time interval the system state variable d is defined, assuming value 0 if the system is down and 1 if the system is up. The values of the state variable are stored into an hourly availability array A_{yh} where subscripts represent the y-th year of equipment life and the h-th hour.

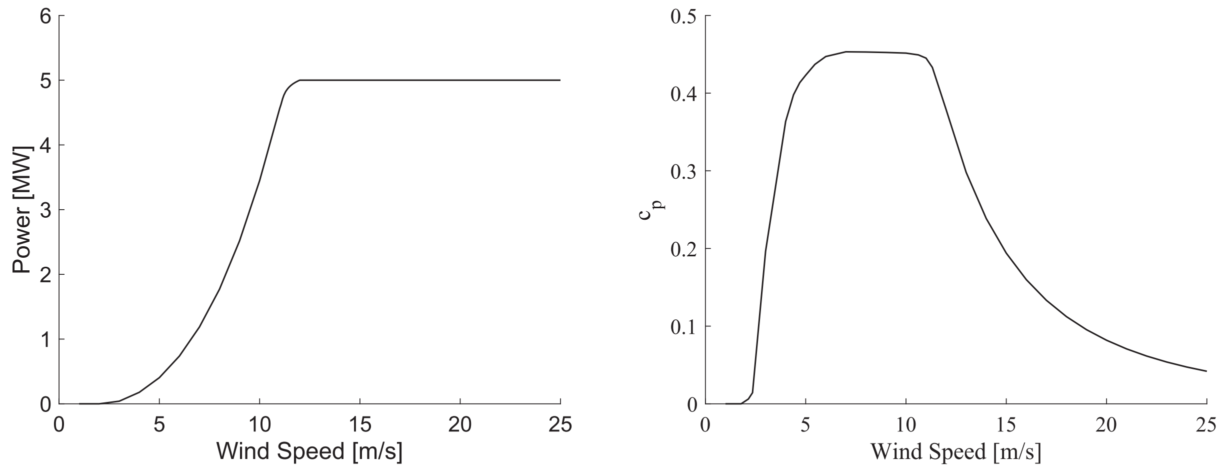

Fig. 5. 5 MW Wind turbine power curve and power coefficient.

Table 3
Cost model items.

Cost Item	Sub-items	Literature source
Investment cost	Wind turbine and floating platform purchase (wind turbine, floating platform, transmission system, mooring and anchoring systems)	([16]; [30]; [50])
	Wind turbine and floating platform installation (loading onto vessel, sea transport, mooring, electrical cable lying, onshore cable installation) and rent of the shipyard	([16]; [50])
Operating cost	Grid access fees, insurance costs, and seabed rental	([14]; [50])
	Maintenance cost (preventive)	([30]; [50])
	Maintenance cost (corrective)	See text

3.3. Technical performance model

The power P (MW) extracted by a horizontal axis turbine from the wind is strictly related to the wind speed (U), the rotor swept area (S), and air density (ρ), through the turbine-specific power coefficient (c_p) [53], and wind speed-dependent efficiencies of the gearbox (η_{gb}), generator (η_g) and power electronics (η_{pe}) according to Eq. (2).

$$P = \frac{1}{2} c_p \rho S U^3 \eta_g \eta_{gb} \eta_{pe} \cdot 10^{-6} \quad (2)$$

As a result, the turbine characteristic power curve can be obtained, describing the power extracted at different wind speed comprised between the cut-in and cut-off velocities. As an example Fig. 5 shows the power curve and power coefficient trend of a NREL 5-MW reference wind turbine [39]. Knowing the hourly wind speed, the electricity produced per hour can be thus calculated.

In the model, the hourly wind speed array WS_{yh}, storing a generated time series of wind speed, is transformed in the hourly Nominal Produced Power array NPP_{yh} resorting to the turbine power curve. Then an hourly produced energy array HP_{yh} (MWh), which covers the whole life of the plant, is thus constructed multiplying elementwise the Nominal Produced Power array NPP_{yh} and the hourly availability array A_{yh}, as shown in Eq. (3).

$$HP_{yh} = NPP_{yh}(\bullet)A_{yh} \quad (3)$$

Wind variability at a given site can be statistically modelled, for instance, by fitting a Weibull probability density function to historical wind speed data [2,10,25,32,42,62,65,75], and the obtained distribution can be used to generate random wind values by performing Monte Carlo simulation. However, this approach may not be accurate, as two independent subsequent samples of the distribution can determine

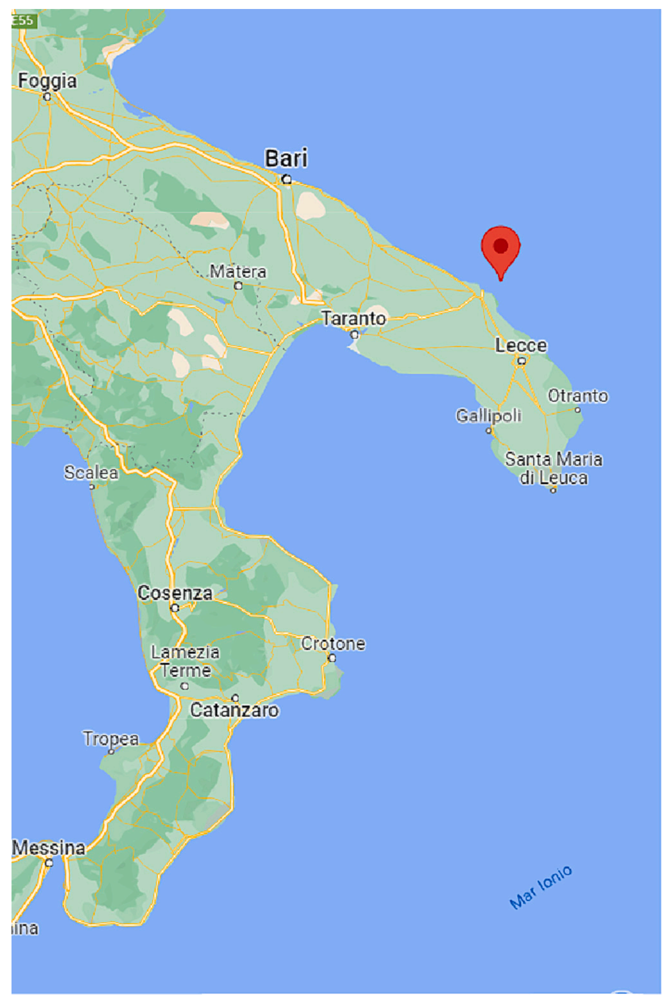

Fig. 6. Site location.

unrealistic abrupt changes in wind speed. Therefore, in this model, a synthetic random time series is generated using a Markov chain approach [21] based on a record of historical hourly wind speed data at the selected site. Since data are usually recorded at a height of 10 m above the sea level, the log law is used to estimate the wind speed values at the hub height [57]. In greater detail, the method proposed in [56] is used in this model to set up a birth-and-death Markov process based on

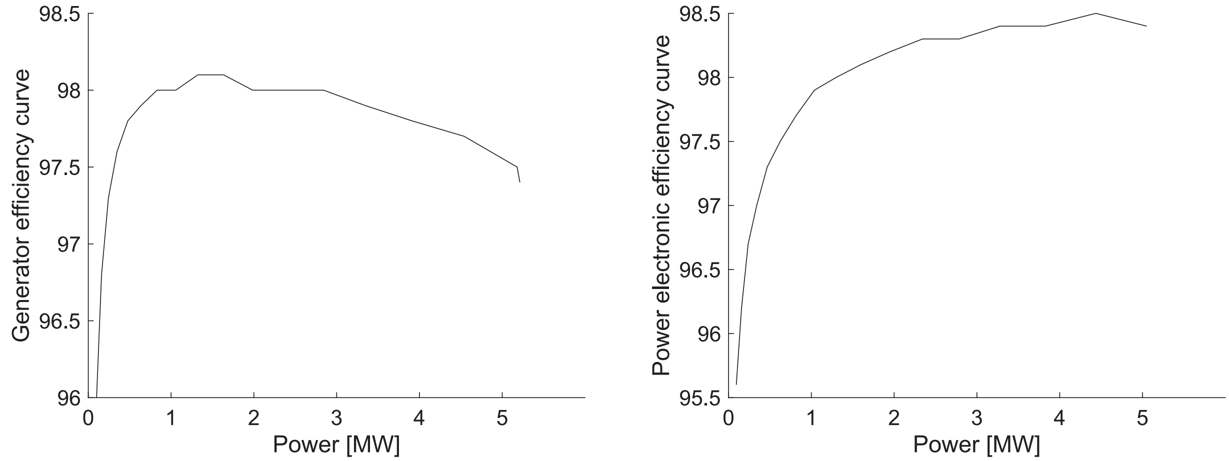

Fig. 7. Generator and power electronic efficiency curves.

Table 4
Parameters for variables showing epistemic uncertainty.

Variable	Nominal value	PD
Power coefficient	See curve in Fig. 5	± 1%
Generator efficiency	See curve in Fig. 7	± 1%
Power electronic efficiency	See curve in Fig. 7	± 1%
Gearbox efficiency	98%	± 1%
Restoration Cost	[13]	±10%
Investment cost	19,500,000 € (Computed by the model)	±·30%
Plant years life	20 (nominal)	± 10%

the site historical wind speed record. This Markov chain has a finite number of states and permit to consider both statistical characteristics of the past values of wind speed and its randomness, allowing to create a time-series of wind speed values for each run, to be stored in the hourly wind speed array WS_{yh}. The historical time series is used to set the number of possible states and the transition rates of the Markov process that will generate the wind speed time series. The number of possible states and the transition rates depend on the maximum and minimum values of wind speed of the training time series and on the time of permanence in certain states respectively.

3.4. Cost and revenues model

We adopt a cost model including the items detailed in Table 3, built resorting to earlier literature models.

Annual corrective maintenance cost is the sum of repair cost for each failure in the generated list according to the procedure described above. Repair costs due to i-th failure ReC_i is calculated according to Eq. (4) by multiplying hourly cost of technicians C_t by recovery time of the i-th failure RT_i and number of required technicians N_t and adding its restoration cost RC_i. The latter is the cost of materials used for the activity.

$$ReC_i = C_t N_t RT_i + RC_i \tag{4}$$

The restoration cost is taken from literature [13] and has a different value for each component depending on the failure mode. Each component has a different restoration cost depending on the failure mode. There are three failure modes, i.e., minor repair, major repair, and major replacement. Finally, the costs of restoring the equipment damaged by a disruptive event, based on the generated disruptive events list, are calculated as a percentage of total investment for low and medium damage level as the external event impacts on the entire system instead of on a single component. For a high damage level, on the other hand, the run is interrupted because the system cannot be restored.

Revenues of the y-year R_y, are computed according to Eq. (5) through elementwise multiplication of the vector of hourly produced electricity HP_{yh} and the hourly electricity price vector EP_{yh} and summation over the

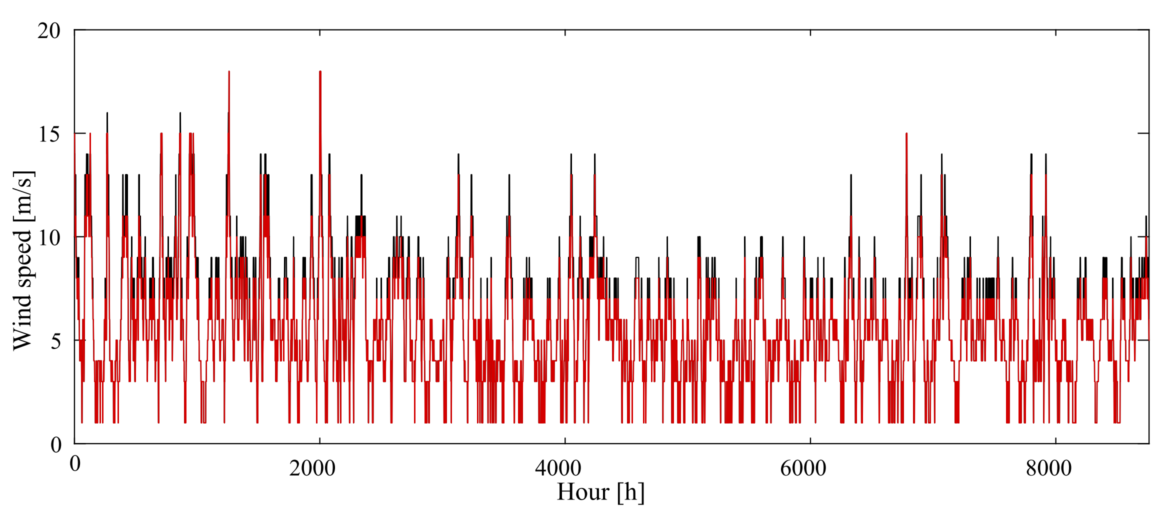

Fig. 8. One year of wind speed time series referring to a generic iteration (black line) and real observation of wind speed (red line). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

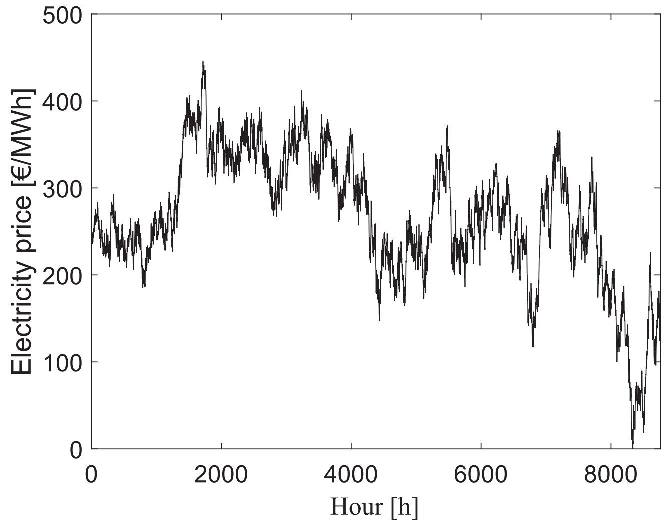

Fig. 9. One year of electricity price time series referring to a generic iteration.

yearly hours.

$$R_y = \sum_{h=0}^{8760} HP_{yh}(\bullet)EP_{yh} \tag{5}$$

The variable hourly electricity price (€/MWh) is obtained resorting to an ARIMA model combined with Monte Carlo simulation. ARIMA processes are a class of stochastic processes used to analyse time series often utilized in the electricity market, [22,37], although ARMA and ARMAX were also explored [79]. Historical records of hourly electricity price was used as input to perform a regression in order to obtain the ARIMA model coefficients [35]. Afterwards, one hundred Monte Carlo simulations are carried out for each run obtaining a set of electricity price time-series. Monte Carlo simulation is performed using the simulate function of ARIMA or ARIMAX models of Matlab. The starting parameters are the coefficient of the regression model and 1000 paths are simulate for each run. The middle time series is then taken from the set, and it is used for revenue calculation of the current run. The possibility to include a corrective yearly trend for the long-term time series estimation is considered. In fact, it is possible to give to the model the mean, minimum and maximum value of a coefficient that in each run for each year is random sampled using Monte Carlo simulation in order to change the trend of the electricity price.

3.5. Net present value computation

All the sources of uncertainty with their propagation influence the Net Present Value. There are several nested uncertainty models in its calculation procedure. To calculate the Net Present Value (*NPV*) of each run (Eq. (6)), it is necessary to compute the investment cost I_0, as shown above, and the annual cash flow of each run (Eq. (8)), where R_y, OC_y and T_y are revenue from the sale of electricity, operating and maintenance cost and taxes of *y*-th year respectively. The investment cost is sampled by a triangular distribution centered in its model-calculated nominal value using Monte Carlo simulation. Revenues are affected by the uncertainty of energy price and the produced power. In addition, the power extracted from the wind is affected by the random uncertainty of the wind speed (modelled resorting to Markov processes) and by the epistemic uncertainty of the effectiveness coefficients and power curve coefficient (Monte Carlo sampled from distribution centered on their nominal values). The generation of random failures and disruptive events and the Monte Carlo sampling of restoration cost and number of technicians act directly on the operating cost. Since the epistemic uncertainty of bank and self interest rate is modelled using Monte Carlo

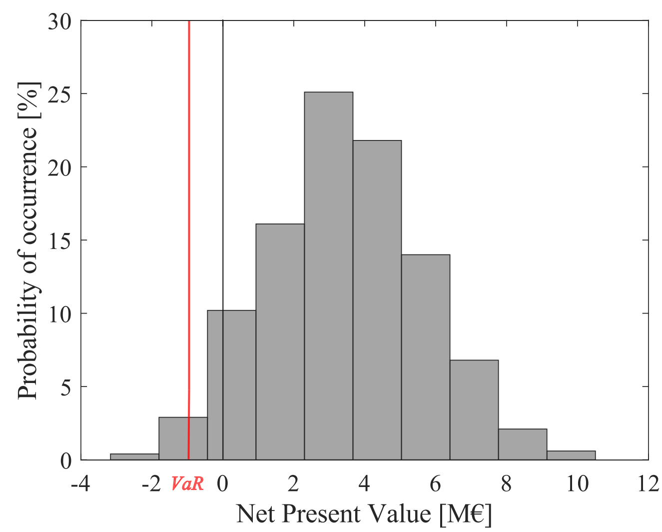

Fig. 11. Net present value frequency distribution of scenario A.

Table 5
Profitability and risk analysis results.

Scenario	A	B	C
Number of Data Points	1000	1000	1000
Min Data Value	$-3.17 \cdot 10^6$ €	$-1.94 \cdot 10^6$ €	$-4.36 \cdot 10^6$ €
Max Data Value	$1.05 \cdot 10^7$ €	$1.21 \cdot 10^7$ €	$8.34 \cdot 10^6$ €
Mode	$2.99 \cdot 10^6$ €	$4.37 \cdot 10^6$ €	$1.36 \cdot 10^6$ €
E[NPV]	$3.47 \cdot 10^6$ €	*$4.97 \cdot 10^6$ €*	$1.87 \cdot 10^6$ €
σ	$2.20 \cdot 10^6$ €	*$2.26 \cdot 10^6$ €*	$2.04 \cdot 10^6$ €
CV	0.63	*0.52*	1.09
P(NPV < 0)	5.7%	*1.2%*	19%
P(NPV < Var)	2.3%	*0.2%*	8.8%

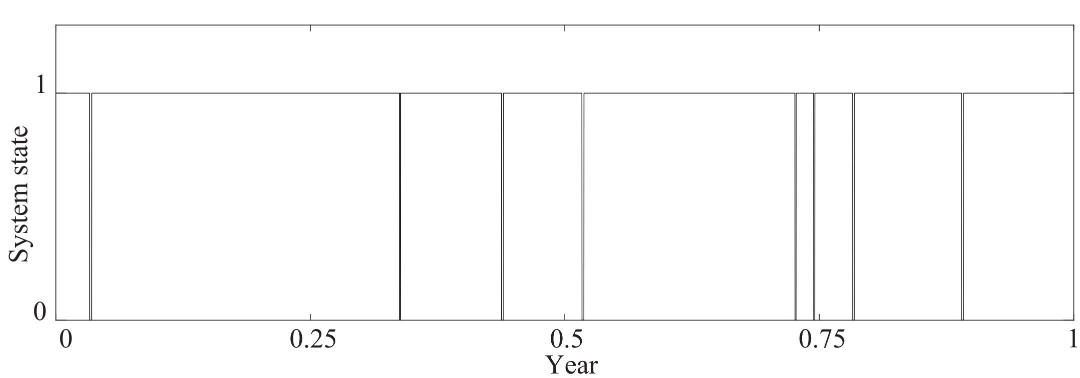

Fig. 10. System failure events of a generic iteration during the first year of operation.

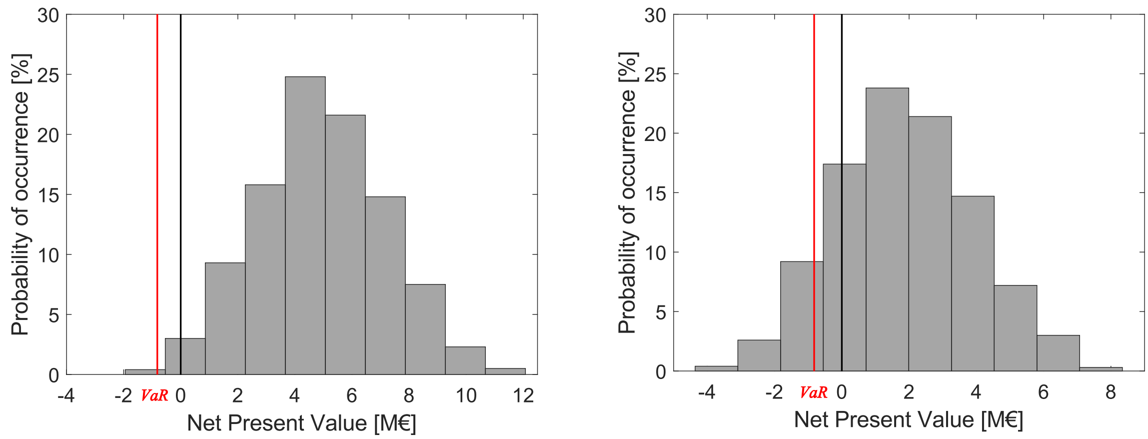

Fig. 12. Net present value distribution of scenario B (left side) and scenario C (right side).

sampling, the weighted average cost of capital uncertainty affects the *NPV* values acting on the discounting operation, but also on the loan instalment, that influences taxes.

$$NPV = -I_0 + \sum_{y=1}^{Y} \frac{CF_y}{(1+WACC)^y} \tag{6}$$

The Weighted Average Cost of Capital (*WACC*, Eq. (7)) takes into account of the cost of equity (c_o), the cost of debt (c_d), the debt (V_0), and the percentage of equity and debt in the total investment.

$$WACC = c_0\left(\frac{I_0 - V_0}{I_0}\right) + c_d\left(\frac{V_0}{I_0}\right) \tag{7}$$

The actual values of plant life (exception made for cases where life is terminated earlier owing to a major disruptive event) are randomly sampled from a user-assigned probability density function in each Monte Carlo run.

$$CF_y = R_y - OC_y - T_y \tag{8}$$

where T_y represents taxes (Eq. (9)). They are measured by considering the tax rate (a), revenue, operating cost, the share interests of the debt (q_y), and the depreciation charge (*AMM*), which is assumed to be constant over the operating life of the plant.

$$T_y = a\left[R_y - OC_y - q_y - AMM\right] \tag{9}$$

Assuming a constant loan instalment L (Eq. (10)), and that V_{y-1} is the outstanding debt from the year y (i.e. equal to the total financed capital minus the capital gave back until the year y-1), the share interest is (Eq. (11)):

$$L = V_0 \frac{c_d(1+c_d)^n}{(1+c_d)^n - 1} \tag{10}$$

$$q_y = c_d V_{y-1} \tag{11}$$

where n is the number of years of repayment of the financed capital, that is set according to the loan agreement.

The set of *NPV* values computed at each iteration is then used to build a frequency histogram of project *NPV*, as well as to compute the standard deviation, expected value of *NPV*, its probability of being <0 and its probability to be less than the value at risk.

4. Application example

In order to show its capabilities the model was implemented in Matlab environment and applied to the example of a single wind generator located 5 km off the port of Brindisi, Italy at coordinates latitude 40.68, longitude 18.06 degrees (Fig. 6). Water depth is approximately 400 m.

Based on the site characteristics a horizontal axis NREL 5-MW reference wind turbine [39], installed on a SPAR platform was chosen, rated for 11.4 m/s wind speed (cut-in and cut-off wind speed 3 and 25 m/s respectively). The rotor diameter is 126 m, and the hub height is 90 m. The wind turbine is equipped with a geared drive train, and it is pitch regulated. The power curve has already been shown in Fig. 5. From [14] all structural and construction data of a spar buoy floating platform for the wind turbine were taken to estimate the costs of the structure using the adopted cost model.

They were adjusted to the present value resorting to the current EU producer price index. ECMFW (European Centre for Medium-Range Weather Forecasts) provides ERA5-Land hourly data from 1950 to present. From there, the hourly time series of wind speed at 10 m from 2015 to 2019 were taken. The real time series is necessary to assess al the possible states and the transition rate of the Markov chain that will be used to simulate the values of wind speed for all the plant life. After the time series generation, the wind speed is adjusted to the hub heigh resorting to a log law.

The hourly time series of Italian energy price in 2021, taken from the GME (Italian Power Exchange) database, is utilized to estimate the parameters of the ARIMA regression model that will be used to simulate the value of wind speed for all the plant life. However, a long term trend component acting on the average base price has been also included to consider both short term and long term variability. In the simulations three different scenarios are considered: one in which the corrective trend coefficient is set to zero (A), to consider a business-as-usual scenario, one in which a constant corrective trend coefficient is set to +1% per year (B), to gradually increase the average electricity price, and another in which the constant corrective trend coefficient is set to −1% per year (C), to simulate a gradual reduction in energy price. However, any other random change of the annual average price trend could be included in the model.

To model failures, data on the average failure rate, average repair time, average cost, and average number of technicians classified according to mainly components and damage level were taken from [13] and used to generate failure histories according to the method described above.

Since in Carroll et al. [13] the failure and restoration data were referred to 2–4 MW wind turbines, the values of restoration cost were increased of 10% to account for a higher power turbine, and adjusted with the European Producer Price Index with the aim to consider inflation.

Considering the site location and the floating platform type, earthquake disruptive events were neglected, because the very low probability and effects of their occurrences.

For each variable affected by epistemic uncertainty their actual values are generated resorting to Monte Carlo simulation based on symmetrical triangular distributions [min, nominal, max], where the minimum and maximum values are respectively Nominal value ±(PD Nominal value), and PD is the percent deviation. Bank interest rate and self interest rate epistemic uncertainty is not described by a percentage deviation, but by an absolute deviation. The bank interest rate and self interest rate are respectively (6 ± 4)% and (4 ± 2) %. Nominal values and adopted PD, taken according to [30,59], are shown in Table 4. Other assumed parameters are Financial loan years 10, Percentual of financed investment cost 50%, Tax rate 35%, Technicians hourly cost 50 €/h person, yearly percentage of amortization 7%.

The adopted wind speed time series generator provides a profile of wind speed very close to the historical one. In fact, for example, considering a generic iteration, the average wind speed during the twenty years of operation is 5.89 m/s, the same as the historical series, and the coefficient of variation of the historical time series is 0.5, whereas the coefficient of variation of the values of synthetic wind speed time series is 0.55. From Fig. 8, which represents the time series of the first year of wind speed of a generic run, it can be seen that the maximum value of the speed is 18 m/s, the same as the historical time series.

Although the electricity price time series generator uses a different method from the wind speed time series generator to construct a fictitious electricity price history, it still provides a good approximation of electricity price behaviour. For instance in Fig. 9, the electricity price values for the same year as shown for the wind speed time series are shown.

The behaviour of the electricity price is similar to the real time series behaviour in terms of mean and maximum and minimum values.

It is interesting to observe the faults history constructed using the method explained above. Resorting to a generic iteration, Fig. 10 shows the system's state for the first year of operation, in which vertical lines represent failures, while the down time duration is too short to be visible.

The system analysis was performed including 1000 iterations for each scenario and *VaR* was stated as −800,000 €.

For scenario A the obtained frequency distribution of the Net Present Value is shown in Fig. 11 and it is well-fitted by a Normal distribution with a mean of 3.47 M€ and a standard deviation of 2.2 M€. The square error of fit is 0.000713. The *VaR*, identified by the red line in Fig. 11, is equal to 2.3%. Instead, the probability of the *NPV* being <0, resulting in economic loss, is 5.7%. Table 5 provides some information on the *NPV* of all iterations and scenarios whereas Fig. 12 shows the NPV distribution of B and C scenarios.

5. Conclusions

In this paper an overall framework for uncertainty propagation in the economic assessment of offshore wind energy systems is proposed. This fills a gap in the existing literature where uncertainty is simply neglected or is tackled using simplified methods such as static Monte Carlo simulation or one parameter at a time sensitivity analysis, or when uncertainty of just a few selected influencing variables is only considered such as wind speed and/or electricity price.

In greater detail the model, apart from suggesting a taxonomy of uncertainty types, and providing a modular and systematic approach to uncertainty effects assessment, includes the following novel features. It is the first model attempting an integrated evaluation of uncertainty propagation including multiple types of variability sources in both short and long term horizon for wind power plants. It is the first model focusing on uncertainty propagation in offshore wind energy systems.

The paper also includes a numerical application showing the model capabilities, which demonstrate the importance of considering uncertainty propagation when assessing the profitability and investment risk of wind energy systems.

The current model at present is limited to a single wind turbine, as this is intended as a building block of multiple unit wind farms. Another limitation of the current model is that variability of scenarios during the system life cycle (classified as Type IV variability) is neglected, as only long term drift of average influencing variables is included. Moreover, disruptive events are limited to earthquakes. As a future work the model will be extended and enhanced in order to include a wider library of uncertain parameters modelling, such as regulatory, social acceptance and construction delay risk. The model will be extended to find farms, including the economy of scale effects in capital investment estimation as well as interference due to wake effect in energy production. The capability of modelling scenarios changes during the system life cycle will be included, and additional types of disruptive events will be considered such as rogue waves, hurricanes, ships collisions. Wind forecast model will be enhanced to account for seasonal variability. In addition, considering the uncertain effects of climate change in wind projects, also the phenomena associated with them will be included. Finally dedicated models will be developed to estimate the capital investment for specific types of floating supporting structures.

The model is mainly intended to be used as a decision support tool during the planning phase of offshore wind investment projects. This allows to carry out a risk-aware profitability evaluation. Furthermore, The capability of assessing the outcome of alternative design choices over the life cycle also allows it to be used by designers when comparing alternative technical solutions. Given the modularity of the model architecture, it can be also used during the operations phase, for instance in order to test alternative maintenance policies or production control strategies based on instantaneous wind and energy price forecast. To this end some of the modules can be disabled in order to perform short term simulations. Overall the suggested approach can contribute to a more detailed and risk-aware design and assessment of offshore wind energy investments.

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CRediT authorship contribution statement

Antonio C. Caputo: Methodology, Supervision, Writing – original draft. **Alessandro Federici:** Software, Validation, Writing – original draft. **Pacifico M.Pelagagge:** Conceptualization, Supervision. **Paolo Salini:** Conceptualization, Methodology, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

References

[1] Abdel-Basset M, Gamal A, Chakrabortty RK, Ryan MJ. Evaluation approach for sustainable renewable energy systems under uncertain environment: a case study. Renew Energy 2021;168:1073–95.
[2] Ajayi OO, Fagbenle RO, Katende J, Ndambuki JM, Omole DO, Badejo AA. Wind energy study and energy cost of wind electricity generation in Nigeria: past and recent results and a case study for south West Nigeria. Energies 2014;7(12):8508–34.
[3] Ali M, Matevosyan J, Milanović J. Probabilistic assessment of wind farm annual energy production. Electr Pow Syst Res 2012;89:70–9.
[4] Apak S, Atay E, Tuncer G. Financial risk management in renewable energy sector: comparative analysis between the European Union and Turkey. Procedia Soc Behav Sci 2011;24:935–45.
[5] Atcheson M, Garrad A, Cradden L, Henderson A, Matha D, Nichols J, et al. Floating offshore wind energy. Cham: Springer; 2016.

[6] Aven T. On how to define, understand and describe risk. Reliab Eng Syst Saf 2010;95(6):623–31.
[7] Avossa AM, Demartino C, Contestabile P, Ricciardelli F, Vicinanza D. Some results on the vulnerability assessment of HAWTs subjected to wind and seismic actions. Sustainability 2017;9(9):1525.
[8] Barberis Negra N, Holmstrøm O, Bak-Jensen B, Sørensen P. Comparison of different techniques for offshore wind farm reliability assessment. In: Proc. sixth international workshop on large-scale integration of wind power and transmission networks for offshore wind farms, Delft, The Netherlands; 2006.
[9] Bessec M, Fouquau J, Meritet S. Forecasting electricity spot prices using time-series models with a double temporal segmentation. Appl Econ 2016;48(5):361–78.
[10] Borowy BS, Salameh ZM. Methodology for optimally sizing the combination of a battery bank and PV array in a wind/PV hybrid system. IEEE Trans Energy Convers 1996;11(2):367–75.
[11] Cadenas E, Rivera W, Campos-Amezcua R, Heard C. Wind speed prediction using a univariate ARIMA model and a multivariate NARX model. Energies 2016;9(2):109.
[12] Carpinone A, Giorgio M, Langella R, Testa A. Markov chain modeling for very-short-term wind power forecasting. Electr Pow Syst Res 2015;122:152–8.
[13] Carroll J, McDonald A, McMillan D. Failure rate, repair time and unscheduled O&M cost analysis of offshore wind turbines. Wind Energy 2016;19(6):1107–19.
[14] Castro-Santos L. Methodology related to the development of the economic evaluation of floating offshore wind farms in terms of the analysis of the cost of their life-cycle phases. Universidade da Coruña; 2013.
[15] Castro-Santos L, Filgueira-Vizoso A, Carral-Couce L, Formoso JÁF. Economic feasibility of floating offshore wind farms. Energy 2016;112:868–82.
[16] Castro-Santos L, Filgueira-Vizoso A, Lamas-Galdo I, Carral-Couce L. Methodology to calculate the installation costs of offshore wind farms located in deep waters. J Clean Prod 2018;170:1124–35.
[17] Castro-Santos L, Silva D, Bento AR, Salvacao N, Soares CG. Economic feasibility of floating offshore wind farms in Portugal. Ocean Eng 2020;207:107393.
[18] Chan KF, Gray P, van Campen B. A new approach to characterizing and forecasting electricity price volatility. Int J Forecast 2008;24(4):728–43.
[19] Chaudhari V, Somala SN. Fragility of offshore wind turbines variation with pulse-period and amplitude: directivity and fling step. Structures 2022:66–76. Elsevier.
[20] Chen J, Rabiti C. Synthetic wind speed scenarios generation for probabilistic analysis of hybrid energy systems. Energy 2017;120:507–17.
[21] Chung KL. Markov chains. New York: Springer-Verlag; 1967.
[22] Contreras J, Espinola R, Nogales FJ, Conejo AJ. ARIMA models to predict next-day electricity prices. IEEE Trans Power Syst 2003;18(3):1014–20.
[23] Dao CD, Kazemtabrizi B, Crabtree CJ. Offshore wind turbine reliability and operational simulation under uncertainties. Wind Energy 2020;23(10):1919–38.
[24] Di Giorgio V, Langella R, Testa A, Djokic S, Zou M. First order non-homogeneous Markov chain model for generation of wind speed and direction synthetic time series. In: 2020 international conference on probabilistic methods applied to power systems (PMAPS). IEEE; 2020. p. 1–6.
[25] Diaf S, Notton G, Diaf D. Technical and economic assessment of wind farm power generation at Adrar in southern Algeria. Energy Procedia 2013;42:53–62.
[26] Díaz G, Gómez-Aleixandre J, Coto J. Wind power scenario generation through state-space specifications for uncertainty analysis of wind power plants. Appl Energy 2016;162:21–30.
[27] Dunn S, Wilkinson S, Alderson D, Fowler H, Galasso C. Fragility curves for assessing the resilience of electricity networks constructed from an extensive fault database. Nat Hazards Rev 2018;19(1).
[28] energyPro. EMD International A/S. https://www.emd-international.com/energypro/; 2023.
[29] Faulstich S, Hahn B, Tavner PJ. Wind turbine downtime and its importance for offshore deployment. Wind Energy 2011;14(3):327–37.
[30] Fingersh L, Hand M, Laxson A. Wind turbine design cost and scaling model. Golden, CO (United States): National Renewable Energy Lab (NREL); 2006.
[31] Gabrielli P, Wüthrich M, Blume S, Sansavini G. Data-driven modeling for long-term electricity price forecasting. Energy 2022;244:123107.
[32] Gaß V, Strauss F, Schmidt J, Schmid E. Economic assessment of wind power uncertainty, world renewable energy congress-Sweden; 8-13 May; 2011. Linköping; Sweden: Linköping University Electronic Press; 2011. p. 4169–76.
[33] HOMER. UL solution. https://www.homerenergy.com/; 2023.
[34] Huang Y-N, Whittaker AS, Luco N. A probabilistic seismic risk assessment procedure for nuclear power plants:(I) methodology. Nucl Eng Des 2011;241(9):3996–4003.
[35] Hyndman RJ, Athanasopoulos G. Forecasting: Principles and practice. Melbourne, Australia: OTexts; 2018.
[36] Ikeda S, Ooka R. A new optimization strategy for the operating schedule of energy systems under uncertainty of renewable energy sources and demand changes. Energ Buildings 2016;125:75–85.
[37] Jakaša T, Andročec I, Sprčić P. Electricity price forecasting—ARIMA model approach. In: 2011 8th international conference on the European energy market (EEM). IEEE; 2011. p. 222–5.
[38] Jan F, Shah I, Ali S. Short-term electricity prices forecasting using functional time series analysis. Energies 2022;15(9):3423.
[39] Jonkman J, Butterfield S, Musial W, Scott G. Definition of a 5-MW reference wind turbine for offshore system development. Golden, CO (United States): National Renewable Energy Lab (NREL); 2009.
[40] Karakatsani NV, Bunn DW. Forecasting electricity prices: the impact of fundamentals and time-varying coefficients. Int J Forecast 2008;24(4):764–85.
[41] Khindanova I. A Monte Carlo model of a wind power generation investment. J Appl Bus Econ 2013;15(1):94–106.
[42] Kwon S-D. Uncertainty analysis of wind energy potential assessment. Appl Energy 2010;87(3):856–65.
[43] Lago J, Marcjasz G, De Schutter B, Weron R. Forecasting day-ahead electricity prices: a review of state-of-the-art algorithms, best practices and an open-access benchmark. Appl Energy 2021;293:116983.
[44] Lee CW, Zhong J. Financing and risk management of renewable energy projects with a hybrid bond. Renew Energy 2015;75:779–87.
[45] Lee JC, Fields MJ. An overview of wind-energy-production prediction bias, losses, and uncertainties. Wind Energy Sci 2021;6(2):311–65.
[46] Lee S-G, Kim D-H, Yoon G-L. Seismic fragility for 5MW offshore wind turbine using pushover analysis. J Ocean Eng Technol 2013;27(4):98–106.
[47] Li Y-F, Valla S, Zio E. Reliability assessment of generic geared wind turbines by GTST-MLD model and Monte Carlo simulation. Renew Energy 2015;83:222–33.
[48] Liebl D. Modeling and forecasting electricity spot prices: a functional data perspective. Ann Appl Stat 2013:1562–92.
[49] Ma X-Y, Sun Y-Z, Fang H-L. Scenario generation of wind power based on statistical uncertainty and variability. IEEE Trans Sustain Energ 2013;4(4):894–904.
[50] Maienza C, Avossa A, Ricciardelli F, Coiro D, Troise G, Georgakis CT. A life cycle cost model for floating offshore wind farms. Appl Energy 2020;266:114716.
[51] Maienza C, Avossa AM, Picozzi V, Ricciardelli F. Feasibility analysis for floating offshore wind energy. Int J Life Cycle Assess 2022:1–17.
[52] Martin del Campo JO, Pozos-Estrada A, Pozos-Estrada O. Development of fragility curves of land-based wind turbines with tuned mass dampers under cyclone and seismic loading. Wind Energy 2021;24(7):737–53.
[53] Mathew S. Wind energy: Fundamentals, resource analysis and economics. Berlin, Heidelberg: Springer; 2006.
[54] Mensah AF, Dueñas-Osorio L. A closed-form technique for the reliability and risk assessment of wind turbine systems. Energies 2012;5(6):1734–50.
[55] Mo R, Kang H, Li M, Zhao X. Seismic fragility analysis of monopile offshore wind turbines under different operational conditions. Energies 2017;10(7):1037.
[56] Negra NB, Holmstrøm O, Bak-Jensen B, Sørensen P. Model of a synthetic wind speed time series generator. Wind Energy 2008;11(2):193–209.
[57] Patel MR, Beik O. Wind and solar power systems: Design, analysis, and operation. Boca Raton: CRC press; 2021.
[58] Petrone G, de Nicola C, Quagliarella D, Witteveen J, Iaccarino G. Wind turbine performance analysis under uncertainty. In: 49th AIAA aerospace sciences meeting including the new horizons forum and aerospace exposition; 2011. p. 544.
[59] Poore R, Lettenmaier T. Alternative design study report: WindPACT advanced wind turbine drive train designs study; November 1, 2000–February 28, 2002. Golden, CO (United States): National Renewable Energy Lab (NREL); 2003.
[60] RETScreen. Natural Resources Canada. Government of Canada; 2023. https://www.retscreen.net/.
[61] Riaz MM, Khan BH. Economic feasibility study to design a large offshore wind farm near coastal region of Rameshvaram, India. In: 2019 international conference on electrical, electronics and computer engineering (UPCON). IEEE; 2019. p. 1–5.
[62] Safari B, Gasore J. A statistical investigation of wind characteristics and wind energy potential based on the Weibull and Rayleigh models in Rwanda. Renew Energy 2010;35(12):2874–80.
[63] Sakki GK, Tsoukalas I, Kossieris P, Makropoulos C, Efstratiadis A. Stochastic simulation-optimization framework for the design and assessment of renewable energy systems under uncertainty. Renew Sustain Energy Rev 2022;168:112886.
[64] Satkauskas I, Maack J, Reynolds M, Sigler D, Panda K, Jones W. Simulating impacts of extreme events on grids with high penetrations of wind power resources. Golden, CO (United States): National Renewable Energy Lab (NREL); 2022.
[65] Saxena BK, Rao KVS. Comparison of Weibull parameters computation methods and analytical estimation of wind turbine capacity factor using polynomial power curve model: case study of a wind farm. Renewables 2015;2(1):1–11.
[66] Shafiee M, Sørensen JD. Maintenance optimization and inspection planning of wind energy assets: models, methods and strategies. Reliab Eng Syst Saf 2019;192:105993.
[67] Sharma KC, Jain P, Bhakar R. Wind power scenario generation and reduction in stochastic programming framework. Elect Power Compon Syst 2013;41(3):271–85.
[68] Sohoni V, Gupta S, Nema R. A critical review on wind turbine power curve modelling techniques and their applications in wind based energy systems. J Energ 2016:2016.
[69] Sørensen JD. Reliability assessment of wind turbines. In: ICASP12: 12th international conference on applications of statistics and probability in civil engineering. Civil Engineering Risk and Reliability Association; 2015. p. 636.
[70] Soroudi A, Amraee T. Decision making under uncertainty in energy systems: state of the art. Renew Sustain Energy Rev 2013;28:376–84.
[71] Sun M, Feng C, Chartan EK, Hodge B-M, Zhang J. A two-step short-term probabilistic wind forecasting methodology based on predictive distribution optimization. Appl Energy 2019;238:1497–505.
[72] System Advisor Model. S.A.M. National Renewable Energy Laboratory; 2023. https://sam.nrel.gov/.
[73] Tavner P. Offshore wind turbines: Reliability, availability and maintenance. IET; 2012.
[74] Tazi N, Châtelet E, Bouzidi Y. Using a hybrid cost-FMEA analysis for wind turbine reliability analysis. Energies 2017;10(3):276.
[75] Ulgen K, Hepbasli A. Determination of Weibull parameters for wind energy analysis of Izmir. Turk Int J Energy Res 2002;26(6):495–506.
[76] Vardar A, Çetin B. Cost assessment of the possibility of using three types of wind turbine in Turkey. Energy Explor Exploit 2007;25(1):71–82.
[77] Wang X, Zhang J, Jiang C, Yu L, Liu D, Weng Y. Reliability assessment of wind farm active power based on sequential Monte-Carlo method. Int J Energ Eng 2013;3(4):122.

[78] Wei K, Arwade S, Myers A, Hallowell S, Hajjar J, Hines E. Performance levels and fragility for offshore wind turbine support structures during extreme events. Struct Congr 2015:1891–902.
[79] Weron R, Misiorek A. Forecasting spot electricity prices with time series models. Eur Elect Market EEM 2005;5:10–2.
[80] Weron R, Misiorek A. Forecasting spot electricity prices: a comparison of parametric and semiparametric time series models. Int J Forecast 2008;24(4): 744–63.
[81] Woo S. Modern definitions in reliability engineering. In: Reliability design of mechanical systems: a guide for mechanical and civil engineers; 2020. p. 53–99.
[82] Yan J, Möhrlen C, Göçmen T, Kelly MA, Goebel G. Uncovering wind power forecasting uncertainty sources and their propagation through the whole modelling chain. Renew Sustain Energy Rev 2022;165:112519.
[83] Yuan C, Chen J, Li J, Xu Q. Fragility analysis of large-scale wind turbines under the combination of seismic and aerodynamic loads. Renew Energy 2017;113:1122–34.
[84] Zhang Y, Wang J, Wang X. Review on probabilistic forecasting of wind power generation. Renew Sustain Energy Rev 2014;32:255–70.