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Cash flow at risk of offshore wind plants

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***Abstract*— Offshore wind power plants might be seen as high risk investments. Their risk depends on technical and financial elements. When some corporations decide to invest in a plant, they decide to take all above-mentioned risks. The question "Given a specific investor, a specific plant, etc., how big are the investment risks?" has not a clear answer. In fact, the impact of the previous risk factors on cash flows is not completely quantified, mainly because all the risks are related, but the dependency structure is difficult to be modelled. Hence, it is important to have a measure of the impact of the risks into the cash flows. Due to the lack of knowledge in this quantification, we have decided to investigate it more in the detail. The paper aims to measure the variability of cash flows and how effective are the strategies for locking electricity prices, ship freight rates, or both in the reduction of this variability. We adopt the Monte Carlo approach for simulating all the possible cash flows and for measuring all the uncertainties. The output shows that seasonal and uncertain cash flows. The strategies, for reducing the probability of negative cash flows, work only with locked electricity prices.**

Keywords—cash flow at risk; offshore wind energy.

I. NOMENCLATURE

OpEx:	Operational expenses
FinEx:	Financial expenditures
CoA:	Contract of affreightment
CapEx:	Capital expenditures
PD:	Probability of default
BM:	Brownian motion
SDE:	Stochastic differential equation
CTV:	Crew transportation vessel
FSV:	Floating service vessel
HLV:	Heavy lift vessel
FCFE:	Free cash flow to equity
FCFF:	Free cash flow to firm
EBIT:	Earnings before interest and taxes
D&A:	Depreciation and amortization
WC:	Working capital
FiT:	Feed in tariff

II. INTRODUCTION

Net cash flows of an offshore wind plant depend mainly on the sold electricity at a specific price, and on the costs that operators pay each month, respectively operational expenditures (OpEx) and financial expenditures (FinEx) for having bought or built the plant. The sold electricity depends on wind speed, power curve and electricity prices. Wind speeds are stochastic, they can have very low or high values. If the wind speed is higher than the maximum limit accepted, or lower than the cut-in speed, the turbine cannot operate. Electricity prices are subjected to upward or downward spikes in the short term, and the long-term trend can be affected by future electricity demand and supply. Further, the plant can be stopped for maintenance and if significant wave heights are higher than a specific limit, the vessels, for maintaining the turbines, cannot operate because the access is denied. The rest of the paper is set out as follows: a review of modeling approaches of electricity prices, wind speeds, operational expenses, financial expenses and cash flows at risk is performed in Section III. Findings from literature review feed into Section IV, where the model developed is presented, while an application of the model is outlined in Section V in the context of a case study. Finally, Section VI summarizes the conclusions derived from the study.

III. REVIEW OF MODELLING RISK FACTORS

A. Electricity Prices

Electricity is a particular commodity that has many characteristics difficult to be modelled in a mathematical manner. In order to understand how electricity is priced, the description of electric power lifecycle is needed [1]. The biggest issue, that makes the electricity pricing very difficult, is the non-storability, because it forces a perfect balance between supply and demand in the local nodes and in the entire network. The lifecycle stages are: energy sourcing, power generation, transportation, supply management, system operation, market trading, market operations, consumption, metering, and disposal [1]. Electricity pricing models should take into account the entire lifecycle because prices should reflect the characteristics of the dynamics imposed by the entire supply chain. Energy markets have already studied in detail the electricity price models. Six large types of electricity price models can be identified [2], [3]: production cost, multi-agent, structural, reduced-form, statistical and, computational intelligence models. New pricing models have been recently developed. As far as the reduced-form models are concerned, a no-arbitrage Heath-Jarrow-Morton term structure model is applied to forecast electricity prices [4]. The novelty is that the periodic behavior of the prices has been considered. In the regression based models, a machine learning method is presented for estimating day-ahead electricity spot prices, which allows to adopt many possible parameters but avoids overfitting [5]. In structural and statistical models, full supply and demand curves have been forecasted elaborating price clustering and using real auction data [6]. In the computational intelligence models, a new one, based on a time series segmentation, recursive feature elimination, and minimum redundancy maximum relevance based support vector machine has been recently introduced [7].

B. *Wind Speeds*

Wind speed modelling is a very important step for an accurate evaluation of offshore wind farms. For forecasting wind speeds, there are two approaches, one is based on mathematical modelling of the historical time series of speeds, the other one is based on the physical characterization of the wind [8], [9]. According to the mathematical approach, three techniques can be identified. The first one adopts stochastic processes, that are described through a stochastic differential equation or through a probability distribution [10], [11], [12], [13]. The second one studies the dataset of wind speeds through linear time series models [14], [15], [16]. The third technique is the spatially correlated technique and it consists in a comparison of data among sites [17]. The application of this technique for offshore wind is in [18], [19], [20]. The physical approach forecasts the wind speed using a meteorological model [21].

C. *Operational expenses*

Operational expenses (OpEx) are the total costs that operators pay for maintaining the plants. They can reach the 30% of the total life cycle cost of the wind farm, and depend on the adopted strategies. Hence, a proper decision tool is needed to help managers and academics to understand which are the main factors affecting the costs and how big is their effect. An overview of existing decision support models can be found in Matthias [22]. Main characteristics about operation and maintenance, offshore logistics, power production and total project cost are analyzed. OpEx and strategies mainly depend on the failure probability of the turbine, and on the weather, that affect the accessibility of the plant. Carrol *et al.* [23] provide a thorough analysis of failure rates for plants up to eight years old. A detailed model that considers the climate and operating strategy has been developed in Dinwoodie *et al.* [24]. A new decision support system model develops two kinds of optimizations, one for stakeholders having reliable deterministic failure data, one for people having uncertain failure rates [25].

D. *Financial expenses and cash flows*

In offshore wind, financing structures are not developed as in other sectors, because the sector has seen a sustained growth only in the recent years. PWC [26] analyzes the cost of capital and insurance models. Authors found that the main technical uncertainties, i.e. the accessibility after a failure, entail an increase in the risk perceived by investors, and hence, in the cost of capital and insurance. Another result is the finding of a strong dependence between the cost of capital and the financing structure. Financing structures can be very different from each other, and all of them are justified by the risk appetite of major shareholders [27]. Arapogianni and Moccia [28] provide a good review of financing structures and major financing players. Based on the financial structure, all the cash flows have different time-profile, hence they need to be properly studied and modelled. Investment analysis in offshore wind has many critical issues [29]. The risk that cash flows are lower than a limit value has been analyzed in other sectors different from offshore wind [30], [31], [32]. A comparison between cash flow at risk and earning at risk is presented in Wiedemann *et al.* [33]. A strategy that can be used for reducing the risk, can be the fixture of the spot price (of the sold commodity) for the future. With this method, we are introducing the concept of the forward agreements. A forward contract is an agreement to buy or sell an asset or service at a certain future time for a certain price. It is usually traded over the counter among an institution and its clients [34]. Since there is rarely a clearing house, at the maturity of the contract, there exists the possibility that the parties do not fulfil the agreement. Hence, they face counterparty risk. Furthermore, since a huge cost during the operation phase is due to the vessel chartering, it is possible to avoid the spot market (where in high demand periods the rates can be very high and the lead times can be years) and employ the vessel with different forms of contracts. Each contract (voyage, contract of affreightment, time charter, bareboat charter) entails a particular cost structure incurred by owner and charterer. Based on the charter contract, ship owner pays some expenses and charterer others. The cost structure sustained by charterers is shown in Figure 1. There are four kinds of different contracts, voyage contract, contract of affreightment (CoA), time charter and bareboat contract. The color represents the type of expense that is paid. I.e. the vessel rate is the amount paid to the ship owner for the vessel, the cargo handling is paid for loading and unloading the cargo, fuel and port costs are paid for moving the vessel or keeping it in a safe port, the operational and maintenance expenses (OpEx) are paid for managing the vessel, the capital expenses (CapEx) are paid for buying or building the vessel. Hence, in time charter contract, charterer pays the vessel rate, the cargo handling and the fuel&port costs, but it does not pay OpEx and CapEx. A very good analysis about the shipping market models is provided by Alizadeh and Nomikos [35].

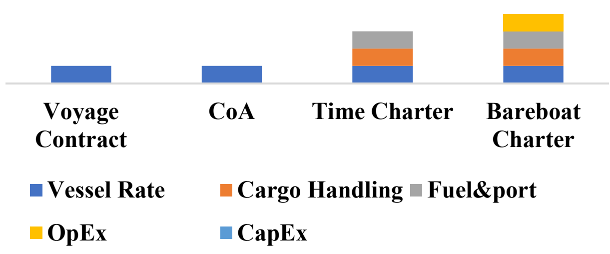

Figure 1 Charterer expenses

IV. MODEL DEVELOPMENT

The target of the model is to compute:

1. future monthly probability distributions of cash flows for an offshore wind plant.
2. the probability of having negative cash-flows, that in this case we define as probability of default (PD), which is a consequence of the previous step
3. the PD in case of some management strategies:
   - Fixed electricity prices,
   - Fixed heavy lift vessel rate,
   - Fixed both electricity prices and heavy lift vessel rate

The future probability distributions of cash flows are computed in each month in advance since the starting operation date.

Since the main factors, that affect the cash flows, are electricity prices, wind speed, operational expenses (OpEx) and financing expenses (FinEx), we will quantify all of them in a proper manner.

The algorithm to compute the cash flows and the probability of negative cash flows in case of spot market is presented in Figure 2.

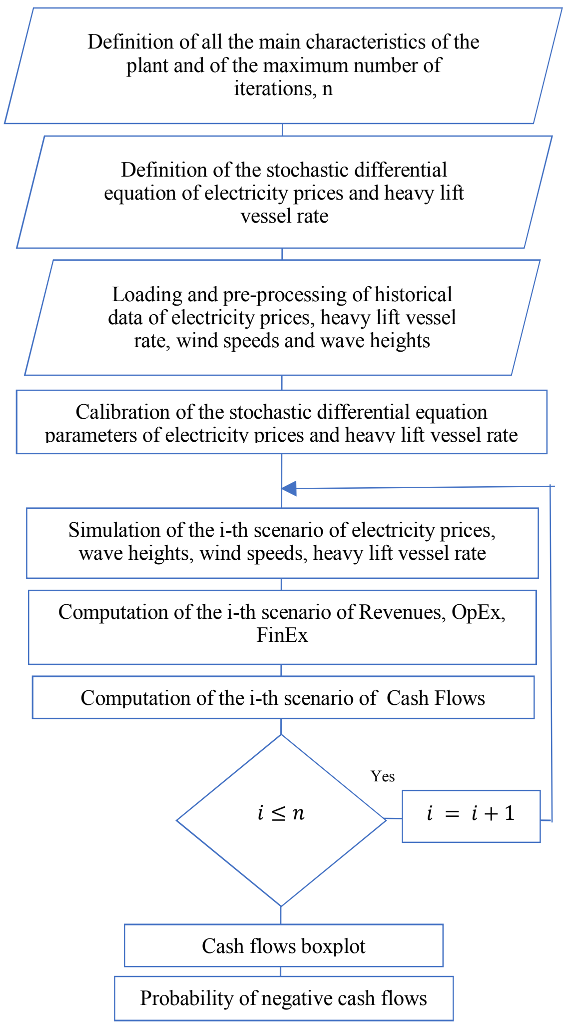

Figure 2 Flow diagram of cash flow at risk computation

After having computed the probability of negative cash flow, we evaluate them with basic strategies of fixing electricity prices, freight rates, or both. The flow of algorithm is presented in Figure 3.

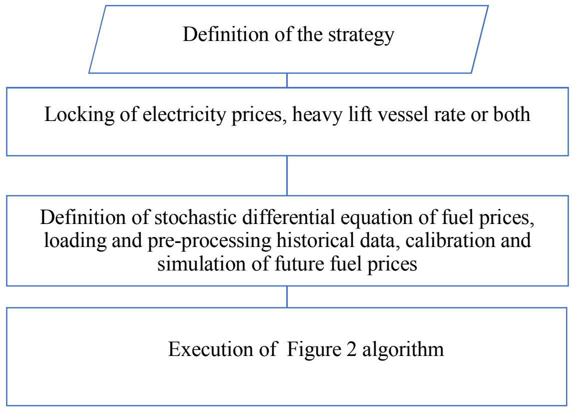

Figure 3 Flow diagram of fixing price strategies

The next sections cover in detail all the main blocks of Figure 2 and Figure 3

A. *Definition of all the main characteristics of the plant and of the maximum number of iterations*

In this section, the plant must be defined in terms of all its physical characteristics. Furthermore, it is set the maximum number of iterations for Monte Carlo simulations.

B. *Definition of the stochastic differential equation of electricity prices and heavy lift vessel rate*

Market prices of electricity can be endogenous or exogenous [3]. In the first case, they are derived through a complete analysis that considers the supply, demand, and the market equilibrium. Since a complete analysis is not the purpose of the present model, we have decided to model the prices following an exogenous approach, which merely studies the statistical characteristics of the time series. In fact, there are many exogenous models that have already been studied and compared [36], [37]. Some of them assume that prices follow a simple Brownian motion (BM), others have observed that in some periods there are seasonal effects, other ones analysed the autocorrelation among the time step prices and/or returns. In our methodology, we decide to adopt the following stochastic differential equation (SDE):

$$dX_t = \mu(X_t, t) \cdot dt + \sigma(X_t, t) \cdot dW_t \quad (1)$$

Where:

X_t is the stochastic variable,

W_t is the Wiener process.

Since it is a simple BM, we assume that:

$$\mu(X_t, t) = \mu \quad (2)$$

$$\sigma(X_t, t) = \sigma \quad (3)$$

In the case of heavy lift vessel rate, no specific reference that provides a study of the market prices has been found.

This is probably due to the fact that it is a niche market. Hence, since this paper does not aim to provide a deep market pricing model of heavy lift vessel rates, we assume that the dynamic of rates follows the same SDE of electricity (with different parameters).

In a more rigorous analysis, all the possible statistical characteristics should be studied and the SDE able to specify all of them should be chosen.

With the maximum likelihood procedure, we have calibrated the terms μ and σ to the real data, and then we have simulated the scenarios of the specified SDE.

C. *Loading and pre-processing of historical data of electricity prices, heavy lift vessel rate, wind speeds and wave heights*

1) *Electricity prices and heavy lift vessel rate*

In this sub-block, all the historical data of the stochastic factors are pre-processed for the calibration of the SDEs. The pre-processing procedure is different for each series. In the case of:

- electricity prices, an ordered time series has been created from older to newer element,
- heavy lift vessel rate, a daily (through a linear interpolation) and ordered time series have been created.

2) *Wind speed and wave heights*

In this case, data used for simulations are retrieved from literature. More details are included in Section V.B.

D. *Calibration of the stochastic differential equation parameters of electricity prices and heavy lift vessel rate*

The equation that will allow to simulate stochastic electricity prices is:

$$dP_t = \mu_{Elec} \cdot dt + \sigma_{Elec} \cdot dW_{Elec_t} \tag{4}$$

where, P_t is the stochastic electricity price, μ_{Elec} and σ_{Elec} are the constant parameters that define the electricity price dynamic W_{Elec_t} is the Wiener process of the electricity prices.

The equation that allows to simulate stochastic freight rate is:

$$dFR_t = \mu_{FR} \cdot dt + \sigma_{FR} \cdot dW_{FR_t} \tag{5}$$

where, FR_t is the stochastic heavy lift vessel rate, μ_{FR} and σ_{FR} are the constant parameters that define the heavy lift vessel rate, dynamic W_{FR_t} is the Wiener process of the heavy lift vessel rate.

The terms μ_{Elec}, σ_{Elec}, μ_{FR}, σ_{FR} are calibrated by the use of real data, through the maximum likelihood procedure. Outcome of this step is the derivation of two stochastic differential equations that will be used for generating the future stochastic dynamics of electricity prices and heavy lift vessel rates.

E. *Simulation of the i-th scenario of electricity prices, wave heights, wind speeds, heavy lift vessel rate*

1) *Simulation of electricity prices*

Electricity prices are simulated according to Equation (4). At each i-th iteration, a scenario of a time series is generated. The total number of iterations is the maximum defined in the first block.

2) *Simulation of heavy lift vessel rate*

Heavy lift vessel rates are simulated according to the Equation (5). At each i-th iteration, a scenario of a time series is generated. The total number of iterations is the maximum defined in the first block.

3) *Simulation of wave heights*

Other simulated variables are:

- Wave height
- Wind speed at 10 m above sea level, because the available historical data are valid only at this position. A function relating the wind speed with the wave height with respect to the height measured from the sea level is used (that will be specified later).

Due to the particular form of available data (monthly percentage of exceedance), the simulation of wave heights starts with the computation of a monthly cumulative density function (CDF). The monthly data are used for computing the cumulative distribution in each month:

$$F_W(w) = 100\% - Exceed.Percent. \tag{6}$$

where, $Exceed.Percent.$ is the percentage of exceedance of the wave height.

Considering monthly series, 12 CDFs are computed, one for each month. Using the Monte Carlo simulation method, always for each month in advance from Jan 2017, we simulate the time series of significant wave height based on its CDF.

4) *Simulation of wind speeds*

The same exact procedure as for wave height series is applied for computing the wind speed at 10 [m] above sea level (asl).

F. *Computation of Revenues, OpEx, FinEx*

1) *Computation of revenues*

Having simulated various scenarios of time series of wind speed at 10 [m] (asl), the wind speed at hub level is computed following the "wind gradient" method. According to this methodology the wind speed follows this formula:

$$w_{h[m]} = w_{10\,[m]} \cdot \left(\frac{h[m]}{10[m]}\right)^a \tag{7}$$

Where:

- $10\ [m]$ is the height asl in [m] at which the wind speed is simulated,
- $h\ [m]$ is the height asl in [m] at which the wind speed should be computed. In this case, it is the hub height.
- $w_{10\,[m]}$ is the wind speed at $10\ [m]$ asl,
- $w_{h\,[m]}$ is the wind speed at $h\ [m]$ asl,
- a is the Hellmann exponent, that depends on the surface above which the turbine is set. In the case of offshore wind field, assuming that the air is neutral (not unstable), the coefficient is $a = 0.1$ [38]

Then, using the power curve as specified by Jonkman *et al.* [39], with the wind speed, the produced power is computed.

Assuming that there is no loss of power in the inter grid and in the exportation cables, and that all the produced power is instantaneously sold in the market at a price of the simulated scenario as specified before, the instantaneous revenues are computed.

2) *Computation of OpEx*

The OpEx are computed considering the number of failures, the material costs per failure, the wait-for-weather, travel and time-to-repair costs.

Using the failure data, the number of failures are computed respectively in cases of major replacements, major repairs and minor repairs. The exact definition of these cases is in Carrol *et al.* [23].

Since the analysis adopts failure rates expressed in failures per turbine per year, for computing the total number of faulted turbines per year, it is sufficient to multiply the data and the total number of turbines of the plant.

The material cost per kind of failure (minor repair, major repair, major replacement) is computed considering a weighted average in which the elements are the material costs for all the sub-parts (gearbox, hub, blades, etc.).

Travel, time-to-repair, wait-for-weather costs are not included. They are summarized in accessibility costs. Now the implemented methodology for computing them is introduced.

Accessibility costs are assumed to be the multiplication between daily price of ships and total time of ships' employment.

The spot rate of the ships is assumed fixed for crew transportation vessel (CTV) and floating service vessel (FSV), and is simulated for heavy lift vessel (HLV) as specified in Section IV.D.

It is assumed that for repairing a minor fault, a CTV is used, for repairing a major fault, a FSV is used, and for implementing a major replacement, a HLV is used.

The total time of vessel employment is defined as the time needed by the vessel for travelling from the port to the farm site, for operating in the site and for going back to the port.

Site operations depend on the time to repair, that is a weighted average of the time to repair for the main objects and the weights are the failure rates.

These operations can be executed:

- in case of calm weather, without any delay because the vessel can travel and operate,
- in case of heavy weather, with some delays because the vessel need to wait for the calm sea.

We define these characteristics in more logical terms. If wave heights are lower than the operational limit of the vessels, they can travel and operate. Hence, the plant is accessible. If the wave height is higher than the operational limit, the vessels cannot travel nor operate. Hence, the plant is not accessible. Since we have simulated wave height time series, we compute the probability of accessibility for each year in advance. Hence, the total time of vessel employment is computed as the ratio of the total time of vessel employment in calm weather and the accessibility probability.

3) *Computation of FinEx*

The financial expenses affect the cash flows. The loan is assumed to be standard, with linear profile of the loan outstanding from the agreement to the end of the tenor.

With these characteristics, the principal repayment (constant and monthly paid, so that at the end there is no any loan outstanding), the interest, and the loan outstanding in each month are computed.

These specifications simplify the computation of financial costs, and they should be refined considering the term structure of interest rates. But, it is leaved for future developments.

4) *Cash Flows*

Cash flows refer to the monetary flows in the considered period. It is a measure of offshore wind power plant auto-financing. In the methodology, we do not follow the entire accounting procedure. To be very precise we would need to have many data about the financial elements of the plant:

$$FCFE = FCFF + borrowing - interest \cdot (1 - tax\ rate) \tag{8}$$

Where:

$FCFE$ represents the free cash flow to equity

$FCFF$ represents the free cash flow to firm

$$FCFF = EBIT \cdot (1 - tax\,\mathrm{rate}) + D\&A - Changes\ in\ WC - CapEx \tag{9}$$

Where:

- $EBIT$ is the earning before interests and taxes
- $D\&A$ are depreciation and amortization,
- Changes in WC are the changes in working capital,
- $CapEx$ is the capital expenditure.

Instead of using these computations, we only approximate the cash flow metric following this assumption:

$$FCFE \approx revenue - OpEx - FinEx \tag{10}$$

A. *Cash flow box plot*

After computing all the scenarios of cash flows, the boxplot is created, so that we can derive the necessary statistical information about cash flows.

B. *Probability of negative cash flows*

Boxplots do not provide information about the probability of negative cash flows. Hence, for counting all the negative cash flows, we compute the probability of default.

After that we have covered in detail all the blocks of cash flow computation (in the case of electricity prices and heavy lift vessel rate on spot markets), we analyse three basic strategies that provide some hints for sub-optimal management decisions.

A. Definition of the basic strategies

After having implemented the entire model for computing $FCFE$, we analyse the effect of locking the prices of electricity and the day rates of the heavy lift vessel (HLV) used for implementing the major replacements.

Precisely, for year 1, …, 5, we have fixed:

- Only electricity prices
- Only HLV day-rates
- Both electrical prices and HLV rates

B. Locking of electricity prices, heavy lift vessel rate or both

1) Electricity prices

The electricity prices should be looked in advance considering the forward pricing theory. In our case, we only assume a fixed level for prices.

2) Heavy lift vessel rate

In the offshore shipping market, renting a ship for a period means to sign a time charter or bareboat contract. Based on the agreement, the cost structure that the charterer has to pay is different. In the case of spot market, the charterer pays only the day rate of the vessel. In the case of time charter or bareboat contract, the charterer pays voyage and cargo handling costs. In our model, the cargo handling cost is ignored and the voyage cost is computed as the multiplication among the employment time of the vessel, the specific consumption and the fuel price. Since the future fuel price is unknown, it adds an uncertainty in the costs. Fuel prices are simulated by means of a specified SDE.

C. Definition of stochastic differential equation of fuel prices, loading and pre-processing historical data, calibration and simulation of future fuel prices

The SDE that defines the evolution of fuel prices is assumed to be:

$$dFU_t = \mu_{FU} \cdot dt + \sigma_{FU} \cdot dW_{FU_t} \quad (11)$$

where:

FU_t is the stochastic fuel price,

μ_{FU} and σ_{FU} are the constant parameters that define the fuel price dynamic,

W_{FU_t} is the Wiener process of the fuel price

Historical fuel prices are, then, loaded and pre-processed so that the frequency is uniform in all the time series.

With the processed and ordered (from the older to the newer element) time series of prices, the Equation (11) is calibrated to the real data.

Finally, with the calibrated series, many scenarios of future fuel prices are generated.

D. Execution of Figure 2 algorithm

Having defined all the strategies and simulated the fuel prices, the algorithm of Figure 2 is executed for computing the cash flows and the PDs. When the HLV rates are locked through a time charter contract, in the OpEx computation, the fuel costs of the HLV are added. The fuel costs are computed as the multiplication of daily consumption of the HLV, the total employment time of the vessel, and the fuel prices.

V. Application of the Model within a Case Study Context

A. Case study description

The case study is an illustrative example; hence, the data are realistic, but not referring to any specific real built nor planned plant. Precisely the main characteristics are summarised in Table 1.

Table 1 General characteristics of the plant

Location	North Sea
Distance to shore	40 km
Water depth	Not available
Total Capacity	500 MW
Number of turbines	100
Nameplate Capacity	5 MW

The plant is assumed to start operations in January 2017, hence, when we provide some results for 1 month in advance, we mean 1 month later than Jan 2017, etc.

B. Data

The data refer to specific characteristics of plant and its services, and historical data are summarized in Table 2 and Table 3.

The speed of each vessel is inserted in km/hours instead of knots only for convenience. The historical data of significant wave height are illustrated in Figure 4. In the x-axis, there are the wave heights, and in the y-axis the percentages of exceedance of the correspondent x-value. Four curves are displayed here: two months corresponding to wave heights with yearly maxima (Jan and Feb) and two corresponding to wave heights with yearly minima (Jun and Jul).

Table 2 Specific characteristics of the plant

	Data	Value	Source
Monte Carlo	Number of simulations	500	Assumed
Revenue	Electricity prices time series	-	[40]
	Wind Speed probability of exceedance	-	[41]
	Hub height	100 m	Assumed
	Wave height probability of exceedance	-	[41]
	Power curve of the wind turbine	-	[39]
OpEx	Years in advance	8	Assumed – due to the form of OpEx data
	Time to repair data	-	[23]
	Failure data	-	[23]
	Vessel day-rates	-	[42]
	Offshore Vessel Characteristics	-	Table 3
FinEx	Loan amount[1]	480 Mill €	Assumed
	Balloon[2]	0	Assumed
	Interest	2%	Assumed
	Tenor	20 years	Assumed
Strategies	Fixed Electricity Price	60 €/MWh	Assumed
	Last year of fixed electricity price	5	Assumed
	Fixed HLV rate[3]	180.000 USD/day	Assumed
	Last year of fixed HLV rate	5	Assumed
	HFO FOB Rotterdam Fuel Prices time series	-	[43]
	HLV daily consumption	30 ton/day	Assumed

Table 3 Offshore Vessel Characteristics

	CTV	FSV	HLV	
Speed [km/hours]	60	45	35	Assumed
Wave limit [m]	2.5	3	4	Assumed

The wind speed data is in the same format; hence, it is not showed. In example, considering the Feb series of Figure 4, waves higher than 5 [m] happen in the 22% of the total cases.

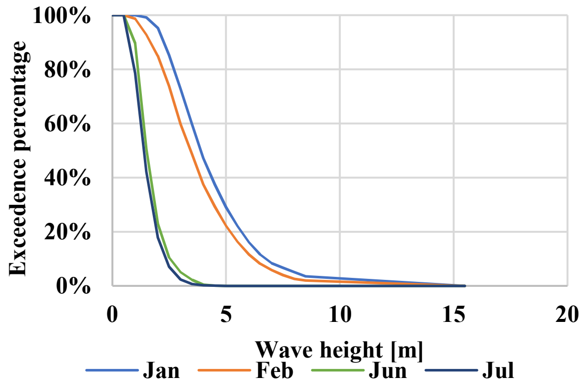

Figure 4 Significant Wave Height - Exceedance Percentage

C. Results

In Figure 5, a simulated scenario of a monthly time series and the seasonal pattern of wave heights are shown.

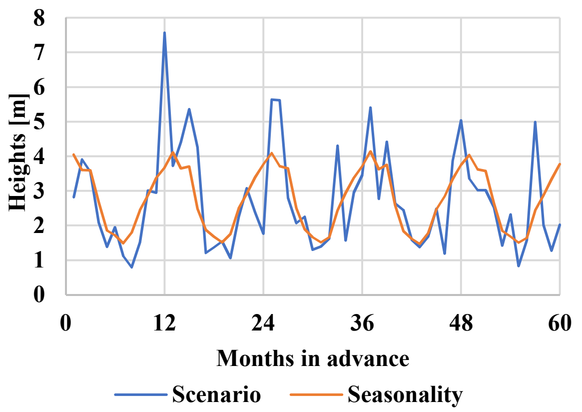

Figure 5 Wave height time series - 5 years in advance

Cash flows are shown in Figure 4. They are given on a monthly basis and in each month a boxplot is presented.

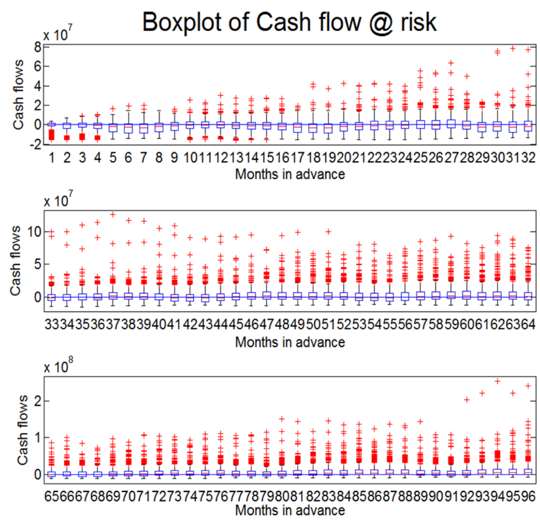

Figure 6 Offshore wind plant cash flow at risk

For each month represented in Figure 6, the following

[1] It is equivalent to the 40% of the loan to value ratio, and it is considered the plant building cost equal to 1.200 Mill €

[2] It is the amount to be repaid at the end of the tenor

[3] It is assumed equal to the mean of the historical rates

information can be observed:

- the horizontal red line is the median. Some median values are positive, others negative. Furthermore, they put in evidence a seasonal pattern that clearly shows strong wind in the winter (and hence more produced power) and low wind speed in the summer (low amount of produced electricity)
- the extremes of each box represent the first and third quartiles. In some months, we find all the quartiles with negative values. The distance between the first and the third quartile measures the dispersion around the mean. The 50% of the observations range between the first and the third interquartile. Smaller the distance, smaller the dispersion around the mean. In the first months, the distance to the mean is very low compared to the later ones. It is obvious, because the future is more uncertain than the present. If the distance between the first quartile and the median is different than the distance between the median and the third quartile, the distribution is asymmetric. In this case, except some few cases, we see asymmetrical distributions.
- the end points of dashed lines represent the inferior and superior adjacent values (IAV and SAV). They give information regarding the dispersion of values, the distribution shape and distribution tails. In almost all the months, the IAV is negative. It means that there is a probability to have negative cash flows.
- red crosses are the outliers, values lower and higher than IAV and SAV. There are some outliers, but we do not dedicate an accurate analysis because it is not the main goal of the paper.

An example that shows the distribution of the cash flows at month 8 is in Figure 7:

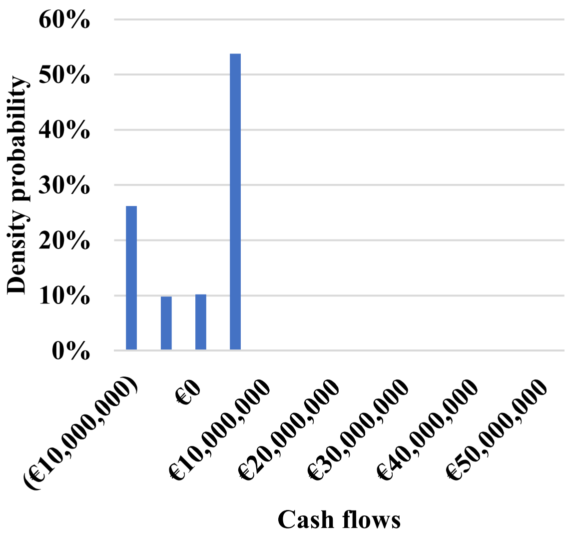

Figure 7 Cash flow probability distribution 8 months after Jan 2017

As shown in Figure 6 and in Figure 7 there is a not null probability of having negative cash flows.

In Figure 8, we provide a graph in which the PD is shown for each month. The most critical years are the first three, and the reason is in the combination of high OpEx and FinEx. There is a downward trend because of two reasons. The first is that the FinEx strongly decreases over the time. The second reason is that OpEx generally decreases from year 1 to year 5 (and from year 6 to year 8) [23]

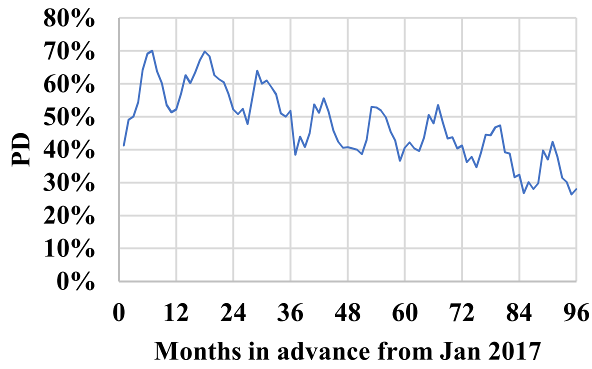

Figure 8 Probability of negative cash flows for every variable on spot market

We have seen that it is highly probable that the offshore wind revenues could be not sufficient for covering the expenditures. Some strategic decisions can be exploited for locking electricity prices or for chartering the ship for some years. Although in some cases probability of default is reduced, it is not obvious. In fact, as shown in Figure 9, the annual averages of default probability are presented. The time charter employment of the HLV, does not reduce the probability of default because the risk of the bunker price remains high.

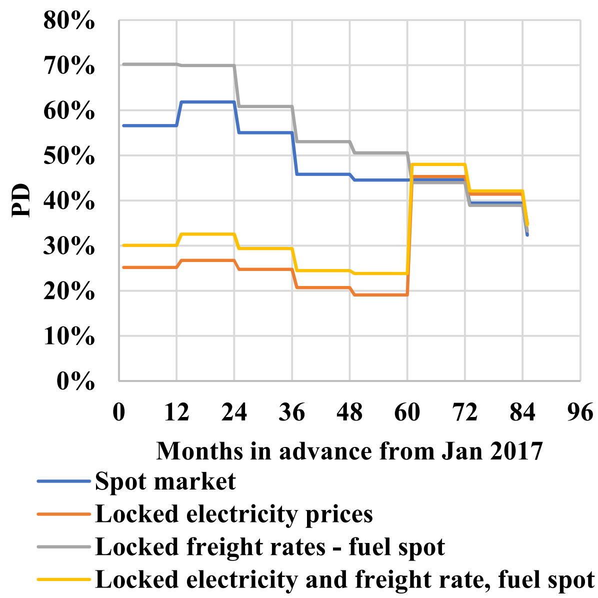

Figure 9 Probability of default (annual series) based on different strategic decisions

VI. CONCLUSION

The aim of the paper was to compute the monthly probability of cash flows, the probability of default, and to analyze some strategies for reducing risks of negative cash flows. The validation of all the results cannot be possible with a direct comparison with another reference because the results depend on the plant's characteristics. But, using a reverse engineering approach, it is possible to have a measure that indicates the robustness of them. Precisely, considering the Equation (10), we countercheck the revenues, OpEx, and FinEx, and then the cashflows. The data used for validating the model can be found in [44], [45] and [46].

As expected cash flows are seasonal and negative with high probability. It is due to the fact that no feed in tariff (FiT) scheme has been considered. This confirms the fact that offshore wind power plant investments might be seen as very risky. The PD is in fact very high, although it decreases over the time. The strategy of locking electricity prices reduces the PD, and seems to be the most effective. This principle is very similar to the FiT Contract for Difference, according to which the electricity price is locked for many years. Obviously, higher the locked price, lower the PD.

Locking the heavy lift vessel rate, will reduce the volatility of OpEx in terms of vessel rates, but it will add the uncertainty of the fuel costs.

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