

Effect of electricity market price uncertainty modelling on the profitability assessment of offshore wind energy through an integrated lifecycle techno-economic model

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Abstract. According to the Contracts for Difference (CfD) scheme introduced to support the deployment of offshore wind installations, an electricity generation party is paid the difference between a constant “strike price” (determined by means of a competitive auction) and the average UK market electricity price for every MWh of power output produced. The scheme lasts for 15 years, after which the electricity output is sold on the average market price. To this end, estimating the long term profitability of the investment greatly depends on the forecasted market prices. This paper presents the simulation results of future electricity prices based on three different simulation methods, namely: the Geometric Brownian motion (GBM), the Autoregressive Integrated Moving average (ARIMA) and a model combining Mean-Reversion and Jump-Diffusion (MRJD) processes. A number of simulation paths are generated for a time horizon of 10 years and they are introduced to a fully integrated techno-economic model developed by the authors. As a result, joint probability distributions of the NPV derived from the three different methods are presented. This study is relevant to investors and policy makers to check the viability of an investment and to predict its stochastic temporal return profile.

1. Introduction

Offshore wind energy has been rapidly expanding in Europe during the last decade. According to WindEurope annual offshore wind statistics, there are currently 92 wind farms in operation across European countries (4,149 grid-connected wind turbines) [1] with UK accounting for 43% and Germany for 28% of all grid-connected turbines.

In the United Kingdom, there is currently a transition from the Renewables Obligation (RO) scheme to the Contracts for Difference (CfD) scheme, introduced by the recent Electricity Market Reform (EMR). The CfD scheme is a private law contract between a producer and the Low Carbon Contracts Company (LCCC), a government-owned company. An electricity generation party with CfD is paid the difference between a constant “strike price” and the average UK market electricity price (“reference



price”). The Generator sells electricity under a Power purchase agreement to a licensed supplier or trader at an agreed reference market price. If the reference price is higher than the strike price, the generation party has to pay back the difference to the LCCC. The bottom line is that company always gets the strike price for the electricity generated. The scheme lasts for 15 years (while the expected lifetime of an OW energy asset is 25 years), after which the electricity output is sold on the average UK electricity market price, hence imposing uncertainty to the revenues yielded by the investment after the 15th year of operation [2]. As such, the forecasting of electricity prices becomes pertinent towards estimating future returns of the offshore wind energy project as well as, the overall profitability of the investment.

This work aims to stochastically assess the impact of volatile market electricity prices on the profitability assessment of offshore wind farms. We develop and formalize a process for more detailed modelling of the future economic cash flow of an offshore wind farm by employing a tested lifecycle techno-economic model which accommodates the uncertainty modelling of electricity prices through employing different forecasting methods in order to test how these can affect the Net Present Value (NPV) distribution analysis of the wind farm. A stochastic cost modelling of the economic profitability is finally derived.

2. Lifecycle techno-economic model

The methodological framework of the techno-economic model is illustrated in Figure 1. The main components of the life cycle cost of a fixed OW farm are the following: (i) the CAPEX module, which includes development and consenting (D&C), production and acquisition (P&A), installation and commissioning (I&C), and decommissioning and disposal (D&D) costs, (ii) the general site characteristics module with details on the weather conditions, site water depth, distance from port, vessels, cost of personnel etc., (iii) the FinEx module with parameters related to the financing expenditures, namely the Weighted Average Cost of Capital (WACC), inflation rate, equity and debt ratio, etc., (iv) the OPEX module, which considers reliability data from literature, cost of personnel, materials, vessels and related maintenance processes, which will provide availability and O&M cost estimates pertinent for the cost analysis and (v) the Revenue model, which considers the net power generation, the strike prices (according to the CfD scheme), and the market electricity price. A detailed description of the model can be found in [3].

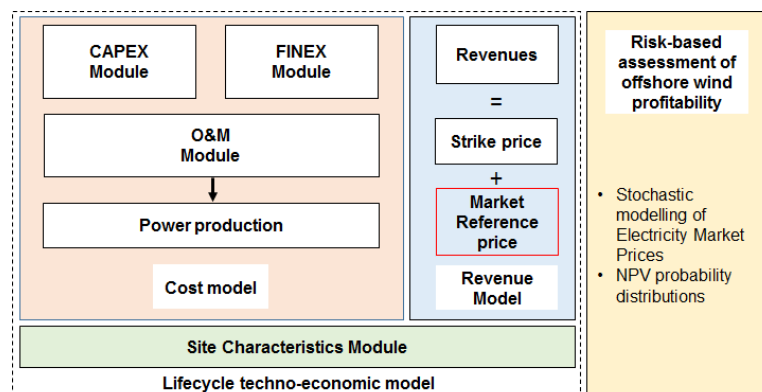


Figure 1 Illustration of integrated techno-economic lifecycle model

3. Modelling & Simulation of future wholesale electricity prices

This section looks at the forecasting methods that were employed to model electricity market prices, towards incorporating the uncertainty and variability in the cash flow model of the analysis. The modelling of market electricity prices has been carried out by numerous authors in literature [4–6], highlighting the advantages and disadvantages of each technique and applying them in various contexts. Time series techniques are usually based on extrapolating a set of historic observations to predict their

behavior in the future. In [5], electricity price forecast techniques are categorized into: multi-agent, fundamental methods, reduced-form models, statistical approaches and computational intelligence techniques. Statistical methods, including autoregressive models forecast the future value of a time series by applying a mathematical correlation of the previous values with the current values. The ARIMA time series model and the Geometric Brownian motion are among the most cited forecasting techniques [4,7,8]. However, statistical methods cannot capture sufficiently the presence of spikes in the dataset, especially for price-only models, but also for models using fundamental variables. Mean-reverting jump-diffusion (MRJD) processes are more appropriate to reproduce patterns of spikes and reversion to a long term mean level [9].

In this study we have tested above forecasting techniques to identify the effect of uncertainty modelling in electric market prices on the profitability of an offshore wind investment. Daily historical data of electricity market prices (found in [10]) were used to stochastically model the future revenues of the investment.

3.1. Geometric Brownian motion

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

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

$$X_t = \mu t + \sigma W_t \quad (1)$$

The generalised form of the Geometric Brownian motion (GBM) process is specified through a stochastic differential equation (SDE) of the form [11]:

$$\frac{dS_t}{S(t)} = \mu dt + \sigma dW(t) \quad (2)$$

where, $S(t)$ denotes the price of the electricity at time t , μ represents the drift parameter, σ the volatility of the electricity prices and W is the standard Brownian motion.

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

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

$$S_{t+T} = S_t \cdot \exp \left[\left(\mu - \frac{\sigma^2}{2} \right) T + \sigma W_t \right] \quad (3)$$

Above equation is the GBM model. This process has the advantage that it always remains positive and it can represent the characteristics of many variables.

3.2. Mean-reverting jump-diffusion (MRJD) process

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

$$dX_t = \mu(X_t, t) + \sigma(X_t, t)dW_t + dq(X_t, t) \quad (4)$$

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

When there is a high electricity demand, more expensive power generation technologies need to be brought online to cover the electricity load. During these periods, electricity prices exhibit jumps. In general, spot electricity prices are characterised by high volatility, seasonal cycles and occasional spikes. In mean-reverting jump-diffusion processes, the drift term $\mu(X_t, t)$ can force reversion to long term mean levels. The Ornstein-Uhlenbeck process, which is the most applied mean-reversion process (initially introduced in finance to model interest rate dynamics [12]), is expressed as:

$$dX_t = (\alpha - \beta X_t)dt + \sigma dW_t \quad (5)$$

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

3.3. Autoregressive Integrated Moving Average (ARIMA)

ARIMA or Box-Jenkins model [13] is a statistical method standing for autoregressive (AR) integrated (I) moving average (MA) and it is a generalisation of the Autoregressive Moving Average model (ARMA), where "I" (standing for Integrated) is a differencing step that is used to remove trend or seasonality from the time series. ARIMA models use standard notation of ARIMA (p,d,q) and (P,D,Q) for their seasonal counterparts. In power systems applications, ARIMA models have been used for load forecasting [14,15], with good results, as well as to model and forecast day-ahead electricity prices [16,17] and weekly prices [18]. ARIMA method was deemed appropriate for this study considering the ability of the method to take into account the seasonal trend of the dataset of electricity prices.

- The Autoregressive part (p) specifies which previous values from the data series are used to predict the current values or else the number of autoregressive orders.
- The Difference part (d) specifies the order of differencing of the time series before the application of the model. To apply the ARIMA model, the dataset is required to be stationary; if not, a transformation of the series to the stationary form needs to take place. Differencing is one of the simplest ways to achieve this. Box and Jenkins (1976) introduced a model that contains not only the autoregressive and moving average parts, but also the differencing part [19].
- The moving average part (q) specifies the order of moving average orders in the model, namely how the mean values deviation of the previous time series are used to predict the current values.

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

$$\varphi(L)(1-L)^d X_t = c + \theta(L)\varepsilon_t \quad (6)$$

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

$$\varphi(L) = 1 - \varphi_1 L - \dots - \varphi_p L^p \quad (7)$$

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

$$\theta(L) = 1 + \theta_1 L + \dots + \theta_q L^q \quad (8)$$

where q refers to the moving average terms [13].

4. Simulation of future electricity prices

4.1. Electricity price prediction under the different methods

Monthly and daily data of the wholesale electricity prices were collected from different sources [10,20] to compile a dataset starting from March 2003 to December 2017. The dataset (178 observations) was divided into two parts, the first consisting of 118 observations, which was used to build the model and the second of 60 observations for testing the model.

- The input data required for the Geometric Brownian (GBM) motion model were the mean instantaneous monthly rates of change of the historic prices dataset (equal to 0.0107) and the instantaneous standard deviation of the rates (equal to 0.1626).
- The parameters of the best-fitting ARIMA model for the monthly electricity prices were identified through Expert Modeler of SPSS [21], eliminating the need to identify an appropriate model through a manual trial and error process. The tool indicated an ARIMA(2,1,2)(1,0,1) model consisting of non-seasonal and seasonal parts with a periodicity set to 12. Above notation means that the series was differenced once at lag-1; further, the model includes X_{t-2} and ε_{t-2} , as well as a seasonal lag-12 AR term and a seasonal lag-12 error term.
- The characteristics of the Mean-Reversion and Jump-Diffusion (MRJD) model were modeled by the following relationship:

$$\log(X_t) = f(t) + Y_t \quad (9)$$

where, X_t is the spot electricity market, $f(t)$ is the deterministic and Y_t is the stochastic part of the model. The deterministic part was further modelled through a trigonometric function [22]:

$$f(t) = s_1 \sin(2\pi t) + s_2 \cos(2\pi t) + s_3 \sin(4\pi t) + s_4 \cos(4\pi t) + s_5 \quad (10)$$

where $s_1, \dots, s_5$ are constant parameters, while the stochastic components were modelled as an Ornstein-Uhlenbeck processes, adopted from [23]. Then, the calibration of both the deterministic and the stochastic part was realized through the least square and the maximum likelihood method, respectively.

After determining the input parameters for the best-fitting ARIMA model, the Geometric Brownian motion, and the MRJD processes using historic monthly electricity prices, we, accordingly, simulated 1,000 sample paths, 10 years into the future. Figure 2 illustrates the simulation results of future electricity prices with the MRJD model from 2017 to 2027.

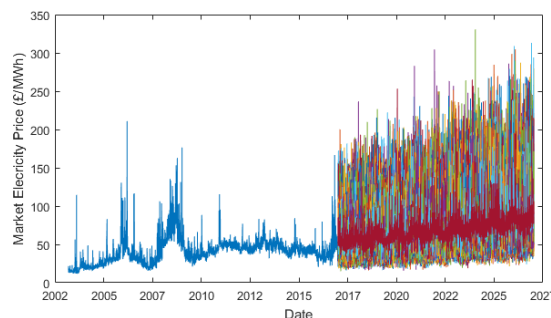


Figure 2 Simulation of future electricity prices with the MRJD model

4.2. Validation of methods

In Figures 3(a)-(c), the 50% upper and lower confidence limits of the resulting model for the first part of the dataset, as well as the observed data for 2015-2017 (2nd part of the dataset) are illustrated for the 3 different forecasting methods. The mean absolute percentage errors and the percentage errors between the observed data and the forecasted values for the four testing years are summarized in Table 1. ARIMA was deemed to have the lowest Mean Absolute Percentage Error in comparison to the other 3 methods namely 14.8%, indicating a relatively better fitness of the ARIMA model to the dataset, followed by the MRJD and the GBM models. MAPE is a measure of prediction accuracy of the forecasting method and is calculated as follows:

$$MAPE = \frac{100\%}{n} \sum_{t=1}^n \left| \frac{F_t - A_t}{A_t} \right| \quad (11)$$

Table 1 Validation of methods

	Error (%)				Mean Absolute Percentage Error (MAPE)
	2013	2014	2015	2016	
GBM	12.6%	44.8%	63.9%	70.7%	48%
ARIMA	-3.3%	14.4%	21.2%	20.4%	14.8%
MRJD	10.0%	30.8%	37.1%	35.7%	28.4%

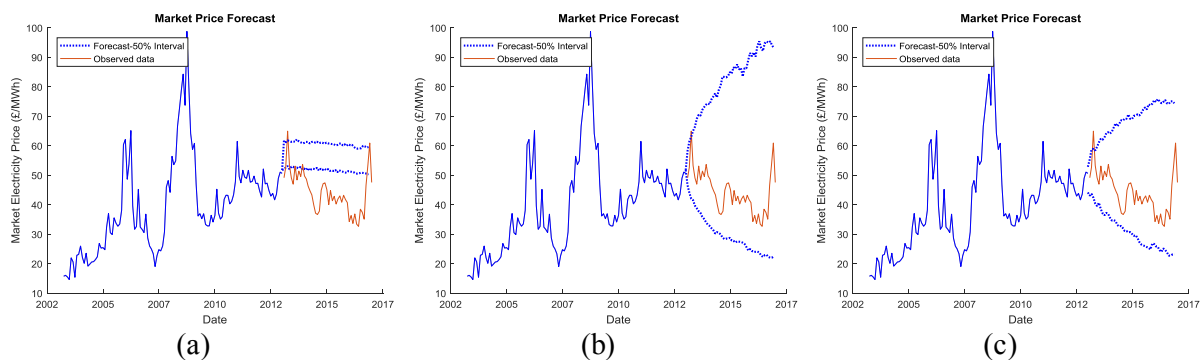


Figure 3 Test cases for electricity prices forecasting: (a) MRJD, (b) GBM, (c) ARIMA

The variability of the simulated electricity prices can be illustrated in Figures 4(a)-(c). It can be observed that MRJD method demonstrates a lower variability probably due to the drift term which forces reversion to long term mean levels (Figure 4(b)). The ARIMA model has the greatest variability as shown in Figure 4(c), probably due to the complex correlations between the previous values with the current values, leading to diverse paths per each simulation. Finally, as far as GBM is concerned, a positively skewed distribution (Figure 4(c)) with a long tail towards higher electricity prices was compiled from the 1,000 simulated paths.

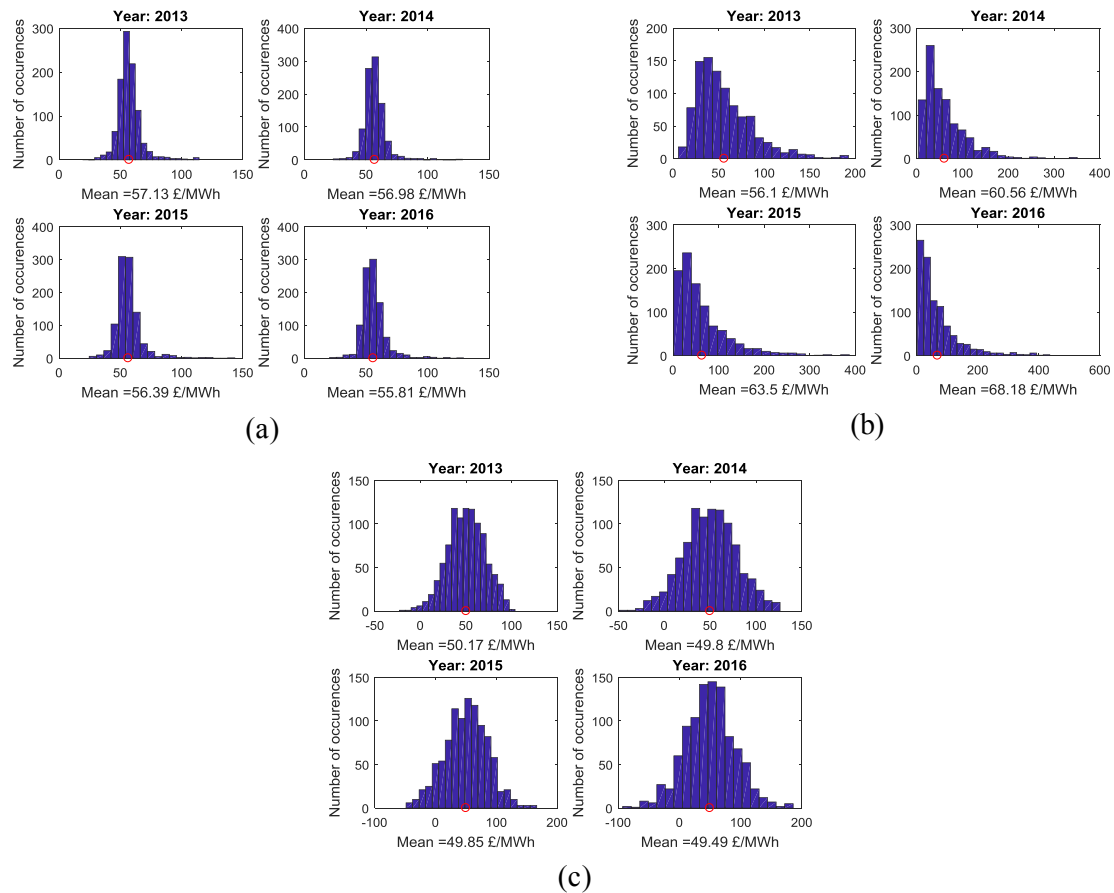


Figure 4 Probability distributions of electricity prices test cases: (a) MRJD, (b) GBM, (c) ARIMA

5. Results

5.1. Case study

Having modelled electricity market prices on a monthly basis, the stochastic modeling, based on distribution of economic outcomes of the investment, is performed. The case study that is used for the application of the method consists of a 504MW capacity wind farm located in the North Sea region, 36km away from shore. Weather data (3-hourly data over a 3-year period) were retrieved from BTM ARGOSS [24] for modelling the operational phase of the asset. The specifications of the wind farm investment are included in Table 2.

Table 2 Base case wind farm investment specifications

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

Economic parameters	WACC	8.81%
	Corporate tax	17%
	Depreciation rate	18%
	Debt share	70%
	Equity share	30%
	Return on equity	15.8%
	Interest rate on debt	7%
	Inflation rate	2.5%
	Strike price	140 £/MWh

Wholesale electricity prices were retrieved from the BEIS 2016 Updated Energy & Emissions Projections [25] for the base case investigated. The total CAPEX was estimated £1.67 billion, annual OPEX £56.6 million, NPV=£174.1 million at a real discount rate of 6.15%, while the LCOE=108.9 £/MWh. The results indicate that P&A costs have the highest contribution to the LCOE value, accounting for 46%, while O&M costs correspond to 30% of the total cost. A breakdown of the costs per Phase of the wind farm under the baseline case is illustrated in Figure 5.

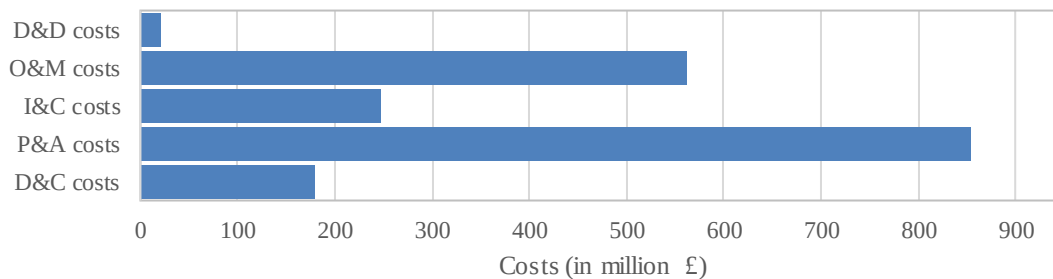


Figure 5 Deterministic lifecycle costs breakdown

5.2. Net Present Value Stochastic Analysis

The joint probability distributions of the NPV derived from the three different methods are plotted in Fig. 6(a)-(c). The assumptions considered for the calculation of the probability distribution curves are the same as the ones compiled in Table 2. The Value at Risk (VaR) is a traditional risk measure approximating the probability that the value of an asset or portfolio will drop below a particular value over a specified confidence level and in the context of a planning horizon. VaR is always specified with a given confidence level α . As such, as shown in Figure 6(a), the NPV of the investment has a VaR 5% of £155million denoting that there is 95% probability that NPV will exceed £155million.

It can, thus, be inferred from the illustrated probability distributions that GBM method has the lowest VaR 5% = £8million, while the MRJD method yields a probability of zero for a negative NPV, as well as the highest mean NPV in comparison to the other three methods. The mean NPV derived from the ARIMA method indicated the closest proximity to the deterministic base case NPV.

As far as the shape of the probability distributions is concerned, following a similar pattern on the electricity prices scatter of data, the resulting NPVs demonstrate a positively skewed normal distribution with a medium variability, when a GBM is employed, implying non-linear relationships between stochastic electricity prices and NPV output. MRJD-derived curve has a low variability, again as a result of the existing drift term, while the opposite applies to ARIMA model which returns a NPV distribution with a high variability.

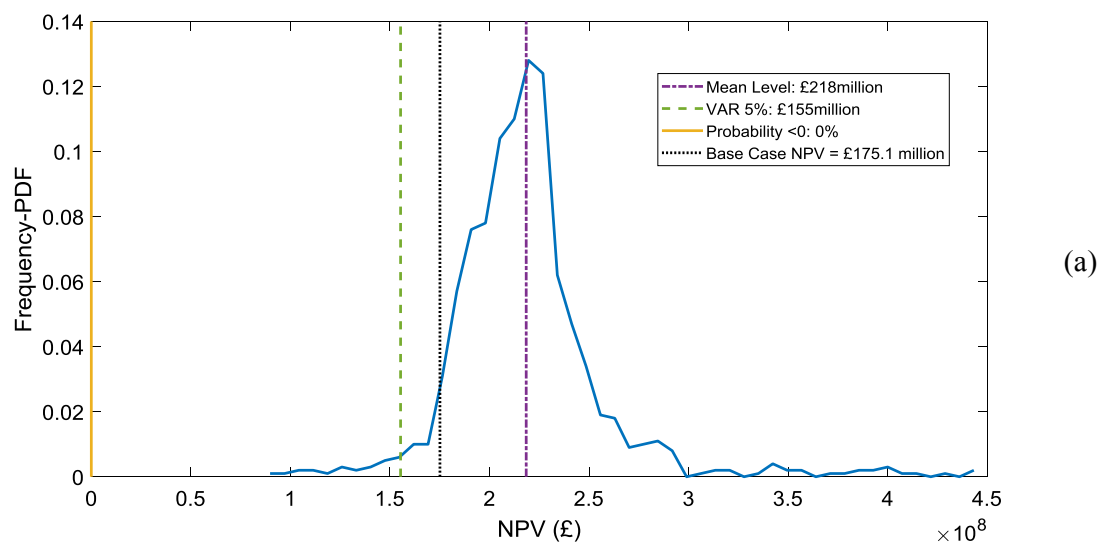
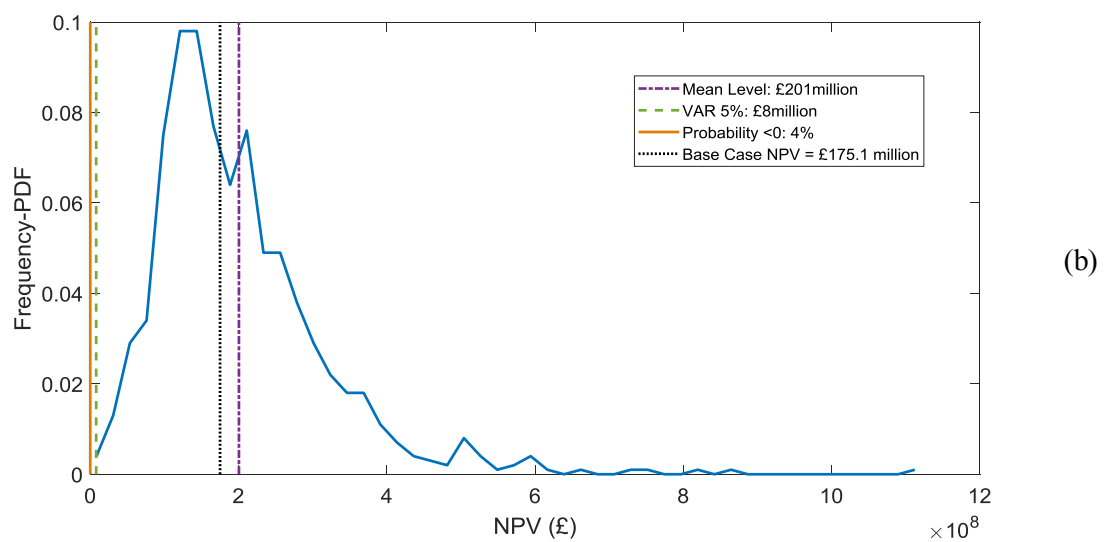
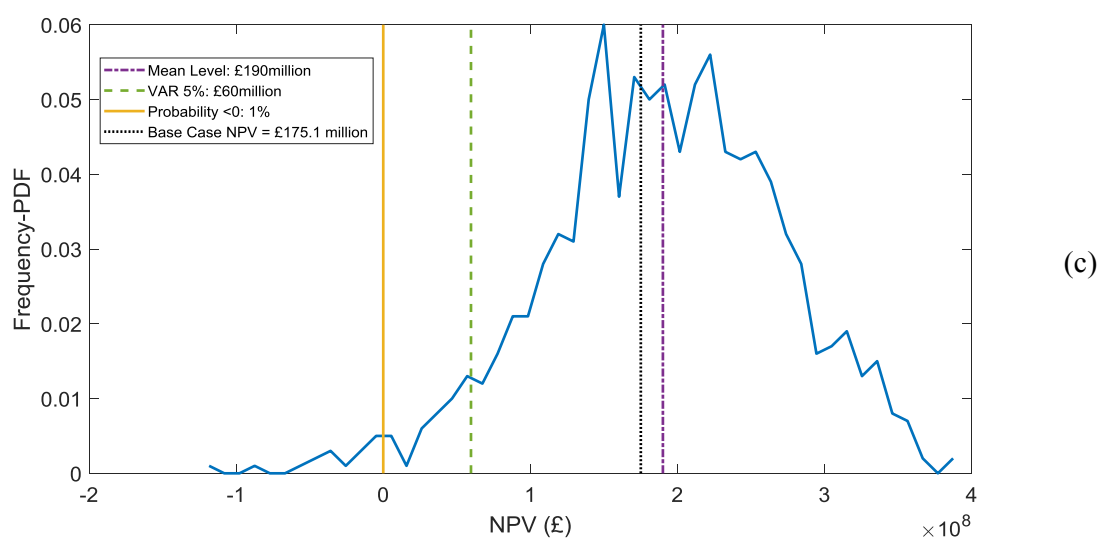


Figure 6 NPV probability distributions: (a) MRJD, (b) GBM, (c) ARIMA

6. Conclusions

In the UK context, following the 15-year period of the CfD scheme, offshore wind generators are obliged to sell their produced electricity on the electricity spot prices; hence, becoming subject to the risk of volatile and uncertain financial cash inflows. To this end, detailed and accurate assessment of expected returns during the post-CfD scheme becomes pertinent towards understanding the real cost and opportunity of investing in new or existing operational wind farms. Such an assessment could facilitate fair valuation of assets, supporting relevant investment/divestment decisions. To identify the best forecasting method for modelling the energy market prices, one has to determine the scope of the analysis. The present paper focuses on stochastically calculating the long-term electricity market prices and estimate the stochastic profitability of the offshore wind energy investment beyond the expiration of the CfD strike price support mechanism.

Statistical methods, such as the Autoregressive Moving Average, have a strong underlying mathematical and statistical theory, accommodating temporal correlations between past observations and current prices; as such, they can attach some physical interpretation to their components. Nevertheless, they are often criticized for their limited ability to capture nonlinear behaviour of electricity prices and they have been reported to perform better for short-term predictions (i.e. forecasts from a few minutes up to a few days ahead) [5]. They can, however, capture the seasonality that electricity prices exhibit on a daily, weekly and seasonal level basis. MRJD are considered to give a simplified picture of the price dynamics and are not expected to provide accurate results on an hourly basis, but rather recover main characteristics of the electricity prices at a daily time scale; thus, they may be considered as appropriate for longer term forecasting, requiring as input only the prior data of a time series to generalize the forecast. Among the methods tested, ARIMA demonstrated the lowest Mean Absolute Percentage Error in the validation cases, denoting a better long-term forecasting capability, which is relevant to service life financial appraisal of offshore wind energy investments.

Other available methods, such as Computational Intelligence techniques can also be considered as more relevant for long term forecasting since they can produce more accurate results, handling complexity and non-linearity. Nevertheless, their application usually requires a larger dataset (in comparison to the price-only models) of fundamental drivers, including the system forecasted demand, weather related data, fuel costs, etc.

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