IET Renewable Power Generation

Research Article

Modelling and design of wind-solar hybrid generation projects in long-term energy auctions: a multi-objective optimisation approach

ISSN 1752-1416
Received on 18th February 2020
Revised 14th May 2020
Accepted on 28th June 2020
E-First on 24th September 2020
doi: 10.1049/iet-rpg.2020.0185
www.ietdl.org

Giancarlo Aquila[1] ✉, Anderson R. de Queiroz[2], Luana M.M. Lima[3], Pedro Paulo Balestrassi[4], J.W. Marangon Lima[1], Edson O. Pamplona[4]

[1]Institute of Electrical and Energy Systems, Federal University of Itajubá, Itajubá MG, Brazil
[2]Decision Sciences, Economics & Finance Department, School of Business at North Carolina Central University, Durham NC, USA
[3]Nicholas School of Environment, Duke University, Durham NC, USA
[4]Institute of Production Engineering and Management, Federal University of Itajubá, Itajubá MG, Brazil
✉ *E-mail: giancarlo.aquila@yahoo.com*

Abstract: This study proposes an approach to help the bidding processes of hiring wind-photovoltaic farms in long-term energy auctions. The proposed approach aims to define an optimal solution to configure wind-photovoltaic farms based on mixture design of experiments and the L_p method, as well as an efficiency metric designed to achieve diversification and to identify the Pareto dominant optimal portfolio. The proposed method is simple and flexible for practical applications. Moreover, its associated goals of choosing the Pareto dominant optimal solutions are aligned with the goals of the electricity regulators responsible to manage the hiring process for a new generation. To validate the method, wind-solar photovoltaic generation configurations in three Brazilian cities are analysed and the results are compared with other methods previously proposed in the literature. The results show that the proposed method has more intuitive criteria for the investor and regulator, without reducing the quality of the information provided to decision making.

1 Introduction

Since the 2000s, renewable energy resources have significantly increased their participation in the electricity generation matrix around the world. Recently, hybrid generation has gained considerable momentum and have been deployed in medium to large-scale projects [1]. One form of hybrid electricity generation that has sparked interest from both regulators and investors is wind-solar photovoltaic (W-PV) hybrid farms [2]. For example, a recent study shows strong temporal synergy for wind and solar and great potential for investors of such type of hybrid projects in Southeastern regions in Australia [3], while in Brazil, the Minister of Mines and Energy has highlighted the country's potential for this type of generation [4].

The intermittency of wind and solar sources pose complex schedule planning tasks that have to be addressed by plant and systems operators. The uncertainty related to the production of electricity from these sources creates the need for a more robust generation planning to diversify the supply portfolio with other technologies such as thermal power plants, offshore renewable power plants, energy storage devices, and others [5] to minimise the supply risk. Moreover, the increase of intermittent sources participation in electric power systems increases operational issues such as reliable generation reserves, ramping capabilities, frequency regulation and others. However, the combined use of these, a subset of these sources, such as wind and solar, reduces the supply/operational risks, since these sources usually have a complementary behaviour (due to solar radiation during the day and more intense wind speed at night in some regions). W-PV farms also have other advantages, such as sharing the same electricity transmission system and economies of scale [6].

In addition, hybrid power generation systems allow to mitigate the disadvantages related to each of the sources that occupy an extensive area in terms of km^2 per installed GW [7]. Among the main problems associated with the space required to install wind farms are: deforestation; cracks in houses near the site; erosions; visual and noise pollution; and limiting the mobility of the local population during the construction phase [5]. In turn, the cost associated with electricity generation from solar PV has been reduced over the last few years and the source is attracting large investments [8–10]. However, this source still has a higher Levelised Cost of Electricity (LCOE) than other renewables, such as wind and biomass, in South American countries and other regions [11].

W-PV hybrid farms are an interesting and potentially viable alternative to be considered in electricity generation planning. However, conducting bidding processes for this type of generation is not a simple task and requires specific criteria to guide the configuration of projects. Brazil is an example of a country that has already recognised the local potential for W-PV projects, but one of the bottlenecks to disseminating this type of generation is the lack of specific criteria to define the generation quota and the compensation of projects. This poses a challenge to be considered and incorporated in models used when planning for future energy systems supply.

To our knowledge, few papers in the literature propose methodologies based on optimisation methods to plan and design hybrid generation projects either in interconnected or isolated power systems. Generally, the objective function of previous work only considers cost minimisation [12–15]. The increase in intermittent renewable generation sources have changed this traditional approach and other objectives such as area utilisation, greenhouse gas (GHG) emissions and others become relevant in energy planning.

Multiobjective linear optimisation methods have been a powerful tool for solving energy planning problems that have more than a single goal [16–18]. However, in many cases, objective functions are represented by non-linear functions and in these situations, it is observed that most studies use optimisation methods by agglutination to solve the designed models. Agglutination methods must have priority in applications, as they allow for the construction of a Pareto frontier with optimal global solutions, in which the best optimal solution is subsequently

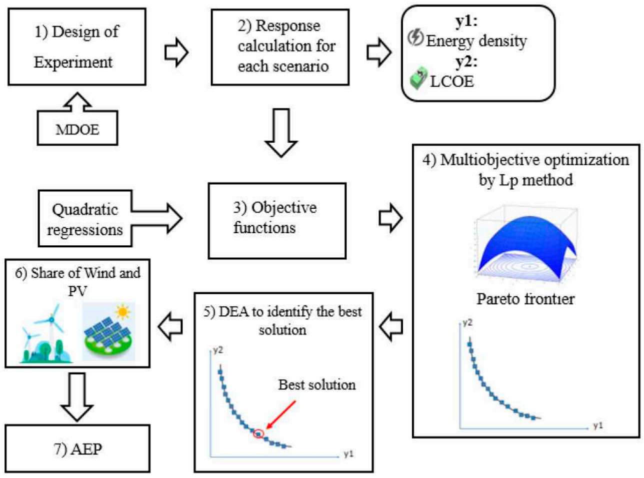

Fig. 1 *Proposed methodology flowchart*

chosen through an ex-post method aligned to the problem to be solved [19].

In the existing literature associated with electricity generation planning, some authors also use multi-objective non-linear optimisation methods, such as the Normal Boundary Intersection, for defining as a priority the optimisation of objectives related to the economic, environmental and reliability aspects of the system [20–22]. Other papers have emphasised in the integration of plants in high voltage networks, aiming at cost reduction and minimisation of GHGs [23]. Regarding hybrid generation systems planning, studies that used multiobjective optimisation methods are still scarce. Most of them are aimed at planning isolated systems, which use one or more renewable energy sources with diesel generators and batteries [24–26]. Recently, the work presented in [6] proposed one of the few existent approaches for planning hybrid W-PV generation systems in interconnected power systems considering a novel multiobjective optimisation framework.

The methodology proposed in [6] is based on normal boundary intersection method to support specific bidding processes for hybrid W-PV projects and it was applied in the context of the Brazilian system. However, the methodology presented in [6] has two shortcomings: (i) The normal boundary intersection is a complex geometric parametrisation method for non-academic planners [27, 28]; and (ii) it uses an ex-post method to identify the best Pareto-optimal solution based on a ratio between entropy and overall percentage error, this metric is not completely focused in the planning aspects of the electrical system, as it divides attention with an inherent aspect of the optimisation method employed in the study.

This study proposes a novel approach based on mixture design of experiments (MDOE) and a weighted metric method called the L_p method [29], which is relatively easy and fast in terms of its application and can be used to analyse practical alternatives in any type of hybrid power generation systems. In the proposed approach, the MDOE [6, 24] is applied to support the construction of the multi-objective optimisation model. To solve the optimisation model, the staggered L_p method [29] is used, which provides a set of optimal solutions of the associated model. Subsequently, Pareto-dominant optimal solution is chosen based on the data envelopment analysis (DEA) where the goal is to achieve diversification of the project as well as the ideal electricity production level in the optimal configuration. The main contribution of this paper is the proposition of an ex-post method exclusively focused on explore cost-benefit relationships in the search for the optimal diversified W-PV portfolio for the decision-maker. This implies indicating the most stable generation share throughout the day at the lowest cost, which is of interest to systems operators, investors and consumers.

The two objectives of this study are minimising the energy density and LCOE. The results are then compared with the previous work [6] for three sites considered for installation of W-PV farm. The remainder of the paper is structured as follows: Section 2 presents a theoretical rationale for the MDOE, the L_p optimisation method and the efficiency metric employed to achieve diversification; Section 3 describes the variables optimised in the study; Section 4 presents the results; and Section 5 concludes this paper.

2 Conceptual framework

The decision variables associated with the optimisation model are the wind power (x_1) and the solar PV (x_2) shares of the W-PV farm. The methodology proposed in this study for designing the hybrid generation project configuration is defined in seven steps, illustrated in Fig. 1 and the steps are described next.

Step 1: A design of experiment is built for each location (city) using the MDOE method.
Step 2: Responses for energy density and LCOE are calculated for each experiment (scenario) generated in step 1.
Step 3: From the mixture compositions in each experiment and the responses estimated in step 2, quadratic regressions are performed to estimate the objective functions.
Step 4: The L_p method is applied to solve the optimisation problem and build the Pareto frontier with global optimal solutions for each location.
Step 5: The entropy value from the optimal solutions is estimated and, posteriorly it is identified as the best Pareto-dominant optimal solution from the set of solutions based on DEA methodology. In this step the LCOE information is considered as the input and the entropy values as output.
Step 6: Extract the share values for wind and solar power from step 5 in addition to the respective energy density and LCOE values.
Step 7: Assess the annual energy production (AEP) estimation, from multiplying the energy density obtained in 6 with the W-PV farm area.

2.1 Mixture design of experiments

The MDOE is characterised as an experiment planning technique that allows the determination of a specific design for a mixture problem [30]. From the MDOE a relationship between the outputs of interest and the proportions is established [31].

The factors are the components (n) of a mixture which represents the relationship between the levels of each component [30]. These relationships are described by the constraints of wholeness:

$$x_1 + x_2 + \cdots + x_n = 1 \tag{1}$$

$$0 \le x_n \le 1 \tag{2}$$

The most popular MDOE is the simplex lattice, with n components and polynomial adjusted in the order m. The planning of this arrangement is made from $m+1$ proportions, equally spaced between 0 and 1, tested for each factor in the experimental design [32]. The levels of factors x_i are generated as follows:

$$x_i = 0, \frac{1}{m}, \frac{2}{m}, \ldots, 1, \quad \text{for} \quad i = 1, 2, \ldots, n \tag{3}$$

where the number of experiments (N) is given by:

$$N = \frac{(n+m-1)!}{m!(n-1)!} \tag{4}$$

As in the simplex lattice arrangements, the experiments occur only with points that lie on the edges of the arrangement. It is recommended to add the centre and axial points in the experiments [32]. This adds the central points represented by $((1/n), (1/n), \ldots, (1/n))$ and the axial points, which lie between the central point and the vertices, which are described by $(n-1)/2n$.

As for the polynomial model used to represent the functions that relate the outputs to the relative proportions of the components in the MDOE, they can be linear, quadratic and cubic [30]. As the linear model does not represent better an adjustment performance above 70% for energy density output [33], a complete quadratic model was applied which performed better when fitting the functions, described by:

$$\hat{y}(x) = \sum_{i=1}^{p} \beta_i x_i + \sum \sum_{i<j}^{p} \beta_{ij} x_i x_j + \sum \sum_{i<j}^{p} \delta_{ij} x_i x_j (x_i - x_j) + \sum \sum_{i<j}^{p} \theta_{ij} x_i x_j (x_i - x_j)^2 \tag{5}$$

where $\hat{y}\ (x)$ is the expected output variable; β_{ij}, δ_{ij} and Θ_{ij} are the regression coefficients; p is the polynomial degree; x_i and x_j are the independent variables.

The formulas for the coefficients, in terms of y, which represents the calculated output in each experiment, are [30]:

$$\beta_i = y_i \tag{6}$$

$$\beta_{ij} = 4y_{ij} - 2(y_i + y_j) \tag{7}$$

$$\delta_{ij} = \tfrac{8}{3}(2y_{iiij} - 2y_{ijjj} - y_i - y_j) \tag{8}$$

$$\theta_{ij} = \tfrac{8}{3}(4y_{iiij} - 6y_{ij} - 4y_{ijjj} - y_i - y_j) \tag{9}$$

MDOE is used to produce an experimental design with scenarios characterised by the share of wind and PV power that composes the hybrid W-PV plant. In each MDOE scenario, the energy density, represented by y_1, and the LCOE, represented by y_2, are defined. After running the experiments, a quadratic regression between the computed outputs and the shares of wind and PV power to estimate the objective functions of y_1 and y_2.

2.2 Weighted metric method (L_p-method)

Agglutination methods are characterised by converting all the objective functions into a single model, reducing the original problem. In addition, they give the decision-maker the choice of the Pareto dominant solution within a set of efficient solutions. The L_p method falls into the class of multi-objective agglutination methods and their application is considered in the literature for two cases. Firstly, this method does not require any preference information from the decision-maker and, moreover, its application is mathematically less complex when compared to other multi-objective optimisation methods [29].

From the ideal staggered solution, it is possible that the outputs with different scales can be used on a single problem [34]. Following the definition in [29], the formulation of the staggered L_p method can be described by the following equations:

$$L_p = \left(\sum_{j=1}^{k} \gamma_j \left[\frac{f_j(\boldsymbol{x}^{\max_j}) - f_j(\boldsymbol{x})}{f_j(\boldsymbol{x}^{\max_j})} \right]^p \right)^{1/p} \tag{10}$$

or

$$L_p = \left(\sum_{j=1}^{k} \gamma_j \left[\frac{f_j(\boldsymbol{x}^{\max_j}) - f_j(x)}{f_j(\boldsymbol{x}^{\max_j}) - f_j(\boldsymbol{x}^{\min_j})} \right]^p \right)^{1/p} \tag{11}$$

where γ_j is a non-negative weight assigned to the jth objective function by decision-maker; p indicates the importance of each objective function deviation from its deal value; $f_j\ (x^{\max})$ is an individual optimal solution for the jth objective; $f_j\ (x)$ is a multi-objective optimal solution for the jth objective; $f_j\ (x^{\min})$ is the worst solution to the jth objective when other objective is optimised.

The estimated objective functions obtained in the previous step are then combined in the formulation of the L_p-method. As mentioned before, L_p-method is the optimisation method that produces the set of optimal solutions. From the multi-objective optimisation model solved using the L_p-method, the ideal shares of wind and PV power in the hybrid W-PV farm will be obtained, as well as the energy densities and the LCOE produced by each optimal configuration.

2.3 Diversification efficiency metric

An efficiency-based metric to achieve investment diversification is used when selecting the Pareto dominant optimal solution. As far as diversification is concerned, the entropy measure allows to identify the optimal solution that provides the highest level of diversification of a system with more than one component. This solution is given from the solution that achieves the highest entropy value [35, 36], which can be calculated by:

$$H = -\sum_{i=1}^{m} p_i \log p_i \tag{12}$$

where H is the entropy value; $p_i$is the proportion of component i in the designed system.

The DEA method is applied to verify which optimal solution of the set is more efficient in achieving diversification. This method is based on the comparison of the performance between a set of decision making units (DMUs), which are distinguished by the amount of input consumed and output produced [37]. The DEA methodology allows identifying which DMU is the benchmarking for the other DMUs of the set [38]. The input and output variable weights of the DEA model can be obtained from the solution of the following model known as constant returns to scale [39]:

$$\begin{aligned} &\max\ w_o = \sum_{q=1}^{b} u_q y_{qo} \\ &\text{s.t:}\ \sum_{p=1}^{a} v_p x_{po} = 1 \\ &\sum_{q=1}^{b} u_q y_{qi} - \sum_{p=1}^{a} v_p x_{pi} \le 0 \quad i = 1, 2, \ldots, n \\ &u_q \ge 0, \quad q = 1, 2, \ldots, b \\ &v_p \ge 0, \quad p = 1, 2, \ldots, a \end{aligned} \tag{13}$$

where i represents the DMU index, $i = 1, \ldots, n$; q the output index, with $q = 1, \ldots, b$; p is the input index, $p = 1, \ldots, a$; y_{qi} is the value of the qth output for the ith DMU; x_{pi} is the value of the pth input for the ith DMU; u_q is the weight associated with the qth output; v_p is the weight associated with the pth input; w_o is the relative efficiency of the DMU_o, which is the DMU in evaluation; y_{qo} and x_{po} are output and input information for the DMU in analysis.

In this case, the DEA super-efficiency model is used, where the hypothesis of the maximum efficiency level is relaxed by removing the DMU under analysis in the construction of the efficiency model as a mathematical program [40]. Thus, the efficiency level can assume any non-negative value.

The DEA super-efficiency model is used to identify the best Pareto-optimal solution for each city in the analysis. For this problem, the input of the DEA super-efficiency is defined to be the LCOE found for each Pareto-optimal solution and as output, we use the entropy estimated from the optimal portions of wind and PV power.

3 Material and methods

To illustrate the efficacy of the proposed method, we apply it to find the optimal configuration for a 30 MW W-PV farm for a set of cities in Brazil, namely Campo Grande (in Mato Grosso do Sul state), Paranaíba (in Piauí state) and Jundiai (in São Paulo state). These are three cities located in the Midwest, Southeast and Northeast regions of Brazil, respectively. Therefore, they are

Table 1 Investment and O&M costs for each source

	Wind fraction (million US$)	PV fraction (million US$)
initial Investment	0.9795 per MW	1.199 per MW
O&M costs	0.002 per MW	0.006 per MW

Table 2 Energy density and LCOE

MDOE scenario, %	Campo Grande		Jundiaí		Parnaíba	
	Energy density, MWh/km^2	LCOE, US$/MWh	Energy density, MWh/km^2	LCOE, US $/MWh	Energy density, MWh/km^2	LCOE, US $/MWh
100 W/0 PV	31.70	32.63	30.04	43.91	32.54	33.05
80 W/20 PV	34.71	38.49	32.89	47.96	36.20	36.91
75 W/25 PV	30.63	46.40	29.01	57.27	32.52	43.70
60 W/40 PV	39.52	44.40	37.44	53.15	42.04	41.73
50 W/50 PV	43.76	47.41	40.92	56.33	46.51	44.60
40 W/60 PV	48.44	52.26	45.89	60.04	52.89	47.86
25 W/75 PV	53.87	69.70	50.65	312.81	62.21	60.36
20 W/80 PV	70.66	63.22	66.95	278.57	79.93	55.89
0 W/100 PV	233.24	76.31	211.97	335.86	66.52	66.89

locations with different potentials for wind and PV sources, which allow us to compare where the installation of the W-PV farm is most attractive. To this end, the goals are set to maximise the energy density and minimise the LCOE. In addition to the ideal proportion of wind power and solar PV that make up the farm, the average energy production value of the plant will be obtained and extracted from the optimal solution with respect to energy density.

3.1 Energy density and LCOE

The energy density indicates the productivity related to the amount of energy capable of being produced per area occupied by a generation system. Producing the maximum amount of energy using the smallest possible area contributes to reducing the environmental impact on the site, in addition to preserving part of the territory for other productive activities [5].

The energy density can be described as the ratio between the energy produced by a plant and the land area it occupies. Mathematically, the energy density calculation can be described as follows:

$$\rho_e = \frac{\mathrm{AEP}}{A} \tag{14}$$

where ρ_e is the energy density (kWh/km^2); AEP is the yearly energy production (kWh); A is the area used to construct the generation project (km^2).

The AEP estimate is based on the sum of wind and solar PV power production similar to what was done in [6]. The computation for the AEP, wind and solar PV production, considering any losses during production, can be described by:

$$\mathrm{AEP} = E_W + E_{PV} \tag{15}$$

where E_W is the wind energy produced during the year (kWh); E_{PV} is the solar PV energy produced during the year (kWh)

$$E_w = \frac{8760 \times 0.93}{2} \rho A_r v^3 C_P \tag{16}$$

where ρ is the air density (kg/m^3); A_r is the rotor swept area (m^2); v is the average wind speed (m/s); C_P =is the turbine power coefficient

$$E_{PV} = 0.8 \eta I_m A (1 - \sigma_T T) \tag{17}$$

where η is the system efficiency (%); I_m is the solar radiation in the region (kWh/m^2); σ_T is the temperature loss coefficient above 25°C; and T is the temperature level above 25°C.

As for the area, the calculation is based on an estimate of the occupied area, in which each installed 1 GW of wind power and solar PV corresponds to 9900 and 630 km^2 [7], respectively, and the function for the area estimation can be described as:

$$A = 9.9 P_w + 0.63 P_{PV} \tag{18}$$

where P_W is the wind nominal power output (MW); P_{PV} is the solar PV nominal power output (MW); A is the occupied area (km^2).

In turn, the LCOE refers to the average cost of a generation project, or more specifically to the total costs related to generation (fixed and variable) discounted to the present, for each unit of energy produced over its useful life [41, 42]. Thus, the classic formulation for LCOE can be described as follows [43]:

$$\mathrm{LCOE} = \frac{\sum_{t=0}^{T} C_t/(1+i)^t}{\sum_{t=0}^{T} E_t/(1+i)^t} \tag{19}$$

where C_t = total costs with electricity generation in period t; T = system lifetime; E_t = electricity produced in period t; i = discount rate.

For the amount disbursed with the initial investment, the estimation was made based on the results of the Brazilian wind and solar PV long-term energy auctions from the last three years. For each MW of installed wind power, the expense is US$ 979.5 million, and for each MW of PV power the amount is US$ 1198 million. For the O&M costs, the values for the wind project portion represents ∼2% of the initial investment [44]. For the installed solar PV portion, the O&M costs are assumed to represent 0.5% of the initial investment [45]. Table 1 summarises the initial investments and the O&M costs of the W-PV farm for each portion of the project.

From the AEP values and the 8.42% discount rate estimated in [6], it is possible to calculate the LCOE for each MDOE scenario. Table 2 describes the energy density for each MDOE scenario and the associated LCOE.

3.2 Minimum price to achieve project feasibility

The minimum price value is an indicator that allows one to identify the remuneration level determined by the generation source. The minimum price is obtained when the net present value (NPV) of a given investment is considered null. The NPV represents the sum of the value of cash flows formed by the difference between cash

Table 3 Cash flow for a W-PV farm

Gross sale balance and additional balances from liquidation of differences
(−) taxes proportional to balance
liquid balance
(−) sector taxes
(−) leasing
(−) O&M costs
(−) insurance and administrative expenses
(−) financial expenses
Profit before income tax
(−) income tax
Net profit after income tax
(−) amortisation of financing
(−) investment
(+) release of financing
Cash flow

Table 4 Energy density objective functions

City	y_1	R^2, %
Campo Grande	$33.71\, x_1 + 76.09\, x_2 - 26.72\, x_1x_2 - 2.51\, x_1x_2\,(x_1 - x_2) + 70.31\, x_1x_2\,(x_1 - x_2)^2$	95.08
Jundiaí	$43.73\, x_1 + 83.69\, x_2 - 7.29\, x_1x_2 + 4.51\, x_1x_2\,(x_1 - x_2) + 69.79\, x_1x_2\,(x_1 - x_2)^2$	91.98
Parnaíba	$32.87\, x_1 + 66.73\, x_2 - 19.36\, x_1x_2 + 4.52\, x_1x_2\,(x_1 - x_2) + 45.35\, x_1x_2\,(x_1 - x_2)^2$	95.28

inflows and outflows, discounted to present value at a cost of capital rate [4]. The NPV calculation can be represented by:

$$\text{NPV} = \sum_{t=0}^{n} \frac{CF_t}{(1+i)^t} \tag{20}$$

where t is the time period in analysis; CF_t is the cash flow.

In Table 3 shows a typical cash flow structure for a W-PV farm.

An NPV of zero is the threshold for considering acceptance of an investment [46] and indicates whether the investor has fully recovered the invested capital, considering its cost of capital [47]. Therefore, the minimum viability price corresponds to the lowest price level that allows the investor to recover the invested capital. In this work, the discount rate considered is the same used for the calculation of the LCOE.

The project cash flow planning horizon is 20 years, which is equivalent to the contracting period of wind and solar PV plants in the regulated market in Brazil. Cash flows for each annual period has been estimated through cash inflows and outflows as described in Table 3 and the basis for calculating cash flows assumptions are detailed in Table 9 of Appendix.

4 Results and discussions

After computing the response variables for each scenario defined by the MDOE, it is possible to estimate the objective functions used in the optimisation. From the quadratic regression model, the objective energy density functions (y_1) and LCOE (y_2) were obtained. These functions are reported on Tables 4 and 5, respectively, and can be viewed graphically in Figs. 2–4 in Appendix. The responses are represented as a function of the power fraction for wind (x_1) and solar PV (x_2).

The objective functions have a coefficient of determination (R^2) above 70%, i.e. they are suitable for use in the optimisation model [33]. In addition, it is observed that the coefficients for the objective functions present different values for each city. These functions reflect the wind potential and site-specific solar PV in

Table 5 LCOE objective functions

City	y_2	R^2, %
Campo Grande	$32.27\, x_1 + 232.51\, x_2 - 355.10\, x_1x_2 + 414.32\, x_1x_2\,(x_1 - x_2) - 441.52\, x_1x_2\,(x_1 - x_2)^2$	99.76
Jundiaí	$30.54\, x_1 + 211.70\, x_2 - 319.65\, x_1x_2 + 368.36\, x_1x_2\,(x_1 - x_2) - 389.20\, x_1x_2\,(x_1 - x_2)^2$	99.74
Parnaíba	$33.15\, x_1 + 265.66\, x_2 - 409.59\, x_1x_2 + 468.31\, x_1x_2\,(x_1 - x_2) - 482.35\, x_1x_2\,(x_1 - x_2)^2$	99.81

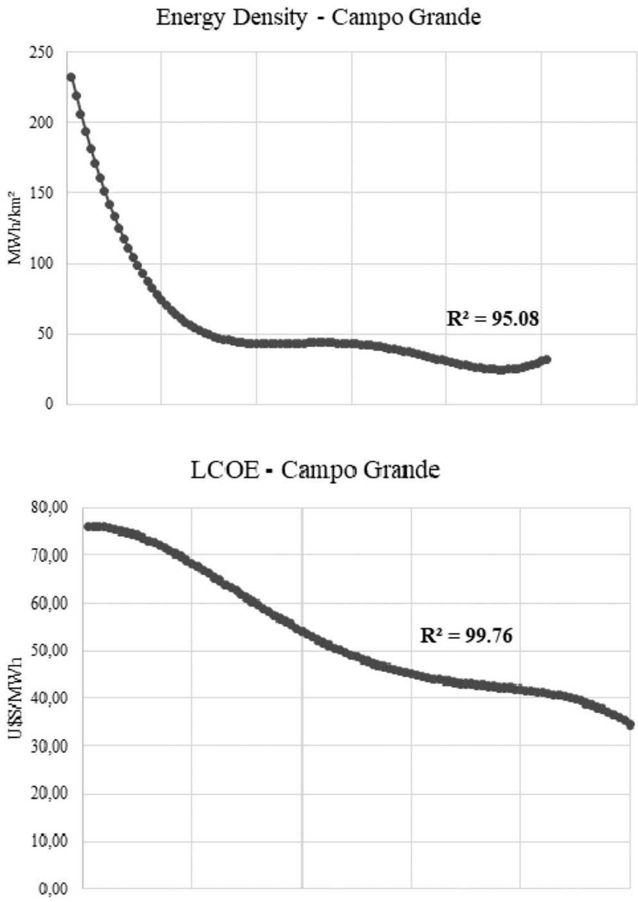

Fig. 2 *Objective functions for Campo Grande*

their coefficients, since to estimate each objective in the MDOE the only variable that distinguishes the responses for each city is the AEP.

It can be observed from Tables 4 and 5, that both the objective functions related to the energy density and to the LCOE are non-linear. However, energy density functions have a higher R^2 than LCOE for all cities.

Table 4 shows that the more PV power, generally the higher the energy density and the more wind power, generally the lower the LCOE. However, the axial points 75%W/25%PV and 25%W/75%PV of the MDOE experimental design present LCOE inferior to the scenarios with 80%W/25%PV and 40%W/60%PV. As for energy density, only the axial point with 75%W/25%PV was lower than with 80%W/20%PV. This factor may have been favorable for the energy density to present a slightly higher adjustment in the quadratic regression performed.

Thus, the optimisation models are designed and solved considering the objective functions that were inserted in the scheduling of the staggered L_p method described in (11). Also, the constraints of the mixture problem described in (1) and (2) are included in the optimisation model design. The weights of each objective are varied from 0 to 1 considering steps of 0.1. Optimal solutions for hybrid W-PV farms of different configurations are then obtained (Table 6). One weakness of the L_p method is that the

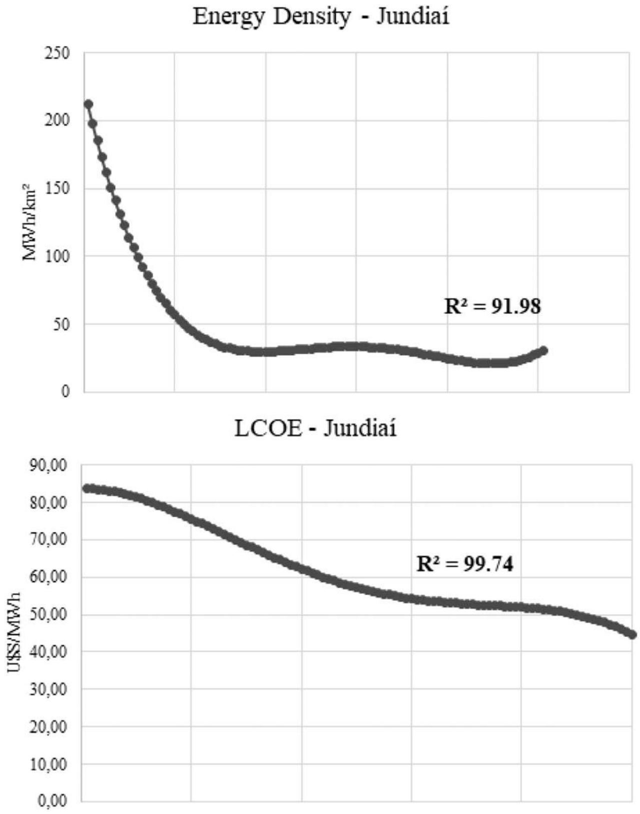

Fig. 3 *Objective functions for Jundiaí*

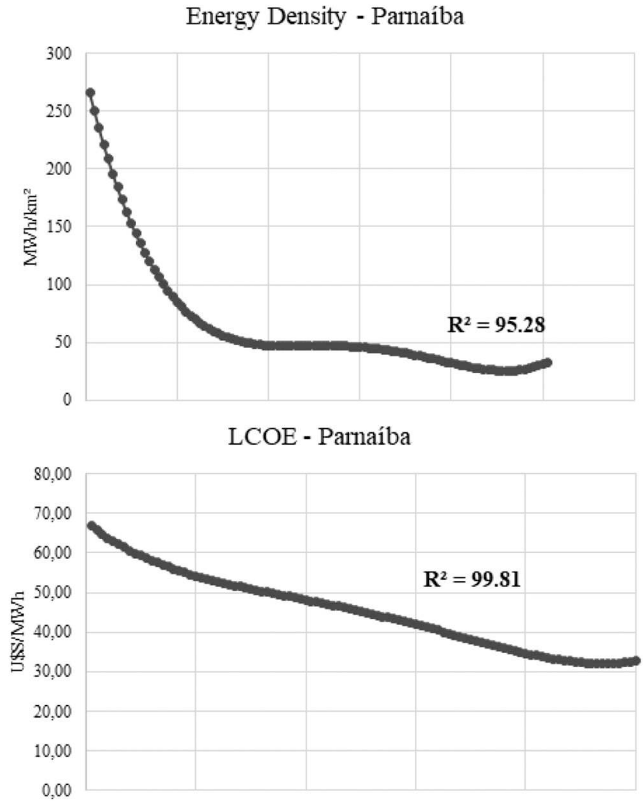

Fig. 4 *Objective functions for Parnaíba*

Pareto boundaries are not constructed with the points distributed evenly between them, as in the NBI method. However, to achieve the goal of finding the optimal setting for each source and W-PV farm AEP level at each location this is not an issue.

Subsequently, the entropy value is calculated for each solution present at each of the boundaries and then the entropy to LCOE ratios are calculated. From the super-efficiency DEA model for comparing entropy to LCOE ratios, the Pareto dominant optimal W-PV farm configurations at each site were identified. The power fraction of each source, the results of y_1 and y_2, and the entropy to y_2 ratio value for the Pareto optimal solutions are described in Table 6.

The percentage levels for wind power and solar PV obtained are distinct from the results of the method proposed in [6]. The values found for the AEP levels are also different, however, it is observed that the order of the AEP levels among cities does not change, and in the city of Parnaíba is where the plant has the highest generation potential. Table 7 compares the levels of the AEP obtained in [7]. For these results, it is observed that the city at Northeast region (Parnaíba) obtained a higher level of AEP, followed by the city at Midwest (Campo Grande), with the worst level being that of the city at Southeast (Jundiaí).

It can also be inferred that the Parnaíba is more attractive than the others with respect to producing higher energy density at a lower cost. From Fig. 5, it is observed that the Pareto frontier to the city of Parnaíba is below the others for all optimal points, which means that the city can achieve higher energy density at lower LCOE values. The city of Campo Grande shows the second highest level of efficiency, and the city of Jundiaí proves to be the least efficient to deploy W-PV farm projects.

Finally, it was estimated the minimum price that enables the W-PV farm in its best configuration and only considering one technology (either 100% from wind or from solar PV), the minimum price results are described in Table 8. The minimum price corroborates that the city of Parnaíba is the most competitive place for an investor to install W-PV among the three cities analysed. It is observed that in the Pareto optimal configuration the minimum price is closest to the wind source, which is the cheapest. Thus, it can be considered that a W-PV farm planned using the proposed approach allows one to take advantage of two sources simultaneously, in the least costly way possible, and taking advantage of the benefits related to each source.

Table 6 Pareto optimal solutions for the W-PV farms

City	% source	y_1	y_2	H/y_2
Campo Grande	W: 59% PV: 41%	43.21	45.06	3.75
Jundiaí	W: 58% PV: 42%	40.67	54.46	3.12
Parnaíba	W: 59% PV: 41%	46.00	42.61	3.97

Table 7 Comparison with respect to AEP

City	AEP, MWh	AEP, MWh in Aquila *et al.* (2018)	Difference, %
Campo Grande	79,070.64	81,030.39	−2.418
Jundiaí	74,410.59	74,653.88	−0.003
Parnaíba	84,164.23	86,303.03	−2.478

In addition, the optimally configured W-PV farm allows for less expensive generation planning and operation of the wind and solar PV. This is beneficial for both industries, as a single bid comes into two sources and thus both supply chains are active simultaneously and obtain spillovers.

Comparing the previous results for the same problem obtained in [6], it was observed a more diversified representation among the sources: Campo Grande (62% W–38% PV); Jundiaí (60% W–40% PV); Parnaíba (63% W–37% PV). The reason for this is that the proposed approach prioritises an ex-post method that reach diversification at the lowest possible cost; while in [6], the distance from the optimal solutions to individual solutions of analysed objective functions were considered as important as the diversification factor. The ex-post method proposed in this paper can be considered more appropriate for the problem at hand, since by focusing only on diversification with low cost, both systems operators and consumers are benefited. Although not quantitatively evaluated, for operators, maximum diversification allows for improved reliance on complementarity benefits among sources, which implies a more stable electricity generation throughout the day for the hybrid plant that uses only intermittent sources. Even for the consumer, the added benefit obtained with diversification at

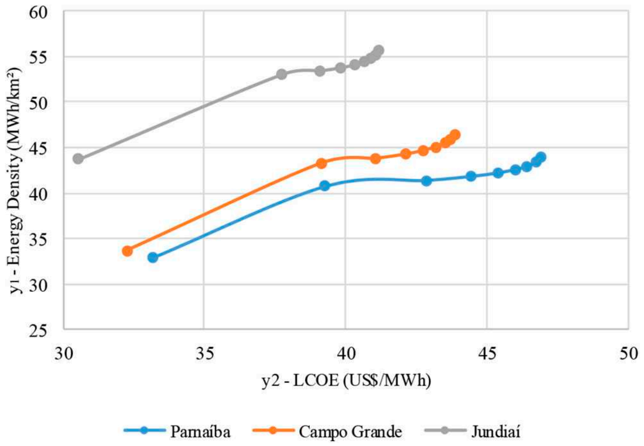

Fig. 5 *Pareto frontier for each local*

Table 8 Minimum price to achieve project feasibility

City	100% W	W-PV	100% PV
Campo Grande	US$ 37.64	US$ 40.30	US$ 44.13
(−6.6%)		(+9.5%)	
Jundiaí	US$ 39.99	US$ 42.88	US$ 46.89
	(−6.7%)		(+ 9.4%)
Parnaíba	US$ 35.36	US$ 37.86	US$ 41.46
	(−6.6%)		(+ 9.5%)

lowest cost implies greater reliability in supply, promoting the smaller costs to their final energy bills.

5 Conclusions

The main goal of this work is directed to find efficient solutions to a practical problem related to the design of hybrid generation projects aimed to compete in long-term energy auctions. This piece is devoted to fill existent obstacles to the dissemination of W-PV farms in power systems due to the lack of proper methodologies to support the bidding processes for these projects. Therefore, a model based on a combination of MDOE, DEA and the L_p method was developed. The novel approach proposes a simpler and easily implementable framework than other models previously presented in the literature while preserving quality of the results.

As for the results, it was observed that a city in the Northeastern region of Brazil would be the most appropriate place among those analysed to deploy W-PV farms. This result converges with the fact that the region is the place with the highest installed power of wind and solar PV plants in the country, establishing itself as the leader for this type of generation. We observe through our analysis that the criterion based on the efficiency of the entropy-LCOE ratio for determining the Pareto optimal solution is quite appropriate. In the study it was seen that entropy is a metric related to diversification, which has been one of the reasons that motivated the insertion of wind and solar PV sources in the Brazilian electricity generation portfolio. In turn, the LCOE is a cost measure, so the lower the LCOE the higher the benefits to a potential investor and to the end consumer.

There are other hybrid generation projects that use combinations of other energy sources, such as: hydro and solar PV; hydro and wind power; helium-thermal with natural gas; coal and biomass; among others. The proposed method with some adaptations can be applied to these variations of hybrid solutions. For these hybrid generation setups there are also shortages of methods and criteria that support the planning analysis, so it is an opportunity for future studies to propose new approaches aimed to improve investment decisions associated with these projects. Models that consider the uncertainties in the response variables can also be considered in future studies, as well as the inclusion of response variables that represent risk measures for the investor, such as Value at Risk (VaR) and Conditional Value at Risk (CVaR).

6 Acknowledgment

The authors thank the Brazilian National Council for Scientific and Technological Development (CNPq) for the scholarship support number 155507/2018-4 of the first author.

7 References

[1] Aquila, G., Pamplona, E.O., Queiroz, A.R., *et al.*: 'An overview of incentive policies for the expansion of renewable energy generation in electricity power systems and Brazilian experience', *Renew. Sust. Energy Rev.*, 2017, **70**, pp. 1090–1098

[2] Khare, V., Nema, S., Baredar, P.: 'Solar–wind hybrid renewable energy system: a review', *Renew. Sust. Energy Rev.*, 2016, **58**, pp. 23–33

[3] Prasad, A.A., Taylor, R.A., Kay, M.: 'Assessment of solar and wind resource synergy in Australia', *Appl. Energy*, 2017, **190**, pp. 354–367

[4] EPE: 'Usinas Híbridas: Uma análise qualitative de temas regulatórios e comerciais relevantes ao planejamento'. Tech. Report, Empresa de Pesquisa Energetica, Rio de Janeiro, RJ, June 2018. Available at http://www.epe.gov.br/pt/imprensa/noticias/usinas-hibridas-epe-publica-analise-qualitativa-de-temas-regulatorios-e-comerciais

[5] Fadigas, E.A.F.A.: '*Wind energy (in Portuguese)*' (Manole, Barueri, 2011), 285p

[6] Aquila, G., Rocha, L.C.S., Pamplona, E.O., *et al.*: 'Proposed method for contracting of wind-photovoltaic projects connected to the Brazilian electric system using multiobjective programming', *Renew. Sust. Energy Rev.*, 2018, **97**, pp. 377–389

[7] Ramanathan, R.: 'Compartive risk assessment of energy supply technologies: a data envelopment analysis approach', *Energy*, 2001, **26**, pp. 197–203

[8] Comello, S., Reichelstein, S., Sahoo, A.: 'The road ahead for solar PV power', *Renew. Sust. Energy Rev.*, 2018, **92**, pp. 744–756

[9] Reichenberg, L., Hedenus, F., Odenberger, M., *et al.*: 'The marginal system LCOE of variable renewables–evaluating high penetraion levels of wind and solar in Europe', *Energy*, 2018, **152**, pp. 914–924

[10] Hafiz, F., de Queiroz, A. R., Husain, I: 'Solar generation, storage, and electric vehicles in power grids: challenges and solutions with coordinated control at the residential level', *IEEE Electrification Mag.*, 2018, **6**, (4), pp. 83–90

[11] REN 21: 'Global status report 2018'. REN 21, Tech. Rep, Paris, 2018. Available at http://www.ren21.net/gsr-2018/

[12] Park, J.B., Park, Y.M., Won, J.R., *et al.*: 'An improved genetic algorithm for generation expansion planning', *IEEE Trans. Power Syst.*, 2000, **15**, pp. 916–922

[13] Kannan, S., Slochanal, S.M.R., Padhy, N.P.: 'Application and comparison of metaheuristic techniques to generation expansion planning', *IEEE Trans. Power Syst.*, 2000, **15**, pp. 916–922

[14] Sirikum, J., Techanitisawad, A., Kachitivichyanukul, V.: 'New efficient GA-benders' decomposition method for generation expansion planning with emission controls', *IEEE Trans. Power Syst.*, 2007, **22**, pp. 1092–1100

[15] Yang, H., Lu, L., Zhou, W.: 'A novel optimization sizing model for hybrid solar-wind power generation system', *Sol. Energy*, 2007, **81**, pp. 76–84

[16] Mavrotas, G., Diakoulaki, D., Papayannayakis, L.: 'An energy planning approach based on 0–1 multiple objective linear programming', *Int. Trans. Oper. Res.*, 1999, **6**, pp. 231–244
[17] Antunes, C.H., Martins, A.G., Brito, I.S.: 'A multiple objective mixed integer linear programming model for power generation expansion planning', *Energy*, 2004, **29**, pp. 613–627
[18] Luz, T., Moura, P., Almeida, A.: 'Multi-objective power generation expansion planning with high penetration of renewables', *Renew. Sustain. Energy Rev.*, 2017, **81**, pp. 2637–2643
[19] Shahraki, A.F., Noorossana, R.: 'Reliability-based robust design optimization: a general methodology using genetic algorithm', *Comput. Ind. Eng.*, 2014, **74**, pp. 199–207
[20] Aghaei, J., Akbari, M.A., Roosta, A., *et al.*: 'Multiobjective generation expansion planning considering power system adequacy', *Electr. Power Syst. Res.*, 2013, **102**, pp. 8–19
[21] Aghaei, J., Akbari, M.A., Roosta, A., *et al.*: 'Integrated renewable-conventional generation expansion planning using multiobjective framework', *IET Gener. Transm. Distrib.*, 2012, **6**, pp. 773–784
[22] Vadihinasab, V., Jadid, J.: 'Normal boundary intersection method for suppliers strategic bidding in electricity markets: an environmental/economic approach', *Energy Convers. Manage.*, 2010, **51**, pp. 1111–1119
[23] Ahmadi, A., Kaymanesh, A., Siano, P., *et al.*: 'Evaluating the effectiveness of normal boundary intersection method for short-term environmental/economic hydrothermal self-scheduling', *Electr. Power Syst. Res.*, 2015, **123**, pp. 192–204
[24] Fonseca, M.N., Pamplona, E.O., Queiroz, A.R., *et al.*: 'Multi-objective optimization applied for design hybrid power generated systems in isolated network', *Sol. Energy*, 2018, **161**, pp. 207–219
[25] Roberts, J.J., Cassula, A.M., Silveira, J.L., *et al.*: 'Robust multi-objective optimization of renewable based hybrid power system', *Appl. Energy*, 2018, **223**, pp. 52–68
[26] Izadbaksh, M., Gandomkar, M., Rezvani, A., *et al.*: 'Short-term resource scheduling of a renewable energy based micro grid', *Renew. Energy*, 2015, **75**, pp. 598–606
[27] Das, I., Dennis, J.E.: 'A closer look at drawbacks of minimizing weighted sums of Pareto set generation in multicriteria optimization problems', *Struct. Optim.*, 1997, **14**, (1), pp. 63–69
[28] Das, I., Dennis, J.E.: 'Normal boundary intersection: a new method for generation the Pareto surface in nonlinear optimization problems', *SIAM J. Optim.*, 1998, **8**, (3), pp. 631–657
[29] Arkadani, M.K., Noorossana, R.: 'A new optimization criterion for robust parameter – the case of target is best', *Int. J. Adv. Manuf. Technol.*, 2008, **38**, pp. 851–859
[30] Cornell, J.: '*Experiments with mixtures: designs, models, and the analysis of mixture*' (John Wiley & Sons, New York, 2002, 3rd edn.), 649p
[31] Oliveira, F.A.: 'Estratégia de comercialização de energia elétrica através da otimização de portfólios de contratos utilizando projetos de mistura'. Phd dissertation, Department of Electrical Engineering, Universidade Federal de Itajubá, Itajubá, 2009
[32] Montgomery, D.C.: '*Design and analysis of experiments*' (John Wiley & Sons, New York, 2013, 8th edn.), 665p
[33] Hair, J.F.Jr., Black, W.C., Babin, B.J., *et al.*: '*Multivariate data analysis*' (Pearson, London, 2014, 7th edn.), 734p
[34] Miettinen, K.: '*Nonlinear multiobjective optimization*' (Kluwer Academic Publishers, Boston, 1st edn., 1998), 293p
[35] Shannon, C.E.: 'A mathematical theory of communication', *Bell Syst. Tech. J.*, July 1948, **27**, pp. 379–423
[36] Shannon, C.E.: 'A mathematical theory of communication', *Bell Syst. Tech. J.*, October 1948, **27**, pp. 623–656
[37] Cook, W., Seiford, L.: 'Data envelopment analysis (DEA) – thirty years on', *Eur. J. Oper. Res.*, 2009, **192**, pp. 1–17
[38] Kao, C.: 'Efficiency decomposition for general multi-stage system in data envelopment analysis', *Eur. J. Oper. Res.*, 2014, **232**, pp. 117–124
[39] Charnes, A., Cooper, W.W., Rhodes, E.: 'Measuring the efficiency of decision-making units', *Eur. J. Oper. Res.*, 1978, **2**, pp. 429–444
[40] Andersen, P., Petersen, N.C.: 'A procedure for ranking efficient units in data envelopment analysis', *Manage. Sci.*, 1993, **39**, pp. 1261–1263
[41] Edenhofer, O., Hirth, L., Knopf, B., *et al.*: 'On the economics of renewable energy sources sources', *Energy Econ.*, 2013, **40**, pp. 512–523
[42] Ueckerdt, F., Hirth, L., Luderer, G., *et al.*: 'System LCOE: 'What are the costs of variable renewables?'', *Energy*, 2013, **63**, pp. 61–75
[43] Short, W., Packey, D., Holt, A.T.: '*Manual for economic evaluation of energy efficiency and renewable energy technologies*' (National Renewable Laboratory, Golden, 1995), 120pp
[44] Mudasser, M., Yiridoe, E.Y., Corscadden, K.: 'Economic feasibility of large community feed-in tariff-elegible wind energy production in Nova Scotia', *Energy Policy.*, 2013, **62**, pp. 966–977
[45] ABINEE: 'Propostas para Inserção da Energia Solar Fotovoltaica na Matriz Brasileira'. Tech Rep, Brasília, DF, 2012. Available at: http://www.abinee.org.br/informac/arquivos/profotov.pdf
[46] Ross, S.A., Westerfield, R., Jaffe, J.F.: '*Financial management*' (Atlas, São Paulo, 2002, 5th edn.), 698pp
[47] Arnold, U., Yildiz, Ö.: 'Economic risk analysis of decentralized renewable energy infrastructures e a Monte Carlo simulation approach', *Renew. Energy*, 2015, **77**, pp. 227–239
[48] Aquila, G., Rotela, P.Jr., Pamplona, E.O., *et al.*: 'Wind power feasibility analysis under uncertainty in the Brazilian electricity market', *Energy Econ.*, 2017, **65**, pp. 127–136
[49] COPEL: '*Technical-economic evaluation manual of wind power projects*' (LACTEC, Curitiba, 2007), 104pp

8 Appendix

The input assumptions for the cash flow computations performed in this paper are represented in Table 9.

To view the adjustments regarding the objective functions obtained from quadratic regression models, the functions for each city were designed. In Figs. 2–4 it is possible to graphically view the objective functions for Campo Grande, Jundiaí and Parnaíba, respectively.

Table 9 Cash flow input assumptions

investment (wind fraction) [6]	US$ 979.5 million per MW
investment (PV fraction) [6]	US$ 1198 million per MW
planning horizon [6]	20 years
lease [6]	US$ 17.18/km^2
O&M costs (wind fraction) [43]	2% of the investment
O&M costs (PV fraction) [43]	0.5% of the investment
transmission system fee [6]	US$1.21 per kW installed
commercialisation tax [48]	US$ 0.02 per MWh of assured energy
operation tax [48]	US$ 0.16 per kW installed
regulator tax [48]	US$ 0.85 per kW installed
insurance expenses [49]	0.3% of the investment
others taxes [49]	3% (PIS) and 0.65% (Cofins)
tax over legal entity [49]	25% over 8% of gross revenue
social contribution over the liquid profit [49]	9% over 12% of gross revenue
WACC (discount rate) [6]	8.42%