Offshore wind power system economic evaluation under uncertainty: scenario analysis

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Abstract: The technical and economic performance of renewable energy systems is affected by the uncertainty and variability of many influencing factors, including the inherent uncertainty in the availability of energy sources and in the economic context as well as equipment availability. Traditional design and evaluation methods are based on the assumption of average nominal values of design parameters. This prevents technical and economic risk assessment, which is a central issue in the proper design of these systems. Software tools and some contributions on this topic are available in the literature, but only a few sources of uncertainty are considered. In a previous work, a framework for evaluating the economic performance of offshore wind power systems considering the main sources of uncertainty was proposed, but the implemented model neglected the uncertainty related to changes in the political and regulatory scenario during system life. To fill this gap, in this paper the random discontinuities arising from this kind of risk are included in a new economic performance assessment model using scenarios analysis. Widely accepted scenarios for energy price, learning rate and subsidies were taken from the literature and combined into consistent stories for the life of the plant. Simulations were carried out on a case study. The main results show the crucial role of this type of uncertainty for a correct economic risk assessment in wind power systems. From the best-case scenario to the worst-case scenario there is a difference of about 290% in the expected value of NPV. In addition, several scenarios were combined to assess a single net present value distribution using their associated probability. Several scenarios on increasing or decreasing subsidies were defined, and an example was carried on. Considering a constant value of subsidies, instead of combining different plausible stories, led to an overestimation of NPV of about 160%.

Keywords: Offshore wind power system, economic evaluation, risk analysis, scenario analysis, uncertainty propagation.

I. INTRODUCTION

Renewable energy power systems (RESs) play a central role in the decarbonization strategy, and energy transition policies represent one of the main actions to counteract climate change and to achieve energy independence. While the cost of electricity produced by RESs has become competitive with, or lower than, that produced from fossil sources, RESs suffer the effect of many aleatory and epistemic uncertainties which affect systems profitability and increase investment and financial risk (Apak et al., 2011). Wind power systems are a typical example and are the focus of this paper. Onshore wind power is a proven technology and the effect of the variability of wind speed and sales price, and the random failures is well known (Carroll et al., 2016; Faulstich et al., 2011; Shafiee and Sørensen, 2019). The impact on the economic and technical performance of onshore systems of disruptive external events due to natural and man-made hazards, and of the imprecise turbine design relationships is also well-known. Some software tools for performance assessment of onshore wind power systems (HOMER; RETScreen; System Advisor Model) are available in literature and have been reviewed by (Tozzi and Jo, 2017). Nevertheless, most of the existing tools consider only few sources of uncertainty recurring to sensitivity analysis. However, the case of offshore wind power plants is different as similar studies focusing on the effects of uncertainty and variability are lacking. A recent model has been developed to evaluate the economic performance of this type of plants, considering both epistemic and random uncertainty to estimate a probability density function of the NPV (Caputo et al., 2023). Nevertheless, another possible source of uncertainty for RESs comes from changes in the political and regulatory scenario during the life of the system. This important issue has been neglected in the literature. To fill this gap, in this work the previously available model (Caputo et al., 2023) is extended by including scenario analysis. Several widely accepted scenarios related to energy price history, learning rate of offshore wind power systems and subsidies policy are taken from the literature, and they are combined to include this additional kind of risk.

The paper is organized as follows. Firstly, the model used for the economic and technical performance assessment is shortly described. Next, the considered scenarios are exposed, and their combinations are explained. Subsequently, a numerical example is carried out to show the relevance of considering scenarios for the correct economic evaluation. Finally, given the probability of occurrence of four scenarios in which subsidies change during the system life, a single NPV probability distribution is assessed and compared to a single scenario in which subsidies are constant during the years to underline the importance of considering these discontinuities.

II. General framework

The general framework of the model (Fig. 1) is based on a modular structure in which blocks can be activated and switched off to cope whit different sources of uncertainty.

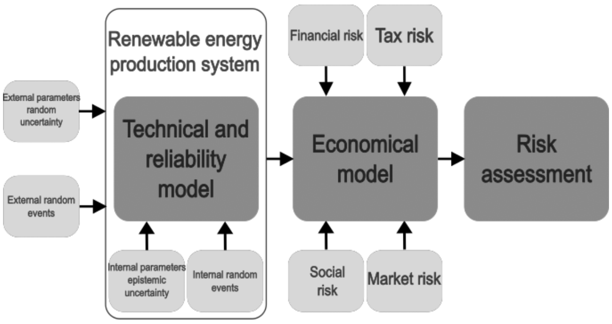

Fig. 1. General framework for economic performance evaluation of renewable energy system

For wind power systems the considered sources of uncertainty are resumed in Table I. In the Table the variability type is classified as follows (see Fig. 2). I) the variables change randomly their value over time, II) variables show a constant but random value according to predefined probability density function, III) variability is represented by random occurrence of point events of either known and unknown intensity, and IV) a random discontinuity occurs where one or more variables experience a random step change in value at a random time.

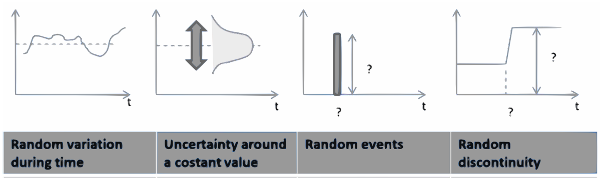

Fig. 2. Classification of variables affected by uncertainty

In essence, a Monte Carlo analysis method is used, simulating a series of random occurrences of the system life over a predetermined number of iterations. First, a location and wind turbine are selected by the user. The program data set is filled with the technical features of the turbine and environmental data.

TABLE I. Sources of uncertainties

Variable	Uncertainty nature/ Variability type	Modelling approach
Bank interest rate	E/II	1
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	2
Power electronic efficiency curve	E/II	“
Number of required maintenance personnel	E/II	“
Repair costs	E/II	“
Disruptive external events	A/I	3
Components failures	A/III	4
Wind speed	A/I	5
Electricity price	A/I	6

Legend. E = Epistemic, A = Aleatory; 1= Monte Carlo sampling from predefined pdf; 2= Monte Carlo sampling from predefined pdf centered on nominal performance curve; 3= Monte Carlo sampling from hazard curve and random generation of failure severity level from fragility curve; 4= Monte Carlo sampling of Time to failure pdf and Monte Carlo sampling of time to repair pdf; 5= Markov chain; 6= ARIMA time series

The simulation is launched after declaring the number of runs, projected system life years, and all other constant input data. In each run the value of variables subject to epistemic uncertainty is derived by sampling the relevant probability distributions throughout each cycle. Then, through simulation of the corresponding stochastic processes, annual time series of failures, wind speed, and electricity prices are produced. This makes it possible to calculate the annual net produced energy neglecting downtime periods. Then, using the economic model, the annual cash flows and the Net Present Value (NPV) are calculated obtaining the NPV frequency distribution histogram. Below each block of the framework is shortly described, and in Fig. 3 the main steps of NPV distribution computational sequence are resumed. External parameters random uncertainty of the technical model represents mainly the wind speed and direction variability. External parameters random uncertainty of the technical model represents mainly the wind speed and direction variability. External parameters random uncertainty of the technical model represents mainly the wind speed and direction variability.

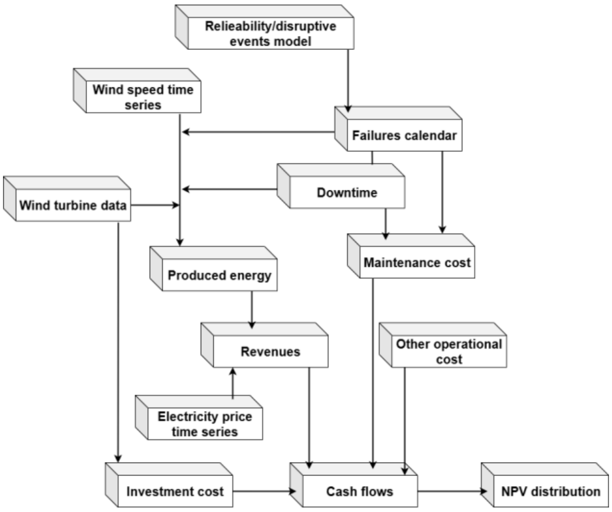

Fig. 3. Main steps of NPV distribution computational sequence

Even if in the literature the usual approach is to recur to Weibull probability distribution sampling built on historical data (Ajayi et al., 2014; Kwon, 2010; Ulgen and Hepbasli, 2002), this method leads to abrupt changes in the speed and direction values. For this reason, in this work a Markov chain is adopted according to (Negra et al., 2008) to generate hourly wind speed time series over the entire plant life. External disruptive random events (e.g., terrorism acts, collision with ships, earthquakes, rogue waves etc.) are modelled according to (Huang et al., 2011). A library of fragility curves and expected damage can be constructed for each type of event or taken from literature (Chaudhari and Somala, 2022; Lee et al., 2013; Martin del Campo et al., 2021; Mo et al., 2017; Wei et al., 2015). A list of disruptive event date, magnitude, and expected damage is generated as described in (Caputo et al., 2023). The technical and reliability model allows to compute the power extracted by a horizontal axis wind turbine given the instantaneous wind velocity value (Mathew, 2006). The internal parameters epistemic uncertainty resides in the efficiency of components and model simplifications. This type of uncertainty is modelled sampling a value on a probability density function build around the central value of the quantities and bounded by their maximum and minimum values. The wind turbine is decomposed into components and subassemblies according to (Tavner, 2012). Components are assumed to be in series, so when a single element fails, the whole system fails and production stops until it is brought back into service. An event list of failures throughout the life of the system is generated resorting to Monte Carlo sampling of the distributions of the mean time between failures, mean time to repair, mean number of technicians, and expected restoration cost of each different components and subassemblies. The economic model performs cost computation and revenue computation, including cost items (CI) resumed in Table II, while repair cost of failures is calculated multiplying hourly cost of technicians by recovery time and required number of technicians, also adding materials cost taken from (Carroll et al., 2016).

TABLE II. COST MODEL ITEMS

CI	Sub-items	Source
Investment cost	Wind turbine and floating platform purchase	[6, 9, 19]
	Wind turbine and floating platform installation and rent of the shipyard	[6, 19]
Operating cost	Grid access fees, insurance costs, and seabed rental	[5, 19]
	Maintenance cost (preventive)	[9, 19]
	Maintenance cost (corrective)	See text

Investment cost computation are subject to epistemic uncertainty that arise from the relationships used. Its value is sampled from a probability distribution built on its computed expected value. Revenues are computed by multiplying the hourly produced power, and the hourly energy price, obviously neglecting the downtime periods. Market risk is mainly accounted for through the hourly energy price that is modelled starting from historical time series used as input to perform a regression and obtain coefficients of an ARIMA model. These parameters are used to simulate 1000 paths for each run and the middle time series is taken from the set and used for revenue computation of the current run. Financial risk is modelled using Monte Carlo sampling from a predefined probability density function of plant nominal life and bank investment cost. Tax risk, social risk, and political and regulatory risk were not included in the original model (Caputo et al., 2023). To include these types of risk, in this paper, scenario analysis is performed as described in the next section. Risk assessment consists in the NPV probability density function computation, and in the assessment of the probability to obtain an expected value of NPV lower than 0, the Value at Risk (VaR), which is fixed at the beginning of the simulation, and the NPV coefficient of variation.

III. SCENARIOS DESCRIPTION

Scenarios were selected to model tax, social, cost, and market risk during a long time-period. To evaluate cost reduction effects over the years, it was assumed that the plant, including a single wind generator, starts its production in 2030. Twenty-one scenarios were built starting from three distinct scenarios forecasting separately energy price evolution in time, three different subsidies policy and three investment cost reduction. Starting from (IEA, 2022), energy price scenarios were constructed according to (Schmitt and Zhou, 2022). Three scenarios were chosen, namely Relief (R), Central (C), and Tension (T). Beyond traditional energy market driver, in the analysis the geopolitical situation was included. Scenario R assumes that relationship between USA, Europe, Russia, and China will ease off again in the next years, continuing imports fossil fuel from Russian pipeline, leading to a reduction in the energy price. Anyway, the reduction of dependence on Russia will continue, so less natural gas is imported than before 2021. Recently adopted targets for renewables are kept in place. In C scenario Europe stops importing Russian pipeline gas by 2027 and renewable resources utilization smoothly increases in next years. Natural gas will be replaced by synthetic fuels, e.g. green hydrogen. To continue power generation from natural gas, its price will fall to remain competitive. In addition, there will be an increase of heat pump utilization and by 2060 electric vehicles and trucks in Europe increases to 95%. In T scenario current tension between Russian and the West continues and intensifies in coming years, leading to energy price increasing. Europe stops the imports of Russian pipeline gas immediately and European consumers are competing with Asian markets. Investment cost reduction is modelled resorting to offshore wind power learning rate (Fortes et al., 2015; Shields et al., 2022). This data are combined with scenarios about the offshore wind power installed capacity in Europe in 2030 (Nghiem and Pineda, 2017), obtaining three scenarios, namely High Investment Cost Reduction (H), Medium Investment Cost Reduction (M), and Low Investment Cost Reduction (L). The higher is the installed capacity in 2030, the higher is the percentage of reduction of the investment cost. Learning rate is considered fixed at value of 9 %, whereas installed capacity in 2030 can be 40.5, 70.2, 98.93 GW according to L, M, and H scenarios. These values are linked to energy economy development in next years. In L scenario no significant progress is made in electricity interconnections between European states, unfavorable national policies for permitting and planning in high potential markets persists, and the European renewable energy target is not achieved. In M scenario regional cooperation mechanisms are established, renewable energy directive is implemented, and national policies for wind energy are boosted. In addition, power interconnection infrastructures are intensified. In H scenario European targets for RES is increased to 35%, power transmission network is intensified beyond the target of 15%, and an acceleration in new installation is achieved, due to the favorable policies of member states. Even though at the time of this study there are not subsidies for offshore wind power plants, Italian government is thinking about a plan for subsidies introduction. Three scenarios are thus considered, namely feed in tariff (F), feed in premium tariff (P), and no subsidies (N). Due to the lack of data, feed in tariff was set on 187 €/MWh, according to the historical levelized cost of energy for offshore wind power systems (Lecca et al., 2017). In this scenario the time series of electricity price has no influence on NPV, because the power produced is sold at a fixed price. Feed in premium tariff is fixed on 31 €/MWh. In this case the selling price are calculated adding to the current market price of energy the feed in premium value. In no subsidies scenario the selling price is the current energy market price. As it is clear, the selected scenarios are strictly related to cash flows (scenarios T, C, R, F, P, N), in particular to revenues, but also to investment cost (scenarios H, M, L). Scenarios belonging to the same group are mutually exclusive, so there are three levels of three different variables. For that reason, doing all the admissible permutation, the resulting total number of scenarios is twenty-one. This happens because, as previously said, if Feed In Tariff subsidy is selected, there is no influence of energy price on the NPV probability density function, but the influence of investment cost reduction still holds. Energy price scenarios and investment cost scenarios are based on the European energy scenarios for 2050, but whereas the driver of the former is the relationship between West and East countries, the main driver of the latter resides in internal policy of European member states. Instead, subsidies scenarios are mainly influenced by Italian internal policy. These assumptions allow to assume the independence of different variable evolution and determine the admissibility of all the permutations. Each scenario is represented by two or three letters corresponding to the evolution story of the associated variables.

IV. NUMERICAL EXAMPLE

Model is implemented in Matlab environment and the wind power system consists in a single wind generator. The wind turbine (WT) is a horizontal axis NREL 5-MW reference wind turbine (Jonkman et al., 2009) located 5 kilometers off the port of Brindisi, Italy at coordinates latitude 40.68, longitude 18.06 degrees. The water depth is about 400 meters, so the WT is installed on a SPAR platform, and it is equipped with a geared drive train, and it is pitch regulated. The hub height is 90 meters and the rotor diameter 126 m. From (Jonkman et al., 2009) are taken all technical model data to estimate technic performance and from (Castro-Santos, 2013) all structural and construction data of the floating platform to assess costs, which are adjusted to the present value resorting to current EU producer price index. The resulting expected investment cost is then reduced according to the three scenarios H, M, L of about 12%, 17%, and 23% respectively. The hourly time series of wind speed at 10 meters from 2015 to 2019 were taken from ERA5 database. Time series are used to set the transition rate of the Markov chain that is used to generate the values of wind speed. Wind speed is adjusted to the hub height resorting to a log law. To estimate the ARIMA parameters for the hourly energy price time series generation, data were taken from Italian Power Exchange database, and they refer to 2021. In this way the behaviour of hourly energy price is captured and then it is adjusted according to the mean of three scenarios R, C, T of 60 €/MWh, 79 €/MWh, and 100 €/MWh and reduced or increased with the yearly corrective trend coefficient of each scenario. Data on failure rate, average repair time, average cost, and average number of technicians aggregated for main components and damage level were taken from (Carroll et al., 2016) and used to build failures events list. These data refer to 2-4 MW wind turbine, so the values of restoration cost were increased by 10% to account for the bigger size of WT and adjusted with the European Producer Price Index. Disruptive events were neglected, because the very low probability and considering the selected floating structure type and the presence of a single turbine. Epistemic uncertainty is modelled with Monte Carlo sampling from a triangular distribution centred on the nominal value of the considered variable and with the minimum and maximum value calculated subtracting and adding a given percentage PD of the nominal value. In Table III nominal values and percentage PD of variables affected by epistemic uncertainty, according to (Fingersh et al., 2006; Poore and Lettenmaier, 2003) are shown. Bank interest rate and self interest rate are respectively (6±4)% and (4±2)%. Financial loan years is 10, percentual of financed investment cost 50%, tax rate 35%, technicians hourly cost 50 €/h, and yearly percentage of amortization is 7%.

TABLE III. PARAMETERS FOR VARIABLES AFFECTED BY EPISTEMIC UNCERTAINTY

Variable	Nominal value	PD
Power coefficient	[15]	±1%
Generator efficiency	[15]	±1%
Power electronic efficiency	[15]	±1%
Gearbox efficiency	98%	±1%
Restoration cost	[4]	±10%
Investment cost	10,500,500 € (Computed by the model)	±30%
Plant years life	20 (Nominal)	±10%

A. *Scenario analysis*

For each scenario 1000 runs were performed and the expected value of NPV and its minimum and maximum values are shown in Fig. 4. Table IV shows the expected values (E), the standard deviations (σ), and the coefficients of variation (CV) of different scenarios. As can be seen, only feed in tariff guarantees an expected value of NPV higher than 0, mainly for two reasons. Firstly, energy price scenarios provide for a significant decreasing of mean energy price in next years in comparison with the mean value of the end of 2021 and 2022. Moreover, the feed in premium tariff value is not enough to obtain a sufficient revenue to cover the investment and operating cost. Secondly, system under analyses is designed with only one wind generator, thus losing the economies of scale effect associated to wind farms but allowing to avoid wake effect and isolating uncertainty propagation effect. In addition, even though in Italy the first offshore wind power systems installation attempts are ongoing, all available current offshore wind turbines are designed to operate in higher wind speed conditions of about 11.4 m/s, whereas in the chosen site the mean is about 5-6 m/s which is typical of Mediterranean sea conditions. This significantly impairs the turbine generation capability when its actual power coefficient curve is considered. Anyway, the aim of this work is not to determine the cost effectiveness of this type of system in a specific application, but to assess the relevance of considering social, political, and regulatory risk with scenario analysis. From the best-case, that is Higher Investment Cost reduction combined with Feed In tariff (HF), to the worst-case scenario, i.e. Low Investment Cost reduction, Relief energy price and no subsidies scenario (LR), there is a difference in the mean value of NPV of about 291%, passing from 4.21 M€ to -8.05 M€. Even if assess a probability of scenarios is a challenging

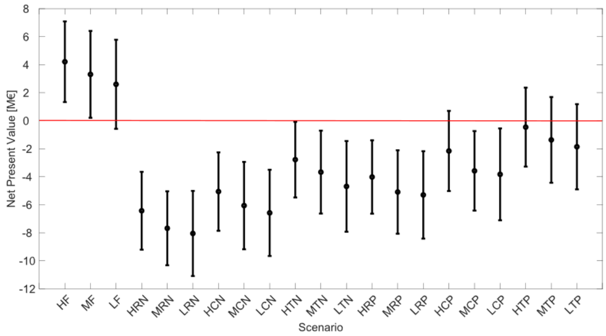

Fig. 4 Expected value of net present value in different scenarios

task, to help decision makers in selecting the more plausible scenario, we try to give a critical contribution resorting to plausibility cone concept (Hancock and Bezold, 1994; Taylor, 1990). We divided the assumed scenarios in four groups: preferable, possible, plausible, and probable. Although from wind power investor perspective scenario HF, MF, and LF are obviously preferable scenarios they are not in the probable group. In fact, subsidies policy around the world is heading towards a feed in premium tariff. Anyway, scenario LF is the more plausible in this set of three, as the regulator may adopt a more effective subsidies policy if the investment cost reduction is lower. Daily news about geopolitical situation depicts a non-relief scenario between West and Est countries, so all scenarios with take relief assumptions (R) are only possible. Other scenarios with no subsidies (N) are plausible, but Italian politician seemed to want to pursuit a subsidies policy, especially for wind and solar energy. Therefore, scenarios with feed in premium subsidies are in the probable group. Finally, considering the continuous investment in all the world, and in Europe, in wind power system the high investment cost reduction is the most probable. Thus, in our opinion, HTP and HCP are the couple of most probable futures.

B. *Scenario combination*

The big weakness of scenario analysis is the decision-making problem under deep uncertainty that arise from the lack of probability assigned to scenarios. Although to assess a probability of a scenario occurrence is a difficult matter, there are some variables for which this probability could be defined. For example, political interest and opinion on RESs can be analyzed to assume the evolution of subsidies policy. Resorting to the claims of European and Italian governments on RESs and wind power technology expected developments, four different stories on subsidies policy development were assumed, and simulation results were combined using their associate probability to obtain a single NPV probability density function (HTPS scenario). Firstly, the NPV probability density function of each scenario is assessed, then they are multiplied by their associated probability and finally summed together. The life of plant was divided in six timespans, and for each one a percentage of change in Feed In Premium tariff value was assigned, as listed in Table V.

TABLE V. PERCENTAGE OF CHANGE IN FEED IN PREMIUM TARIFF VALUE FOR EACH SCENARIOS AND THEIR ASSOCIATE PROBABILITY

Probability	**Timespan**					
	1	2	3	4	5	6
35%	0%	0%	0%	0%	0%	0%
5%	5%	10%	15%	20%	25%	25%
20%	-5%	-30%	-50%	-60%	-70%	-70%
40%	0%	0%	-70%	-70%	-70%	-70%

For each scenario 1000 runs were performed, and results were compared with the case in which no changing in subsidies policy is experimented during the system life. The consistent basis for comparison is the scenario HTP. Results show that considering a constant value of subsidies, instead of combining different plausible stories, led to an overestimation of NPV of about 158%, changing from -1.18 M€ to -0.46 M€.

V. CONCLUSION

In this paper an attempt is made to address a gap existing in the literature pertaining to RESs economic assessment which neglects risk of scenario changes. We consider social, political, and regulatory risk in an overall framework for uncertainty propagation in the economic assessment of offshore wind energy systems. Widely adopted scenarios on energy price, investment cost reduction, and subsidies policy were merged in order to build more complex and complete scenarios

TABLE IV. EXPECTED VALUE, STANDARD DEVIATION, AND COEFFICIENT OF VARIATION OF THE NPV ACROSS DIFFERENT SCENARIOS (NEGATIVE VALUES OF NPV ARE IN *ITALIC*, POSITIVE VALUES OF NPV ARE IN **BOLD**)

Code	HF	MF	LF	HR	MR	LR	HC	MC	LC	HT	MT	LT	HRP	MRP	LRP	HCP	MCP	LCP	HTP	MTP	LTP
E [M€]	**4.21**	**3.31**	**2.60**	*6.43*	*7.68*	*8.05*	*5.06*	*6.06*	*6.58*	*2.78*	*3.67*	*4.69*	*4.02*	*5.09*	*5.30*	*2.16*	*3.58*	*3.83*	*0.46*	*1.37*	*1.86*
σ [M€]	1.44	1.55	1.59	1.39	1.32	1.52	1.40	1.56	1.54	1.35	1.48	1.62	1.31	1.49	1.56	1.43	1.42	1.64	1.41	1.53	1.52
CV	0.34	0.47	0.61	0.22	0.17	0.19	0.28	0.26	0.23	0.48	0.4	0.34	0.32	0.29	0.29	0.66	0.40	0.43	3.09	1.11	0.82

to increase the number of considered sources of uncertainty. A numerical example is carried out to show the relevance of scenario analysis. Results show that there is a difference in the expected value of NPV between the best-case to worst-case scenario of about 290% and of about 160% when scenario variability is included. Overall, this work, offers the possibility to achieve a better risk estimation of offshore wind power system investments. In addition, it demonstrates the relevance of considering scenarios analysis to obtain a better assessment of NPV probability density function. Even if scenario forecasting is an art by itself, and we do not claim that our analysis is exhaustive, we showed that changes in the external scenarios including legal, social and economic parameters may significantly affect the profitability of renewable energy systems, and offshore wind power in particular. Therefore, scenario analysis, which is usually neglected in the economic evaluation should be given due attention. The current model at present is limited to a single wind turbine and it will be extended to wind farm to consider wake effects due to variability of wind direction and including economy of scale effects in capital investment. In addition, also disruptive events will be included.

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