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Wind power feasibility analysis under uncertainty in the Brazilian electricity market

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ABSTRACT

Investors must be able to plan and analyze their investments in order to optimize decisions and turn them into profits associated with a particular project. Since electricity producers in the Brazilian electric power system are exposed to a short-term market, the goal of this paper is to propose a framework for investment analysis capable of encompassing different uncertainties and possibilities for wind power generators in a regulated market, characterized by auctions. In order to reach the proposed objective we employ a simulation technique which allows modeling cash flows considering uncertainties in variables related to project financial premises, electricity generation and producer exposure to the short-term market. For such goal, this study presents a new approach for investment analysis that allows the identification of the main uncertainty parameters and risks associated to this class of projects in the Brazilian electricity market. We also employ the Value at Risk technique to perform a risk management analysis in such context.

1. Introduction

Brazil experienced a broader policy with international repercussion directed to the renewable energy sector after 2000, with the creation of the alternative source incentive program (PROINFA). Through a strategy similar to the European *feed-in tariffs* (FIT), 3300 MW of energy was hired and built in the first phase of PROINFA. Investments were mostly directed to small hydroelectric power plants (SHPs), biomass power plants and wind farms. The second PROINFA phase began after 2009 and gradually incentivized the purchasing of renewable energy through auctions (Dutra and Szklo, 2008).

As a manner of complementing the support to the insertion of renewable energy sources (RES), special financing lines from the Brazilian national development bank BNDES along with targets for minimum participation requirement of national equipment in the hired projects created new strategies to leverage the sector. Such initiatives were relevant to motivate the sector growth, since the environment until 2001 was adverse for investments in RES in the country (Wachsmann and Tomalsquim, 2003), besides hydro.

Concerning the results of such applications, since PROINFA creation, RES, especially wind power generation has been gradually reaching more space in the Brazilian energy matrix (Juárez et al., 2014; Martins and Pereira, 2011). According to Silva et al. (2013), Brazil has more wind power plants than any other Latin American country. In August of 2012 Brazil presented around 2 GW of installed wind power capacity and in December of 2014 this value jumped to 5.9 GW, according to the Brazilian wind power association (ABEEólica, 2015), accounting for 4.4% of the country's energy matrix.

With the steady expansion of the wind power installed capacity and its production, it is important to perform analysis related to this type of investment. Several studies have emphasized in this type of analysis, such as Simons and Cheung (2016), who develop a quantitative approach focusing on the selection of wind farm projects to evaluate different parameters such as profitability and payback, energy efficiency and carbon emissions. Ayodele et al. (2016) assessed wind power potential and economic feasibility in different regions in Nigeria, the study provides guidelines on which regions of the country it is

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worthwhile to adopt incentive policies for the insertion of wind energy. Colmenar-Santos et al. (2015) analyzed whether repowering is a financially viable alternative to allow the continued integration of wind energy into the Spanish energy sector when the electricity generated is valued at the market-clearing price. The work presented in (Ramadan, 2017) evaluated the viability of the use of wind power as an alternative for generating electricity in the eastern part of Sinai. In this study the economic evaluation of a 200 MW wind farm was performed, the results show significant benefits for wind power exploration in the region.

In order to perform a more robust analysis, it is important to consider the fact that the producer gains and losses are intimately connected to generation uncertainties. Therefore, in this work, we consider the intrinsic uncertainties related to energy production of a wind farm project contracted in an auction, see more in Del Río (2014), and also the market conditions where this electricity must be traded.

Monte Carlo Simulation (MCS) techniques have rarely been used within the context of risk management of RES structures as they require considerable data processing and the definition of probability density functions for random variables (Arnold and Yildiz, 2015). In the literature there are some applications in the wind energy sector presented in (Aquila et al., 2016; Li et al., 2013; Ertürk, 2012; Montes et al., 2011; Walters and Walsh, 2011).

In this present work, we follow the consideration of the settlement of the differences in the investment analysis presented in Aquila et al. (2016). Aquila et al. (2016) analyzed the impact of incentive mechanisms and different market environments on the risk of investment in wind farms in Brazil. For this, a quantitative approach that allows an analysis of investments from the simulation of NPV values for different scenarios was used. However, the main contribution of this study is not to compare incentive mechanisms, we build in the previous work to propose the use of Value at Risk (VaR), considering the settlement of the differences, which depends on the behavior of the wind energy and the electricity prices in the spot market. This novelty approach suggests the evaluation of the wind power project under uncertainty in the Brazilian market as a mean to enhance decision-making for a potential investor.

Therefore, in general terms, this paper aims to propose a risk analysis approach, through VaR, useful to capture the impact of settlement of the differences in the short-term market for wind power generation projects contracted in auctions of alternative sources.

Besides this introductory section, this paper is divided as follows: Section 2 presents the theoretical foundations of evaluation of the energy production by wind generators and the short term market (STM) exposure for power generators in Brazil. Section 3 presents the proposed framework for investment analysis under uncertainty for wind power plant in a Brazilian energy auction, and the VaR methodology used for risk management. Section 4 presents a case study for a wind farm project to be located in Brazil along with a discussion of the main results obtained. Section 5 presents the final considerations and conclusions about this work.

2. Wind power generation and the Brazilian electricity market

Over the past decade renewable integration expanded in the Brazilian interconnected power system following global trends (Solangi et al., 2011; Pereira et al., 2012; REN 21, 2015). The main reasons for this expansion in the country are the country's on-shore (Northeast and South regions) (Martins and Pereira, 2011) and off-shore wind power potential, growth of the wind energy industry (Blanco, 2009; Islam et al., 2013), and the long-term auctions for alternative energy sources with BNDES loans support (Juárez et al., 2014).

Wind power generation has been attracting new investments and providing a sustainable path for the development of the country energy matrix (Fidelis et al., 2013). Mastropietro et al. (2014) explain that renewable energy sources can be hired through regular auctions or through energy reserve auctions, the second have been oriented towards a competition among renewables. In these auctions specific products are tailored according to the peculiarities of the wind energy source. Moreover, specific accounting mechanisms are used to allow wind farms to compensate for seasonal and inter-annual wind fluctuations in the long-run.

In the present context, where wind generation is growing along with the success of the long-term auctions, it is appropriate to evaluate new investments for this source in Brazil. Our goal is to incorporate uncertainties in terms of electricity production, electricity prices and analyze the producer exposure to the STM. In this work we consider an investment in a wind farm that will negotiate its electricity production in long-term regular auctions. In this section we present the basis to compute wind power production for a wind farm, and the circumstances where the producer can be exposed to the STM.

2.1. Electricity production from wind power plants

In order to perform statistical analysis and evaluate the energetic potential from wind sources, the Weibull distribution is broadly used in the literature. According to (Li et al., 2013; Safari and Gasore, 2010; Akdag and Guler, 2009; Custódio, 2013) the Weibull distribution is considered to be the most adequate probability density function (pdf) to represent the behavior of wind speed. According to Safari and Gasore (2010), the use of Weibull distribution is also justified due to its simplicity in estimating parameters to approximate wind speed distribution of presented wind speeds. The probability density function for a Weibull distribution with two parameters is given by Eq. (1), proposed by Justus et al. (1978).

$$f(v) = \frac{k}{C}\left(\frac{v}{C}\right)^{k-1} e^{-\left(\frac{v}{C}\right)^k} \tag{1}$$

where, v is an average wind speed given in [m/s], C is the Weibull scale parameter given in [m/s], k is the Weibull form parameter (dimensionless). In order to obtain both the scale and the form parameters, Custódio (2013) presents a calculation that uses Eqs. (2), (3), respectively:

$$C = \frac{v}{\Gamma\left(1 + \frac{1}{k}\right)} \tag{2}$$

where, Γ represents the gamma function.

It is worth to emphasize that the Gamma function, also called exponential integral function, is often used as a function of the Weibull k form parameter (Custódio, 2013). Eq. (3), presents the Gamma function from Eq. (2) as a function of the arguments $(1+\frac{1}{k})$ for the k values accordingly described in (Custódio, 2013).

$$k = \left(\frac{\sigma}{V}\right)^{-1.086} \tag{3}$$

where, σ is the wind speed standard deviation in [m/s] and V is the average wind speed in [m/s].

Regarding the calculation of the wind energy potential for wind power generators, it is important to mention that a wind turbine captures a portion of the wind kinetic energy, which passes through an area swept by the rotor and transforms it into electricity. The electric power output in [W] is a function of wind speed to the cube (Amarante, 2010) as presented in Eq. (4).

$$P = \frac{1}{2}\rho A_r v^3 C_P \eta \tag{4}$$

where, ρ is the air density given in [kg/m^3], A_r is the area swept by the rotor (given by $\pi D^2/4$, with D being the rotor diameter) in [m^2], C_P is the rotor aerodynamic power coefficient, and η is the efficiency of the mechanical rotor and electric generator-transmission set.

According to Custódio (2013), the C_P of a wind turbine varies according to the wind speed at the wind farm location. From this assumption, through the computation of a cubic regression, it is possible to update the C_P value based on random wind speed values obtained at the wind farm location. In the next section, we discuss how we employ MCS to obtain wind speed ensembles to be used when evaluating uncertainties in the project investment analysis.

According to Amarante et al. (2001), with Weibull distribution parameters, k and C, and the average air density, it is possible to estimate the production of a wind turbine with good accuracy. The wind turbine monthly electricity production (MEP) in [kWh] can be calculated by integration of power profiles and wind speed occurrence frequency as presented by Eq. (5).

$$MEP = 0.73 \int_{v_{\min}}^{v_{\max}} P(v) f(v) dv \tag{5}$$

where, $P(v)$ is the energy produced as function of randomness of wind speed monthly average and $f(v)dv$ is the probability density function that describes the monthly wind speed average. It is worth mentioning that *MEP* has to satisfy the maximum power generation limit of each turbine.

The *MEP* computation must be compared to the sum of electricity that the wind farm can sell in the electricity market, known as assured energy or physical guarantee. The concept of physical guarantee is similar to firm energy rights, presented by Faria et al. (2009), which refers to the maximum continuous production of electricity from a power generation plant during a specific period. However, in the case of wind power plants, the physical guarantee is calculated after the studies of performance regarding the wind profile at the specific location during a certain period of time.

2.2. Producer exposure to the STM in Brazil

In a situation where the wind power producer cannot generate 100% of the electricity amount stated in the sell-purchase contract, it is necessary to calculate and liquidate the differences in the STM and fulfill the contract coverage (CCEE, 2010). Fig. 1 illustrates a particular example where the producer generates more electricity than the contract values.

With this picture in mind, the producer also becomes exposed to market clearing prices (MCP) fluctuations, it is possible to valuate the energy traded in the STM computed through the use of data considered by the independent system operator (ISO) represented by ONS in Brazil when optimizing the operation of the interconnected electric power system (Signorini et al., 2015). The MCP is determined on a weekly basis in Brazil for each load baseline (low, medium, and heavy), limited by maximum and minimum values, effective for each electrical region

Fig. 1. Settlement of the difference between the energy hired and the energy verified in the STM.

(also known as electric submarket) Southeast/Center-West, South, North, and Northeast (CCEE, 2015).

Dalbem et al. (2014) explain that since the main source of electricity generation in Brazil is hydroelectric, the MCP value goes down in wet seasons or in moments when the reservoirs are full. On the other hand, in dry periods, the thermal plants with expensive operational marginal costs may be needed and dispatched, and that increase the MCP values. Because ISO decisions to use or not the stored water volumes from hydro plants reservoirs also influence price formation, the methodology for MCP calculation relies on mathematical optimization models and algorithms, such as those described in the work of Maceira et al. (2002). It is worth mentioning that MCP prices are volatile and play a fundamental role in the economic viability of a power generation project such as a wind farm.

However, in a low MCP scenario, the differences between contract and generation are liquidated by the Annual Reference Value, which is used to regulate the transfer of the final acquisition costs of electricity to the tariffs for final electricity consumers (ANEEL, 2015a, 2015b, 2015c). We adopted a criterion based on the higher value between the MCP and the Annual Reference Value to serve as a computation baseline of the electricity production differences in the STM.

3. A framework for wind power investment analysis under uncertainty

In this section we present a general framework for investment analysis in wind power generation under uncertainty. Such methodology is further applied to evaluate new investments in the Brazilian electricity market in Section 4. Fig. 2 shows a flowchart with the steps defined in our framework to perform the wind generation project evaluation.

We aim to use economic feasibility analysis in order to support decision-making processes in terms of whether or not a potential investor should invest in a specific project. The initial step is used to compute the project discount rate, according to the methodology defined in Section 3.1. Discount rates are used to bring the future cash flows to the current date. A deterministic analysis is then performed to obtain the net present value (NPV) results for the project, where the main input variables of the analysis model are known a priori. After this step, a sensitivity analysis is created to identify input variables that are more sensitive in the NPV computation.

The next step defines a stochastic analysis where uncertainties in the variables regarding electricity production by wind generators are considered. Such analysis is performed using the MCP and the Annual Reference Value to monetize gains or losses and quantify dues regarding exposures of the wind power producer in the STM. With the results obtained through the proposed cash flow simulations, it is possible to perform a risk management analysis with more accuracy by applying VaR.

Three scenarios are analyzed in this study. The first scenario deals with the investment in a wind farm without loan support and without the possibility to trade carbon credits. The second scenario analyzes a situation where there is loan available from BNDES for the project. Finally, the last scenario evaluates a project that could be part of the clean development mechanism (CDM) during a 10-year period, where it would be possible to commercialize carbon credits.

3.1. Calculation of the discount rate

Discount rate is used to bring the future cash flows to the current date, in this work the discount rate of the wind power plant is considered to be equivalent to the weight average capital cost (WACC), model recommended by the UNFCCC (2012), and in Brazil by ANEEL (2015a), and adopted in papers such as Ertürk (2012), Castro-Santos et al. (2016) and Aquila et al. (2016).

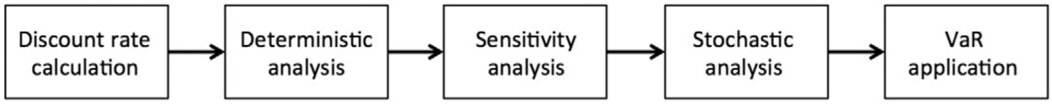

Fig. 2. Procedures performed in the investment analysis.

According to Ertürk (2012), the WACC is obtained through the use of Eq. (6).

$$WACC = k_d D(1-\tau) + k_e E \tag{6}$$

where:

- k_d represents the cost of debt;
- D stands for the weight of debt capital applied in the investment (%);
- k_e is the cost of equity;
- E is weight of equity applied in the investment (%);
- τ is the income tax.

In order to obtain BNDES loan, a final percentage of tax rate is assumed discounting the inflation rate for the cost of debt. For calculation of the cost of equity, the capital asset pricing model (CAPM) is employed, adding the Brazil risk premium, similar to the model adopted by Ertürk (2012) and recommended by ANEEL (2015a) with value of 2.62%, mentioned in a technical note that provides the methodology for WACC calculation.

Eq. (7) presents the mathematical expression for CAPM calculation (represented by the first two portions of the equation) added to the Brazil risk premium.

$$K_e = R_F + \beta_l(R_M - R_F) + R_B \tag{7}$$

where:

- R_F is the risk free rate;
- β_l is the leveraged beta (measures the project risk regarding the market);
- R_M is the expected market return;
- R_B is the Brazil risk premium.

The leveraged beta is calculated from the unleveraged beta for the renewable energy sector, which is mentioned in Damodaran's (2015) sector beta table. For calculation of the leveraged beta, a capital structure of 70% is considered as weight of debt and 30% weight of equity, besides an income tax (τ) equivalent to 34%. It is worth mentioning that the unleveraged beta in this study corresponds to the beta from the renewable energy sector indicated by Damodaran (2015), which is equivalent to 0.63. Through the use of the procedure to obtain the leveraged beta from Eq. (8), a leveraged beta (β_l) value of 1.60 is achieved.

$$B_l = B_d\left[1 + \frac{D_p}{E_p}(1-\tau)\right] \tag{8}$$

where:

- D_p is the weight of debt in the project investment;
- E_p is the weight of equity in the project investment.

Regarding R_F, R_M and R_B used to calculate CAPM, values of 5.64%, 13.20%, and 7.56% are adopted. These values are indicated in ANEEL (2015a, 2015b) for WACC calculation regarding installation of electricity generation. Through the application of the data indicated in the calculation of leveraged beta, CAPM and WACC, a result for WACC equivalent to 6.99% per year is obtained.

3.2. Deterministic and sensitivity analysis

For the purpose of investment analysis we use cash flows to represent the value of the project for different conditions. In the deterministic analysis all the information related to the project is considered to be known. In this case, for a wind farm project selling electricity in the STM we consider that the electricity production, the electricity prices and every other variable/parameter are known from the beginning. In such case, NPV calculations are performed using cash inputs and outputs as indicated in Table 2. The final result of earning and disbursements obtained in each period are the cash flow liquid balances, which are discounted by the appropriate rate to reach the NPV result.

According to Arnold and Yildiz (2015) and Grieser et al. (2015), the sensitivity analysis saves time for application of the MCS, since it makes sense to restrict the number of input variables, only using those that are more significant to generate results for the deterministic model. Arnold and Yildiz (2015) still reinforce that within the sensitivity analysis, one single input parameter is systematically varied within a pre-defined interval of values. We employ sensitivity analysis in this work in order to define the most important variables for the project NPVs.

3.3. Monte Carlo Simulation in the context of investment analysis

Similar to other studies found in the literature (Arnold and Yildiz, 2015; Holdermann et al., 2014; Peña et al., 2014; Schmidt et al., 2013; Li et al., 2013; Ertürk, 2012; Martins et al., 2013; Walters and Walsh, 2011; Montes et al., 2011) that apply feasibility analysis to projects related to RES, the decision criterion employed in this study to perform the investment analysis is the NPV. Brigham and Houston (2007) state that the main advantage of using NPV is to quantify how much the project will impact the position of the capital initially invested. On the other hand, the Payback method, which is commonly used in investment analysis, does not provide any guidance regarding the investor cash flow.

In order to obtain reliable results for the NPV of wind power energy generation projects, Montes et al. (2011) emphasize that mathematical techniques such as MCS allow the analysis of this type of project with proficiency. Instead of considering all input data in a deterministic manner in the cash flow to obtain the project NPV, the MCS allows the incorporation of probability distributions. The insertion of probabilities distribution in the cash flow allows the representation of stochasticity through the use of random input variables that are more sensitive to NPV results.

The study presented in Jiang et al. (2013) explains that MCS is performed through numerous executions of different models, using different values for the stochastic parameters. Values for the stochastic parameters are randomly selected from pre-determined probability distributions. Several ensembles of input parameters can be obtained through carrying out many rounds of simulations. By applying MCS it is possible to input more information in the analysis regarding projects risk and design a reliable and robust framework for the decision making process (Williams, 2007).

The synthesis of all iterations generates a range of possible results (Tziralis et al., 2009). Since an economically attractive project in this work has a NPV > 0, at a certain discount rate (r), the project feasibility probability is given by Eq. (9).

$$P_{NPV>0}(x_1,\ldots,x_n;r)=\int_0^{\infty} pdf\left(N\tilde{P}V\right)dN\tilde{P}V \tag{9}$$

In which: $P_{NPV>0}$ is the accumulated positive NPVs of the project, $pdf(N\tilde{P}V)$ is the probability density function of the project NPVs and x_i is a vector associated with the project random variables.

In the present work, MCS is used to simulate the monthly electricity production for the wind farm in each month over a 20-year period. MCS also is used to incorporate uncertainties in the variables that calculate the amount to be paid in the STM and the most sensitive variables for the NPV.

For the NPV calculation annualized cash flows for the 20-year period, calculated using the structure shown in Table 2, are brought to the present date using the computed discount rate.

3.4. VaR for risk management in the project

According to Hung et al. (2008), VaR is one of the most popular approaches to quantify risk. The use of VaR is employed by managers and financial institutions to get protection and hedge against market risks. VaR is broadly employed to analyze financial risks (Jorion, 2002; Yamai and Yoshiba, 2005; Artzner et al., 1999) since it is easily comprehended, focusing on normal market conditions. In other words, the distribution area from $-\infty$ to a minimum W^* value, which can also be defined as the distribution percentile, must sum up to $P = 1 - c$, with c being one level of confidence, such as 5% for example (Jorion, 1999). Eq. (10) illustrates the VaR calculation for general distribution functions, discrete or continuous, with thick or thin tail.

$$1-c=\int_{-\infty}^{W^*} f(w)dw=P(w\leq W^*)=p \tag{10}$$

According to Jorion (1999), VaR calculation can be simplified when a normal distribution is assumed. In this case, VaR can be directly derived from the standard deviation, using a multiplying factor based on the confidence level. This calculation is named parametric approach since it involves a parameter estimation, such as in the case of the standard deviation, and not an observed distribution percentile.

Eq. (11) shows the VaR calculation for the parametric approach. In this case it is initially necessary to transform the general distribution $f(w)$ in a normal standardized distribution $\Phi(\in)$ in which $\in$ has an average of zero and standard deviation equivalent to 1. The minimum W^* value is associated to an R^* critical value, so that $W^*=W_0(1+R^*)$, with R^* generally being negative and written as $|R^*|$. Thus, VaR is characterized as a multiple of the probability distribution standard deviation multiplied by an adjustment factor directly related to the confidence interval (Jorion, 1999).

$$1-c=\int_{-\infty}^{W^*} f(w)dw=\int_{-\infty}^{-|R^*|} f(r)dr=\int_{-\infty}^{-\alpha}\Phi(\in)d\in \tag{11}$$

Dahlgren (2003) explains that two variants of the VaR are also used for risk analysis: the Cash Flow at Risk (CFaR) and the Earnings at Risk (EaR). The CFaR is the maximum fall in the value of the net cash flow generated in relation to a specific period and confidence level, due to the impact of changes in market rates on a given set of exposures. The EaR is defined as the minimum value of an accounting indicator or derivative thereof (such as EBIT, EBITDA, Total Assets, Return on Assets) at a given date (t1) in the future, for a given level of significance α %. According to La Rocque et al. (2003), the EaR is a kind of CFaR plus accounting considerations.

Another important measure of risk analysis is the Conditional Value at Risk (CVaR). The CVaR is able to detect the presence of catastrophic events (Hemmati et al., 2016). The main difference between the CVaR and the VaR is that while the VaR is related to the probability of excess loss, the CVaR is related to the expectation of excess loss. In addition, different from CVaR, VaR does not have property as differentiability and convexity, which makes it difficult to apply mathematical programming problems.

In this paper, we aim to measure the risk in terms of potential loss, considering the generation settlement of differences that the producer is exposed in the STM. Since VaR is a risk analysis tool applied in an extensive number of practical cases and well established in the literature, and that it is not among the objectives of this work to perform analysis using mathematical programming models to minimize losses, we consider the use of VaR to be sufficient to perform and accomplish such task.

4. Case study: wind farm investment analysis in Brazil

We consider as a case study a wind farm project to be located onshore in the state of Bahia in Brazil (Northeast region of the country). Due to the wind power potential of this region, there are several existent wind farms operating there and contributing with electricity production to the Brazilian interconnected power system.

4.1. Data and analysis regarding the wind farm project

The wind farm used in our analysis has 30 [MW] of nominal power, with 15 wind power generators with 2 [MW] of nominal power each, installed at 80 [m] of height. For the current study, the following values, extracted from (Amarante, 2010), are considered when calculating the wind power potential energy: $\rho = 1.225$ [kg/m^3]; $D = 3.72$ [m]; and $\eta = 0.98$. Eq. (12) shows the function obtained for the cubic regression performed in Aquila et al. (2016) through the performance of C_P from the wind generators using 25 different wind speeds, presented on Table 1.

According to (Hair et al., 2014), the regression equation must have an adjusted determination coefficient (R^2_{adj}) above 70% in order to be considered acceptable. Therefore, since the performed regression

Table 1
$C_P \times$ Wind speed.
Source: Aquila et al. (2016).

C_P	Wind speed
0	0
0	1
0.12	2
0.29	3
0.4	4
0.43	5
0.46	6
0.48	7
0.49	8
0.5	9
0.49	10
0.42	11
0.35	12
0.29	13
0.23	14
0.19	15
0.15	16
0.13	17
0.11	18
0.09	19
0.08	20
0.07	21
0.06	22
0.05	23
0.05	24
0.04	25

Table 2
Structure of a wind power plant cash flow.

Gross sale balance and additional balances from liquidation of differences
Balance from CDM
(−) taxes proportional to balance
Liquid balance
(−) sector taxes
(−) leasing
(−) O&M costs
(−) additional costs for liquidation of differences
Gross result
(−) expenses with insurance
(−) general and administrative expenses
(−) depreciation
Results before tax over legal entity/social contribution over the liquid profit and financial expenses
(−) financial expenses
Profit before tax over legal entity/social contribution over the liquid profit
(−) tax over legal entity/social contribution over the liquid profit
Net profit after income tax
(+) depreciation
(−) amortization of financing
(−) investment
(+) release of financing
(+) terminal value
Cash flow

shows an adjustment $R^2_{adj} = 90.5\%$ it can be considered adequate.

$$C_P = -0,08114 + 0,1771v - 0,01539v^2 + 0,00034v^3 \tag{12}$$

In addition, the aforementioned wind farm represents a project hired in a new energy auction within the circumstances of a contract by quantity, in which the producer assumes monthly risks to fulfill the generation values established in the contract. Table 3 presents the main information regarding the analysis.

The evaluation of the investment value considers a typical composition of projects for wind farms in Brazil, indicated by Custódio (2013) and shown in Fig. 3. However, for the investment value, an average of investments from wind farm projects with 30 [MW] of installed capacity is used (average values for power plants that won the auctions for alternative sources) of US$ 47,701,655.84 in April of 2015. We consider as the electricity sale prices the average price value from the same auction of 57.62 [US$/MWh].

Table 3
Data regarding the analyzed wind power plant project.

Parameter	Value
Investment	US$ 47,701,655.84
Project useful life	20 years
Installed power capacity	30 MW
Price for energy sale	57.62 [US$/MWh]
Operation hours of the power plant per year	8760 h
Physical guarantee of energy supply	13 MW
Leasing	1% of the investment
O&M costs (includes administrative expenses)	12% of the gross revenue
Transmission wheeling charges (TUST)	0.87 [US$/MW] of power
CCEE Tax	6.49 [US$/kW] of contracted energy
ONS Tax	25.97 [US$/kW] of contracted energy
ANEEL Tax	US$ 22,552.99 per year
Insurance expenses	0.30% of the investment
Power plant depreciation	5% of the investment, except pre-operational costs
Deferral of pre-operational expenses	20% of pre-operational expenses
Tax over gross revenue	7.60% (Cofins) and 1.65% (PIS)
Tax over legal entity	25% over 8% of the gross revenue
Social contribution over the liquid profit	9% over 12% of the gross revenue
Deadline for payment of financing (years)	16 years (shortage 6 months)
Loan interest rate (without inflation)	3.76%
Discount rate − WACC [%] (without inflation)	6.99%
Emission factor	0.1355 kg (CO_2)/kWh
Price per ton of carbon	€ 7.46
Euro exchange rate	US$ 1.12
CDM annual registration rate	US$ 1594.74

Table 4
Deterministic analysis results.

Scenario	NPV results
A	US$ 3,886,824.39
B	US$ 11,307,280.21
C	US$ 12,037,510.23

Calculation baselines for annual value data spent with leasing, O&M costs (including administrative costs), expenses with insurance, power plant depreciation and deferral of pre-operational expenses, were extracted from the wind power electrical enterprise manual from COPEL (2007). For calculation of the transmission costs, the transmission wheeling charges (TUST) paid by power plants connected in the South of Bahia state are considered. In Brazil, for power plants with installed capacity up to 30 [MW] there is a 50% discount on TUST values. For estimation of taxes paid to ONS (Brazilian ISO) and CCEE, an annual budget from respective organizations is divided by the total electricity produced in the interconnected power system. The ANEEL tax is calculated based on the methodology indicated in ANEEL (2015b).

Regarding the price per ton of carbon, the value corresponds to the average between 12.05.2015 and 12.06.2015, with the emission factor being equivalent to the reference value determined by (MCT, 2015). BNDES loan conditions for wind power plants and tariffs regarding tax calculation are equivalent to the current values up to the end of May 2015. In order to formulate cash flows, the inflation of the taxes from the financing interest is discounted from the equity cost, from the depreciation and from deferral of the power plant pre-operational expenses. A tax of 5.6% is also considered to discount the inflation, corresponding to the inflation expectation considered by ANEEL (2015a).

4.2. Results for the deterministic analysis

As mentioned before we perform a deterministic analysis to obtain the NPV results for three different scenarios: without loan and sales of carbon credits (Scenario A), with loan and without sales of carbon credits (Scenario B) and with loan and with sales of carbon credits (Scenario C). The final earnings and disbursements results in each period are the liquid balances of the cash flow, which were discounted by the discount rate to reach the NPV result.

Since there are no inputs or disbursements of cash in the initial date, the NPV calculation is only performed by discounting the cash flow balances from periods 1 to 20 through a discount rate equivalent to 6.99% per year. Results for the deterministic analysis are presented in Table 4, in which the projects' feasibility can be observed since the NPV values are positive.

BNDES loan plays an important role in the results of the cash flow analysis for the wind farm. The entrepreneur almost triples his cash returns when using the loan. In a market in which the technological costs are uncertain throughout the years, as the sales prices, financing lines capable of supporting investors are key to provide higher financial security to RES generation projects.

Table 5
Probability distribution adopted for the investment, MCP and Annual Reference Value.

Variable	Distribution	Distribution parameters
Investment	Triangular	(32,467,532.47; 47,701,655.8; 61,688,311.69)
MCP	Gamma	(7.13; 154.99; 0.55)
Annual Reference Value	Triangular	(25.97; 38.96; 48.70)

Table 6
Probability distribution used to represent wind speed in each month of the year.

Month	Monthly average wind speed	Weibull parameters (c; k)
January	8.375	(9.44; 2.41)
February	9.158	(10.33; 2.41)
March	9.063	(10.22; 2.41)
April	7.895	(8.90; 2.41)
May	8.640	(9.74; 2.41)
June	9.266	(10.45; 2.41)
July	9.881	(11.14; 2.41)
August	10.297	(11.60; 2.41)
September	10.079	(11.36; 2.41)
October	9.761	(11.00; 2.41)
November	7.402	(8.35; 2.41)
December	7.038	(7.94; 2.41)

The project participation in the CDM resulted in earnings for the investor, contributing to an increase of US$ 730,230.02. This reveals that trade of carbon credits can increase cash returns for the project investor, however it does not provide significant increases in the NPV, in the same way as loans.

After deterministic analysis results were obtained, the following step is to formulate a sensitivity analysis, considering all variables involved in the project, including those related to the CDM, in order to identify which of them had major impacts on project feasibility.

4.3. Sensitivity analysis

In this study, all the relevant cash flow model input variables are changed by −10% to +10% interval regarding their base values from the deterministic case. These variations will cause an impact in the project NPV. Variables that impact more the NPV results are selected and represented in the stochastic analysis as random variables. Variables with smaller influence on NPVs are considered further in their base values.

Fig. 4 refers to the sensitivity analysis results. It is possible to notice that the most significant variables for the wind farm project are: local wind speed, energy prices, and investment costs. In Section 4.4 uncertainties are added in these parameters through different probability distributions and we use MCS in order to perform the stochastic analysis and compute the project NPV. Uncertainties regarding price and amount of the contracted energy will not be incorporated since the regulated environment neutralizes these variables, which is characterized by energy auctions, decreasing risks and producer uncertainties.

Table 5 shows the probability distributions and their respective parameters for main variables that we incorporate uncertainties.

The distribution of MCP values was defined from the software adjustment function (goodness of fit) in which the simulations were performed (Sanchez et al., 2004). For this, the MCP series from January 2008 to August 2015 were collected and the Gamma distribution was the best suitable function to represent the data series.

For the Annual Reference Value, since there is only one series for a few years in the country, a triangular distribution was chosen with the minimum and maximum values being the smallest and largest values already observed, and the most likely value is set to be the one related to the year when the analysis was carried out.

Table 7
Levene's test results.

Scenario	Confidence interval (95% for St Devs)	P-value
A × B	A: (6,979,003.14; 7,061,340.89) B: (6,319,645.74; 6,396,031.64)	0.000
A × C	A: (6,979,003.14; 7,061,340.89) C: (6,300,663.95; 6,376,256.21)	0.000
B × C	B: (6,319,645.74; 6,396,031.64) C: (6,300,663.95; 6,376,256.21)	0.574

Table 8
Results for expected average return, standard deviation, P-value and VaR.

Scenario	Average	Standard deviation	P-value	VaR
A	US$ 7,825,270.80	US$ 7,019,913.71	0.13	−$ 3,721,458.73
B	US$ 14,862,525.76	US$ 6,357,599.36	0.18	$ 4,405,205.38
C	US$ 15,545,541.92	US$ 6,338,223.16	0.12	$ 5,120,092.56

Finally, for the investment values, a triangular distribution is also adopted, since between 2014 and 2015 the number of projects contracted in auctions was not enough to create a well sized time series. The parameters are based on the investment value of the projects contracted between the years of 2014 and 2015.

Table 6 separately presents average wind speeds and scale parameter (C) of the Weibull distribution used to represent the wind speed in each month of the year.

The parameter used for the Weibull distribution form factor (k) is equal to 2.41, which is equivalent to the smaller value with two decimal places within the $2.4 < k < 3.7$ interval indicated by the follow-up report of anemometric measurements from EPE (2013b) for Bahia state. The smallest possible parameter with two decimal places is chosen because a smaller form factor (k) results in a more conservative analysis. For the C variable, we use Eq. (2) for the parameters choice, with the values of v shown in Table 5, and the values of gamma (Γ) based on Custódio (2013).

4.4. Stochastic analysis and VaR

After the incorporation of uncertainties in each one of the variables described in Tables 4 and 5, 50,000 simulations were performed to obtain NPV results for three scenarios analyzed. The investment analysis and the energy production calculation were structured in an Excel spreadsheet, and later Crystal Ball software was used to perform the MCS. Then, through the obtained series of NPVs, parameters are collected and used in the VaR analysis in order to identify the worst loss expected by the electricity producer in each scenario. Fig. 5a, b, and c shows the results for project feasibility probability in each scenario.

First, it should be noted that, different from deterministic analysis, stochastic feasibility analysis allows us to identify scenarios and consider in the analysis with NPV values smaller than zero, indicating economic infeasibility for projects. However, in the three scenarios analyzed it is possible to notice that the probability of the project being viable is larger than the opposite case.

Results obtained through the stochastic analysis reinforce the important role of BNDES loans as a complementary strategy for long-term contracts with a portion of fixed remuneration, as it occurs with enterprises hired through auctions. Without financing lines the probability of the project to be feasible would be of 86.53%, while the

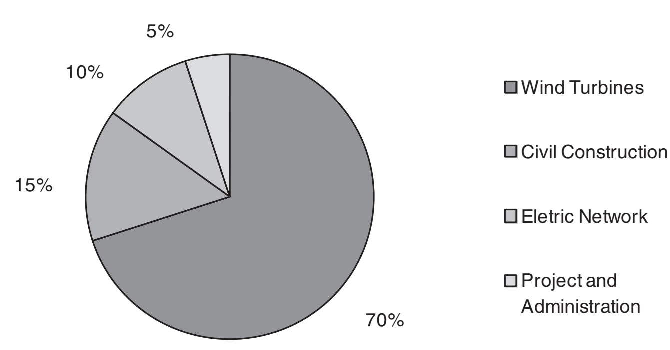

Fig. 3. Composition of the investment costs in a wind farm in Brazil.
Source: Adapted from Custódio (2013).

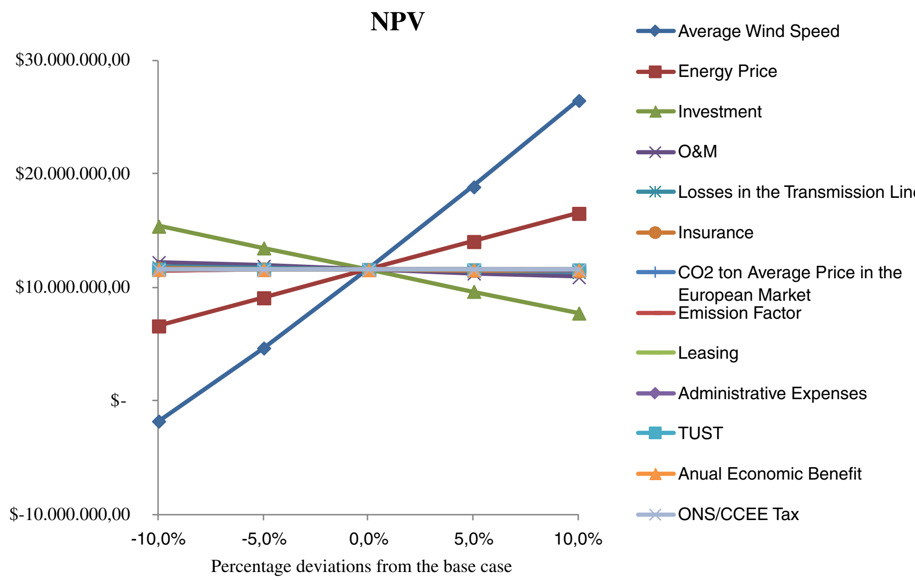

Fig. 4. Results for sensitivity analysis.

probability of feasibility goes up to 99.17% in the scenario that considers financing without trading carbon credits.

Similar to Aquila et al. (2016), the Levene test was performed with significance level of 5%, as a hypothesis test to verify if the variances between the scenarios analyzed presented a statistically significant difference. The results of the Levene test are shown in Table 7. The p-value of less than 0.05 for the comparison of the scenarios A × B and A × C reinforces the importance of the loans to reduce the risk of the wind power producer. It is still possible to highlight that the p-value above 0.05 for the Comparison B × C indicates that the possibility of trading carbon credits does not contribute statistically to risk reduction.

In addition, the presence of a loan guarantees a higher average return for the investor, as it is observed in Table 8. The standard deviation for the returns in all scenarios, including the scenario that considers participation in the CDM, reveals a dispersion regarding the average between US$25 and US$28 millions, which indicates volatility and a consequent risk in relation to the returns of the producer due to exposure in the STM.

With regard to the results of project feasibility certainty, considering participation in the CDM, it is verified that the feasibility influence goes from 99.17% to 99.46%. Therefore, there is a significant increase in feasibility certainty, as it occurred with the increase of NPV observed in the deterministic analysis. However, it is possible to notice that the standard deviation does not decrease with participation in the CDM, and it is even higher than in that scenario without participation, which indicates that selling carbon credits is not the most efficient mechanism to reduce the risks in this market.

In terms of the VaR application, the series of results presented a p-value higher than 0.05 in all cases, which proves the normal adjustment for the distribution curve, for this reason, the parametric VaR is chosen and calculated using Eq. (11). The data shown on Table 8 reveals that results in scenarios with financing lines reduce the expected worst loss, bringing the result to an expected worst gain. The scenarios where carbon credits sales are considered reveal an increase in the expected worst gain.

Another important finding regarding the STM is that the possible settlement of differences can provide smaller NPV results than those observed in the deterministic analysis. The presented results are only achievable in a framework that represents the exposure of the power plant to the STM with the resource of MCS.

Considering the settlement of the differences, the VaR results obtained with the proposed model is more appropriate for the circumstances in which the wind energy producer is inserted in Brazilian market. It should also be pointed out that the VaR results reinforce the importance of the loan for risk reduction, since in scenarios which loans are considered, the worst-case scenario is characterized by a positive value. The inclusion of carbon credit trades also contributes to an increase in VaR results for the producer, though not as relevant as in the scenarios with loans.

From the point of view of renewable energy investors, investment risks are associated with a possible lack to compete for new technologies with respect to conventional ones, since they depend on the availability of random natural resource. Thus, policies such as BNDES loans and long-term auctions, which contribute to increase the chance of project viability, are fundamental in attracting investments with financial return security. Another point associated with the investment risk to the investor is potential changes in the legislation that will eventually modify contract basis, however, this type of risk is difficult to be accounted and is not considered in this work.

Possible delays in the project initial operational date also create a risk for both: the investor, who may have already signed electricity selling contracts; and the government, who may consider the venture to be operating on a wrong date in planning and operational studies. The government is also responsible for evaluating interconnection and operational studies considering the integration of the project, and its associated effects, into the existing power infrastructure. As a way to mitigate energy security risks associated with the unavailability of renewable energy ventures, the government can create actions to encourage the increase of energy capacity reserves.

5. Conclusions

A framework for investment analysis of wind power generation under uncertainty using MCS was presented. In the VaR calculation, the proposed methodology is capable of incorporating generation uncertainties and the exposure of the producer in the STM. In the performed deterministic investment analysis, the obtained results indicated an economic feasibility for the project. Through the stochastic analysis the project shows a high probability of economic feasibility in the three scenarios, especially when considering the possibility of BNDES loans.

This verifies that the financial safety of the producer in the regulated environment is high, even with the producer exposure to the STM, which impact directly in VaR results. The inclusion of the impact of

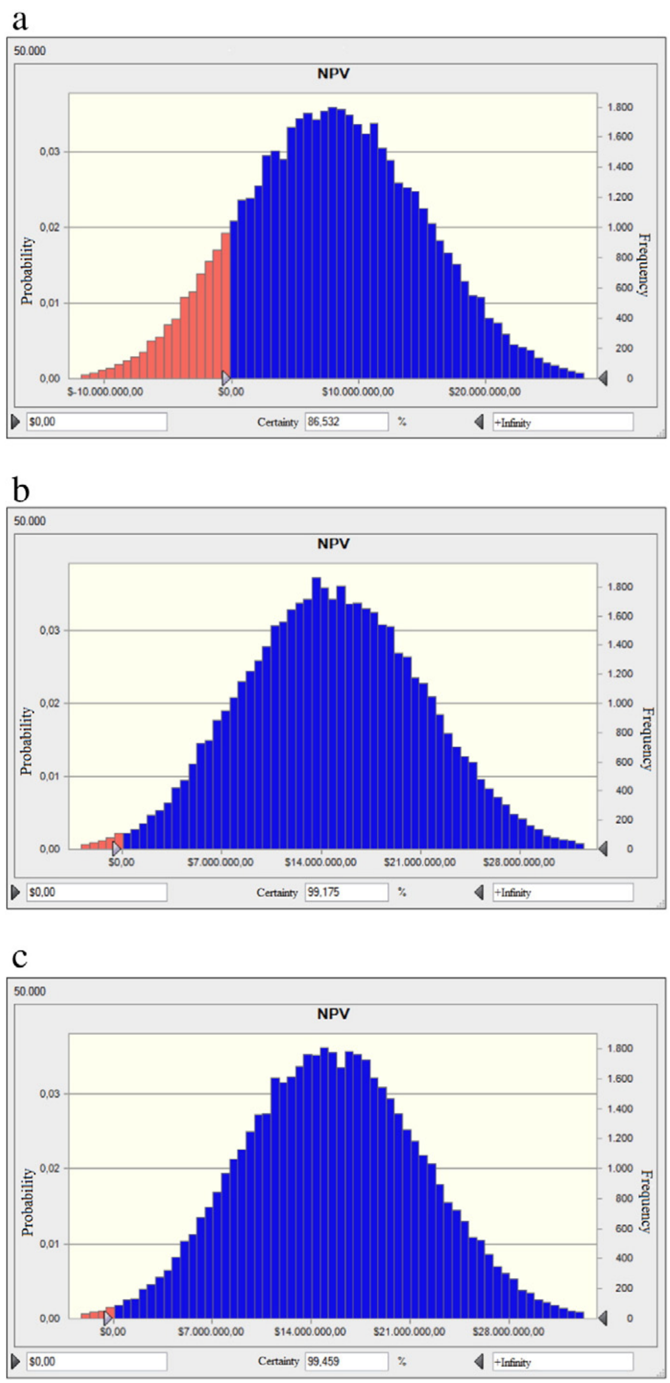

Fig. 5. a. Results for stochastic analysis without loan and sales of carbon credits. b. Results for stochastic analysis with loan and without sales of carbon credits. c. Results for stochastic analysis with loan and sale of carbon credits.

settlement of differences in investment analysis is important and difficult to be measured for wind power generation projects in Brazil. The proposed approach provides a model for calculating VaR considering generation uncertainties which may be used by potential investors. The model is able to capture the impact of the uncertainty in wind power and electricity prices in the market and use this information to identify the worst possible expected return for the producer.

In the scenario that considers participation of the project in the CDM, we conclude that additional revenues from sales of carbon credits can be an important source of profit for the producer, but contribute minimally in the reduction of the investment failure risks. Finally, but not less important, the application of VaR contributed to analyze the worst scenario expected from the producer's point of view. Risk management provided by VaR indicated that the producer NPV results can reach much smaller values than those observed in the deterministic analysis, due to uncertainties present in the investment disbursement, as well as the exposure of the producer in the STM and to MCPs.

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References

ABEEólica - Associação brasileira de energia eólica, 2015. Boletim de dados — Janeiro 2015.Available at:. http://www.portalabeeolica.org.br/index.php/dados.html (Access in: July, 2015).

Akdag, S.A., Guler, O., 2009. Calculation of wind energy potential and economic analysis by using Weibull distribution—a case study from Turkey. Part 1: Weibull parameters. Energy Sources Part B 4, 1–8.

Amarante, O.A., Brower, M., Zack, J., Sá, A.L., 2001. Atlas do potencial eólico brasileiro. CEPEL, Brasília.

Amarante, O.A.C., 2010. Atlas Eólico: Minas Gerais. CEMIG, Belo Horizonte.

ANEEL, 2015a. Nota Técnica n° 22/2015-SGT/ANEEL, de 29 de janeiro de 2015.Available at:. http://www.aneel.gov.br/aplicacoes/audiencia/arquivo/2014/023/resultado/nt_22_2015_sgt_custo_de_capital.pdf (Access in: April, 2015).

ANEEL, 2015b. Despacho n°16, de 15 de janeiro de 2015.Available at:. https://duto.aneel.gov.br/concessionarios/taxafiscalizacao/aplicativo/default.asp?flag=2 (Access in: April, 2015).

ANEEL, 2015c. Submódulo 6: Regras de repasse dos preços de contratos de compra de energia, de 1° de janeiro de 2015.Available at:. http://www.aneel.gov.br/aplicacoes/audiencia/arquivo/2011/078/documento/submodulo_6_1_-_limites_de_repasse.pdf (Access in: November, 2015).

Aquila, G., Rocha, L.C., Rotela Jr., P., Pamplona, E., Queiroz, A.R., Paiva, A.P., 2016. Wind power generation: an impact analysis of incentive strategies for cleaner energy provision in Brazil. J. Clean. Prod. 137, 1100–1108.

Arnold, U., Yildiz, Ö., 2015. Economic risk analysis of decentralized renewable energy infrastructures — a Monte Carlo Simulation approach. Renew. Energy 77, 227–239.

Artzner, P., Delbaen, F., Eber, J.-M., Heath, D., 1999. Coherent measures of risk. Math. Financ. 9, 203–228.

Ayodele, T.R., Ogunjuyigbe, A.S.O., Amusan, T.O., 2016. Wind power utilization assessment and economic analysis of wind turbines across fifteen locations in the six geographical zones of Nigeria. J. Clean. Prod. 129, 341–349.

Blanco, M.I., 2009. The economics of wind energy. Renew. Sust. Energ. Rev. 13, 1372–1382.

Brigham, E.F., Houston, J.F., 2007. Fundamentals of Financial Management. 11 ed. Cengage Learning, Florence, KY.

Castro-Santos, L., Filgueira-Vizoso, A., Carral-Couce, L., Formoso, J.A., 2016. Economic feasibility of floating offshore wind farms. Energy 112, 868–882.

CCEE, 2010. Visão Geral das Operações. (94 pp.).

CCEE, 2015. Câmara de Comercialização de Energia Elétrica — O que fazemos: Preços Available at:. http://www.ccee.org.br/portal/faces/oquefazemos_menu_lateral/leiloes?_afrLoop=5547777042548#%40%3F_afrLoop%3D5547777042548%26_adf.ctrl-state%3Dp6tr9dqjl_112 (Access in: May, 2015).

Colmenar-Santos, A., Campiñez-Romero, S., Pérez-Molina, C., Mur-Pérez, F., 2015. Repowering: an actual possibility for wind energy in Spain in a new scenario without feed-in-tariffs. Renew. Sust. Energ. Rev. 41, 319–337.

COPEL, 2007. Companhia Paranaense de Energia. Manual de avaliação técnico-econômica de empreendimentos eólio-elétricos. LACTEC, Curitiba (104 pp.).

Custódio, R.S., 2013. Energia Eólica para a Produção de Energia Elétrica. 2ªed. Synergia, Rio de Janeiro (319 pp.).

Dahlgren, R., 2003. Risk assessment in energy trading. IEEE Trans. Power Syst. 18 (2), 503–511.

Dalbem, M.C., Brandão, L.E.T., Gomes, L.L., 2014. Can the regulated market foster a free market for wind energy in Brazil? Energy Policy 66, 303–311.

Damodaran, A., 2015. Betas by sector (US).(January). Available at:. http://people.stern.nyu.edu/adamodar/New_Home_Page/datafile/Betas.html (Access in: February, 2015).

Del Río, P., 2014. Back to the future? Rethinking auctions for renewable electricity support. Renew. Sust. Energ. Rev. 35, 42–56.

Dutra, R.M., Szklo, A.S., 2008. Incentive policies for promoting wind power production in Brazil: scenarios for the alternative energy sources incentive program (PROINFA) under the new Brazilian electric power sector regulation. Renew. Energy 33, 65–76.

EPE, 2013. Reference: EPE. Nota Técnica DEA. Acompanhamento de Medições Anemométrica – AMA: Caracterização do Recurso Eólico e Resultados Preliminares de sua Aplicação no Sistema Elétrico. EPE, Rio de Janeiro, p. 46.

Ertürk, M., 2012. The evaluation of feed in tariff regulation of Turkey for onshore wind energy based on the economic analysis. Energy Policy 45, 359–367.

Faria, E., Barroso, L.A., Kelman, R., Granville, S., Pereira, M.V., 2009. Allocation of firm-energy rights among hydro plants: an Aumann–Shapley approach. IEEE Trans. Power Syst. 24 (2), 541–551.

Fidelis, N.F., Rosa, L.P., Freitas, M.A.V., Pereira, M.G., 2013. Wind energy in Brazil: from the power sector's expansion crisis model to the favorable environment. Renew. Sust. Energ. Rev. 22, 686–697.
Grieser, B., Sunak, Y., Madlener, R., 2015. Economics of small wind turbines in urban settings: an empirical investigation for Germany. Renew. Energy 78, 334–350.
Hair Jr, J.F., Black, W.C., Babin, B.J., Anderson, R.E., 2014. Multivariate data analysis. 7th ed. Pearson, London.
Hemmati, R., Saboori, H., Saboori, S., 2016. Stochastic risk-averse coordinated scheduling of grid integrated energy storage units in transmission constrained wind-thermal systems within a conditional value-at-risk framework. Energy 113, 762–775.
Holdermann, C., Kissel, J., Beigel, J., 2014. Distributed photovoltaic generation in Brazil: an economic viability analysis of small-scale photovoltaic systems in the residential and commercial sectors. Energy Policy 67, 612–617.
Hung, J.C., Lee, M.C., Liu, H.C., 2008. Estimation of value-at-risk for energy commodities via fat-tailed GARCH models. Energy Econ. 30, 1173–1191.
Islam, M., Mekhilef, S., Saidur, R., 2013. Progress and recent trends of wind energy technology. Renewable and Sustainable Energy Reviews 21, 456–468.
Jiang, Y., Nan, Z., Yang, S., 2013. Risk assessment of water quality using Monte Carlo simulation and artificial neural network method. J. Environ. Manag. 122, 130–136.
Jorion, P., 1999. Value at Risk – A nova fonte de referência para o controle de risco do Mercado. 2ª Edição. Bolsa de Mercados e Futuros, São Paulo (305 pp.).
Jorion, P., 2002. How informative are value at risk disclosures? Account. Rev. 77 (4), 911.
Juárez, A.A., Araujo, A.M., Rohatgi, J.S., Oliveira Filho, O.D.Q., 2014. Development of wind power in Brazil: political, social and technical issues. Renew. Sust. Energ. Rev. 39, 828–834.
Justus, C.G., Hargraves, W.R., Mikhail, A., Graber, D., 1978. Methods for estimating wind speed frequency distributions. J. Appl. Meteorol. Climatol. 17, 350–353.
La Rocque, E.C., Werlang, S.R., Coelho, F., 2003. Risco de Mercado – Gestão de Risco de Mercado em Empresas Não - Financeiras. (47 pp.). Documento Preliminar.
Li, C.-B., Lu, G.-S., Wu, S., 2013. The investment risk analysis of wind power project in China. Renew. Energy 50, 481–487.
Maceira, M.E.P., Terry, L.A., Costa, F.S., Damázio, J.M., Melo, A.C.G., 2002. Chain of optimization models for setting the energy dispatch and spot price in the Brazilian system. Proceedings of the Power System Computation Conference — PSCC (pp. 24-28).
Martins, F.R., Pereira, E.B., 2011. Enhancing information for solar and wind energy technology deployment in Brazil. Energy Policy 39, 4378–4390.
Martins, D.E.C., Seiffert, M.E.B., Dziedzic, M., 2013. The importance of clean development mechanism for small hydro power plants. Renew. Energy 60, 643–647.
Mastropietro, P., Batle, C., Barroso, L.A., Rodilla, P., 2014. Electricity auctions in South America: towards convergence of system adequacy on RES-E support. Renew. Sust. Energ. Rev. 40, 375–385.
Ministério de Ciência e Tecnologia – MCT, 2015. Arquivo dos fatores de emissão. Available at:. http://www.mct.gov.br/index.php/content/view/321144.html (Access in: March, 2015).
Montes, G.M., Martin, E.P., Bayo, J.A., Garcia, J.O., 2011. The applicability of computer simulation using Monte Carlo techniques in windfarm profitability analysis. Renew. Sust. Energ. Rev. 15, 4746–4755.
Peña, I., Azevedo, I.L., Ferreira, L.A.F.M., 2014. Economic analysis of the profitability of existing wind parks in Portugal. Energy Econ. 45, 353–363.
Pereira, M.G., Camacho, C.F., Freitas, M.A.V., da Silva, N.F., 2012. The renewable energy in Brazil: current status and potential. Renew. Sust. Energ. Rev. 16, 3786–3802 (Apr.).
RAMADAN, 2017. Wind energy farm sizing and resource assessment for optimal energy yield in Sinai Peninsula. Egypt. Journal of Cleaner Production http://dx.doi.org/10.1016/j.jclepro.2017.01.120. In Press.
REN 21, 2015. Global status report-key findings.Available at:. http://www.ren21.net/ren21activities/globalstatusreport.aspx (Access in: April, 2015).
Safari, B., Gasore, J., 2010. A statistical investigation of wind characteristics and wind energy potential based on the Weibull and Rayleigh models in Rwanda. Renew. Energy 35, 2874–2880.
Sanchez, D.P., Rodriguez, I.M., Munoz, W.Z., 2004. Crystal Ball Software de Analisis y Simulacion de Riesgo. Universidad Nacional de Colombia, Bogotá.
Schmidt, J., Lehecka, G., Gass, V., Schmid, E., 2013. Where the wind blows: assessing the effect of fixed and premium based feed-in tariffs on the spatial diversification of wind turbines. Energy Econ. 40, 269–276.
Signorini, G., Ross, R.B., Peterson, H.C., 2015. Governance strategies and transaction costs in a renovated electricity market. Energy Econ. 52, 151–159.
Silva, N.F., Rosa, L.P., Freitas, M.A.V., Pereira, M.G., 2013. Wind energy in Brazil: from the power sector's expansion crisis model to the favorable environment. Renew. Sust. Energ. Rev. 22, 686–697.
Simons, P.J., Cheung, W.M., 2016. Development of a quantitative analysis system for greener and economically sustainable wind farms. J. Clean. Prod. 133, 886–898.
Solangi, K.H., Islum, M.R., Saidur, R., Rahim, N.A., Fayaz, H., 2011. A review on global energy policy. Renew. Sust. Energ. Rev. 15, 2149–2163 (Jan.).
Tziralis, G., Kirytopoulos, K., Rentizelas, A., Tatsiopoulos, I., 2009. Holistic investment assessment: optimization, risk appraisal and decision making. Manag. Decis. Econ. 30, 393–403.
UNFCCC – United Framework Convention on Climate Change, 2012. Guidelines on the Assessment of Investment Analysis.
Wachsmann, U., Tomalsquim, M.T., 2003. Wind power in Brazil — transition using German experience. Renew. Energy 28, 1029–1038.
Walters, R., Walsh, P., 2011. Examining the financial performance of micro-generation wind projects and the subsidy effects of feed-in tariffs for urban locations in the United Kingdom. Energy Policy 39 (9), 5167–5181.
Williams, D.G., 2007. Scenario simulations do not yield results stochastically consistent with alternative Monte Carlos results: U.S. nuclear plant decommissioning funding adequacy (2000). Energy Economics 29 (5), 1101–1113.
Yamai, Y., Yoshiba, Y., 2005. Value at risk versus expected shortfall: a practical perspective. J. Bank. Financ. 29 (4), 997–1015.