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Economic planning of wind farms from a NBI-RSM-DEA multiobjective programming

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ABSTRACT

One of the challenges of energy regulatory-agencies is to guide the agents decision-making process towards maximization of the overall welfare of the electricity sector. However, this is not a simple task since it requires meeting expectations of many stakeholders, from investors to consumers. This paper proposes an optimization methodology aimed at helping define the optimal combination of wind farm layout and type of equipment deployed, so that the electricity sector overall welfare is maximized in the process. The optimization objectives are (i) the energy density and (ii) the Net Present Value (NPV), and the parameters are (a) the power levels and (b) the selling price of the energy. The objective functions are modelled with the aid of a design-of-experiment technique known as Response Surface Methodology, relying on the multi-objective programming method of Normal Boundary Intersection for the optimization. The methodology is applied to four different scenarios arising from the combination of two different locations (Santa Vitória do Palmar-RS and Macau-RN, both in Brazil), and two different wind turbine manufacturers (A and B). The final step comprises the application of the Data Envelopment Analysis technique in order to sort one from the set of optimal solutions identified by the four different scenarios. The results show that the proposed methodology is capable of supporting bidding processes and wind farms certification programs, in line with what should be expected by regulatory agencies, investors and electricity consumers alike. The deployment of the methodology proved discriminant and allowed selection of one final scenario (Macau-RN, brand A equipment) as overall optimal. It was also observed that equipment efficiency is dependent on siting location.

1. Introduction

The wind power growth impulse in Brazil started by the mid-2000s, when the Brazilian government included wind energy in the PROINFA, an incentive program for alternative energy sources, and later, in the electricity auctions [1,2]. Thus, due to high wind energy potential in some states combined with the incentives for buying this source of energy and dedicated lines of financing from the BNDES (National Bank for Economic and Social Development), the wind energy started to increase its share in the Brazilian electricity matrix [3,4].

As a result, in June 2019 the Brazilian wind energy installed capacity reached just over 15 GW, growing from a 2012 value of 2 GW [5,6]. Also, Brazilian wind farms have a high capacity factor, reaching 42,2% in 2018 against a world average of 25% [7].

Wind power over Brazilian territory is currently estimated at up to 500 GW [7] and at this time 14 States are providing wind energy to the interconnected National electricity grid, with the largest contributors being the States from Northeast and South Regions [8,9]. However, since Brazil has continental dimensions, the wind

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distributions may present quite strong variability from one region to another [9]. Also, wind turbines from different manufacturers with the same approximate nominal power may display actual power curves versus wind speed with significant differences. Together, these variances of wind and equipment combine to make the planning of wind farms quite complex, especially if solutions are sought to maximize the welfare of the electricity sector, as highlighted by ANEEL [10].

The benefits associated with the electricity converted from the wind energy are many and include reduction of greenhouse-gas (GHG) emissions and fossil fuel dependency [11,12]. However, like any form of energy conversion, there are also some downsides that must be minimized.

Wind farms belong to a group of energy conversion facilities that demand the most terrain area for installed MW. In accordance with Ramanathan [13], a typical wind farm requires 9,900 km^2 per installed GW, lagging behind only of biomass generation.

In this regard, large-size wind farms may impose significant risks to the vicinity of the site, like restrictions to the mobility of the local community; aerodynamic and/or mechanical noise emission; property damage deriving from excavation and nearby traffic of large truckloads and heavy machinery necessary for the logistics operations; deforestation; significant changes to the landscape and local ecosystems [14,15].

Based upon the preceding arguments, the objective of the present research is to propose a methodology in order to help the economic planning of wind farms so that the requirement of welfare maximization of the electricity sector is met. The novelty of this study is the development of a method based on multiobjective programming focused on individual wind power generation project planning, considering quantitative and qualitative variables. In this sense, the proposed method allows to solve a trade-off problem, i.e., to reach the best solution of a problem with conflicting objectives. In addition, the interaction between turbine brand characteristics and site specific wind speed behavior was also verified.

For that purpose, the model is made up of an association of the (i) Response Surface Methodology (RSM), (ii) the Normal Boundary Intersection (NBI) optimization algorithm and (iii) Data Envelopment Analysis (DEA) tool. The association of these three techniques is also a novelty of this study to the literature related to the resolution of energy planning problems. Thus, RSM allows modeling the problem; NBI allows all ideal solutions, without prejudice to the construction of the frontier; and DEA presents itself as a subjectivity-free method to determine the best ideal solution for the problem.

Energy density and Net Present Value (NPV) were considered the response variables of the optimization problem, as they are related to socio-environmental and economic aspects that maximize the welfare of the electricity sector. In this respect, a higher energy density indicates the project's ability to produce as much electricity as possible, occupying the smallest space. Thus, site degradation can be mitigated and an area preserved for other productive activities without compromising the wind farm productivity. In turn, a NPV above zero ensures the project's profitability to the investor, so that the energy selling price is as low as possible, making the traded energy less costly to the end consumer.

From this point on, the paper is organized in the following manner: in Section 2 a brief literature review is presented on techniques applied to energy planning, including the multi-objective optimization and other tools employed in the proposed methodology; in Section 3 materials and methods are introduced; in Section 4 the results and discussion are presented and; in Section 5, the conclusions are presented.

2. Literature review

2.1. Multi-objective optimization as a support to energy projects and the method of the Normal Boundary Intersection

For Oree et al. [16], energy planning optimization models in which the sole objective is to minimize costs are little robust, and that other variables should be considered in the analysis. On the other side, multi-objective optimization problems are complex, since different objective functions depend upon the same set of decision variables and are often conflicting [17]. Trade-offs are always present in multi-objective problems, requiring relaxation of one objective in order to improve another [18].

According to Aghaei et al. [19], the most common objectives in energy planning issues involve cost minimization, environmental impacts and the search for appropriate levels for the use of the system.

Luz et al. [20] present solutions from different multiobjective linear programming techniques for scenarios of expansion of the Brazilian electric system. The models are based on the new government targets for renewable energy sources, considering three objective functions: total cost minimization, peak load generation maximization and non-hydro RES contribution maximization.

Aghaei et al. [21] propose a multiobjective model with the purpose of minimizing costs, environmental impact, energy consumption from fossil fuels, exposure to fossil fuel import price volatility and increasing system reliability. The problem is formulated through mixed integer linear programming, and solved by the ε-method.

Vahidinasab [22] used the augmented ε -constraint method to optimize the resources of a distributed energy project, including wind turbine, photovoltaic, fuel cell, micro turbine, gas turbine and diesel engine. The optimization seeks to minimize the monetary cost and minimize GHG in the presence of electrical load, as well as uncertainties in electricity market prices. To find the best Pareto optimal solution a fuzzified decision making approach was used.

Among methods used for the solution of multi-objective problems, the Normal Boundary Intersection (NBI) method has been standing out from others [23]. A standard method for generating the Pareto frontier in multi-objective optimization problems is the weighted sum method. However, according to Das and Dennis [24], this method can only obtain points from all parts of the Pareto frontier when it is convex. Furthermore, an evenly distributed set of weights fails to produce an even distribution of points from all parts of the Pareto frontier, even for convex ones. In order to overcome these drawbacks, the NBI method was proposed showing that the Pareto surface is evenly distributed independent of the relative scales and convexity of the objective functions. It is based in the concept of coalescence of different objective functions and allows a full construction of a Pareto frontier with the resulting set of optimal decisions, in order to help the final decision-making process [24].

NBI is a geometric parameterization method capable of producing the entire set of solutions on a Pareto frontier evenly distributed, even when it comes to nonconvex problems. This enables to the decision maker easily identify the best Pareto-optimal solution to the economic planning problem of wind farms.

According to Das and Dennis [24], the first step for the application of NBI method is to build the payoff matrix. For each objective function f_i, the individual optimal solutions are employed in building the payoff matrix [21,25]. The payoff matrix, $f_i^*(x_i^*)$, described in Eq. (1), represents the optimal value resulting from f_i, with $\mathbf{x}$ representing the vector of decision variables that optimize the objective functions.

$$\Phi = \begin{pmatrix} f_1^*(x_1^*) & \cdots & f_i(x_1^*) & \cdots & f_p(x_1^*) \\ \vdots & \ddots & & & \vdots \\ f_1(x_i^*) & \cdots & f_i^*(x_i^*) & \cdots & f_p(x_i^*) \\ \vdots & & & \ddots & \vdots \\ f_1(x_p^*) & \cdots & f_p(x_p^*) & \cdots & f_p^*(x_p^*) \end{pmatrix} \quad (1)$$

In accordance with Ahmadi et al. [26], in order to understand the NBI mechanism it is necessary to understand the meaning of the utopia and nadir points. While the best possible values for all objective functions in a problem is represented by the utopia point, the nadir point represents the worst possible values that the same objective functions can attain simultaneously. The objective functions are then normalized based on the values of the utopia and nadir points, as shown below:

$$\bar{f}_i(x) = \frac{f_i(x) - f_i^U}{f_i^N - f_i^U} \qquad i = 1, \ldots, p \quad (2)$$

where: $\bar{f}_i(x)$ = normalized objective function; f_i^U = utopia function; f_i^N = nadir function.

The normalization of the objective functions also implies the normalization of the payoff matrix Φ, according to Ahmadi et al. [26], with a set of points R^P characterizing the so-called utopia line, which is formed by the convex combination of each line of the payoff matrix Φ. This utopia line is also referred to as Convex Hull of Individual Minima (CHIM), and is illustrated in Fig. 1.

If w is a convex weighting, then Φw represents a point in the utopia lines. If a unit normal to the CHIM in respect to the origin is indicated by n, one may represent the set of points assembled at the Pareto frontier by: $\Phi w + D\hat{n}$, where $\hat{n}$ is a vector of unitary values.

Thus, as explained by Das and Dennis [24], the intersection point of the normal and the frontier of the viable region closer to the origin corresponds to the maximization of the distance between the CHIM and the Pareto frontier, and may be expressed in the following manner:

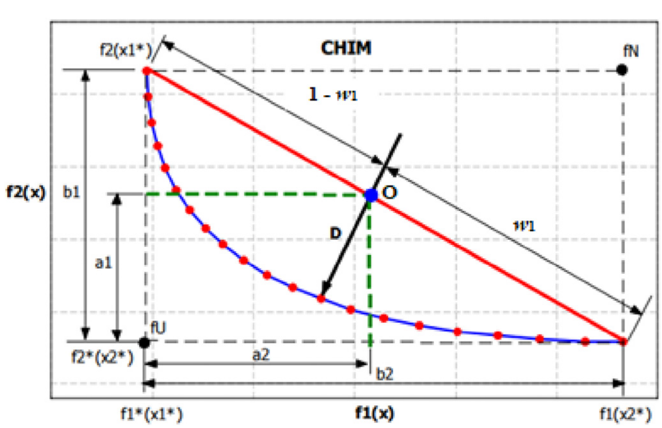


Fig. 1. Normal Boundary Intersection (NBI) graphical representation. Source: Brito et al. [27].

$$\begin{aligned} &\underset{(x,\,D)}{\text{Max}} \quad D \\ &\text{Subjectto}: \quad \bar{\Phi} w + D\hat{n} = \bar{F}(\mathbf{x}) \\ &\qquad\qquad \mathbf{x} \in \Omega \end{aligned} \quad (3)$$

where: $\bar{F}(\mathbf{x})$ = vector containing the objectives normalized values; Ω = viability region, generally including equality and inequality-type restrictions of the problem.

Vahidinasab e Jadid [28] formulated a NBI model to be applied in the strategic analysis of contracting electricity-generation projects for one electricity system, based on (i) combined power flow minimization and (ii) a set of coefficients representing the emission of polluting substances. Also, (iii) the individual project income is optimized while keeping the final energy price as low as possible for the final consumer, with all the physical restraints of the generation duly considered.

Another case of the NBI-method deployment in order to support problem solving in the field of energy-planning is described by Aghaei et al. [21]. In that research, a multi-objective programming based on the NBI method is developed to help plan the expansion of energy conversion activity with the objectives of (i) minimizing costs and (ii) maximizing reliability.

Aghaei et al. [19] developed a multiobjective programming from NBI for generation expansion planning that prioritizes the following objectives: minimizing costs and environmental impacts, and maximizing reliability.

Ahmadi et al. [26] deployed NBI-based multi-objective programming in order to integrate thermal conversion plants to high-voltage power grids. The objective functions are related to (i) cost minimization and (ii) GHG emission minimization. In order to help select the Pareto-optimal solution, a technique known as Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), was employed.

Izadbakhsh et al. [29] developed an optimization model set to determine the best mix of equipment among micro wind turbines, PV panels, battery banks, diesel generators and large-size wind turbines, in order to assemble a small, isolated, generation system. The NBI method is programmed with two objective functions: (i) overall system cost minimization and (ii) minimization of the emission of pollutants. In order to sort out the Pareto-optimal solution, the TOPSIS fuzzy-logic tool was also employed.

Fonseca et al. [30] also proposed an optimization model to determine the best mix for a hybrid, isolated system, which entails solely solar PV energy, at the Amazon region. The results were compared with output from the Homer® software. The authors employed mixture design of experiments and Monte Carlo simulation in the experiments in order to formulate the objective functions and the NBI method to perform the multi-objective optimization based on the following objectives considered: (i) GHG emission minimization and; (ii) a *Levelized Cost of Electricity* (LCOE), based on the local level of energy demand.

Aquila et al. [23] developed a method to guide regulatory-authorities of the electricity sector in bidding processes for hiring hybrid, on-grid, wind-solar (PV) energy plants. The method is assembled from a mixture design of experiments in order to formulate the objective function; NBI is deployed for the optimization process while a metric based on the ratio of the entropy to the global percent error is deployed to identify the single best optimal solution. The model is validated considering the scenarios of assembling the hybrid plants in twelve different Brazilian cities and the objectives considered are: (i) the maximization of reduced emission density and, (ii) the minimization of the classical LCOE function, leveled by the energy production.

The literature has emphasized the generation expansion planning with integration of renewable sources and the configuration of energy matrices and hybrid systems. In this respect, the present study fills some gaps in the literature, since besides referring to the planning of a generation unit using a multi-objective optimization method, it considers both quantitative (energy density and NPV) and qualitative (wind turbine brand) variables. The study also seeks to investigate whether the turbine brands analysed are more efficient when installed in a particular region. Moreover, another novelty is the association of NBI, RSM and DEA techniques to solve a multi-objective problem in energy planning.

2.2. Data Envelopment Analysis

Among various tools for measuring efficiency, such as statistical conventional methods, non-parametric methods and artificial intelligence methods, the Data Envelopment Analysis (DEA) can effectively measure the relative efficiency of Decision-Making Units (DMUs), which demand multiple inputs to generate multiple outputs [31]. The DEA is a non-parametric method which has been broadly employed for problem-solving at many types of business and organizations, such as banks, schools, hospitals, the agricultural sector and the energy sector [31,32].

The advantage of the DEA method lies in its ability to evaluate the individual relative efficiency, or performance, of an individual DMU inside an interest group, operating inside a certain application domain [33]. The individual DMUs are compared among themselves and differentiate from one another by the quantity of consumed resources (inputs) and also by the quantity of outputs they produce [34]. Kao [32] states that the DEA method allows, among other things, to identify the benchmark DMUs against which the other DMU should be compared to.

The weighting for the input and output variables of the general DEA model may be obtained from the model proposed by Charnes et al. [35], given by (4):

$$\begin{aligned}
&\max w_o = \frac{\sum_{q=1}^{b} u_q y_{qo}}{\sum_{p=1}^{a} v_p x_{po}} \\
&\text{Subjectto}: \frac{\sum_{q=1}^{b} u_q y_{qi}}{\sum_{p=1}^{a} v_p x_{pi}} \leq 1, \quad i = 1, 2, ..., n \\
&u_q \geq 0, \quad q = 1, 2, ..., b \\
&v_p \geq 0, \quad p = 1, 2, ..., a
\end{aligned} \tag{4}$$

where i is the DMU index, with values in the interval $i = 1, \ldots, n$; q is the output index, $q = 1, \ldots, b$; b is equal the number of outputs in the problem; p is the input index, $p = 1, \ldots, a$; a is equal the number of inputs in the problem; 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 DMU_o relative efficiency, which is the DMU undergoing evaluation; and y_{qo} and x_{po} are output and input data from DMU_o, respectively.

The model introduced in (4) is non-linear and represents a case of fractional programming, however, it lends itself to linearization. This exercise was performed by Charnes et al. [35], who proposed a linearized form known as Constant Returns to Scale (CRS), shown in (5), also known as the *multipliers model*.

$$\begin{aligned}
&\max w_o = \sum_{q=1}^{b} u_q y_{qo} \\
&\text{Subjectto}: \sum_{p=1}^{a} v_p x_{po} = 1 \\
&\sum_{q=1}^{b} u_q y_{qi} - \sum_{p=1}^{a} v_p x_{pi} \leq 0 \quad i = 1, 2, ..., n \\
&u_q \geq 0, \quad q = 1, 2, ..., b \\
&v_p \geq 0, \quad p = 1, 2, ..., a
\end{aligned} \tag{5}$$

For $w_o = 1$, DMU_o, the DMU undergoing analysis should be considered efficient in relation to the other DMUs. For $w_o < 1$, this DMU should be regarded as inefficient [36].

For a geometrical interpretation of the CRS model, a Constant Returns to Scale problem may be represented as seen in Fig. 2. This figure illustrates a case with a single input and output, where the slope of the line represents a linear production function with constant scale yields, i.e., the increase of production (ordinate axis) and input consumption (abscissa axis) are proportional.

2.3. RSM experiment planning

In order to set the objective functions of an optimization problem, the Design of Experiments (DOE) may be employed for model estimation. According to Montgomery [38], one experiment may be defined as a test or a series of tests where changes are imposed to the input variables of a process in order to observe the way the outputs respond to those changes in input.

If the process depends on more than one factor, then the recommended approach is to conduct a factorial experiment. However, if the aim is to determine the region where the factors induce the best possible outcome, that is, if the objective is to maximize the results, another experimental arrangement should be done whose objective is to develop an empirical model of the process in order to result in more accurate estimates of the optimal operating conditions. This approach for optimizing the process is a key feature of the RSM methodology [38].

Considering that for the majority of the industrial processes the relations among the results and the independent variables are not known *ex ante*, a suitable approximation is sought to represent the answers of interest as functions of those variables. In general, polynomial functions are employed to describe the relations. When

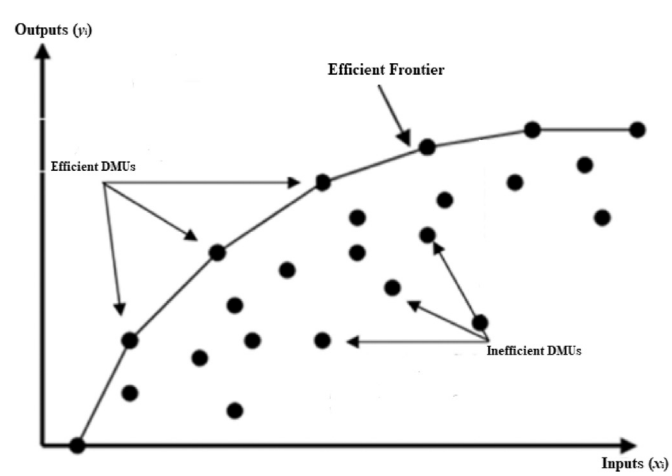


Fig. 2. Constant scaling return for a single input and output.
Source: Pedroso et al. [37].

the answers are well modelled by a linear function, the approximate relation may be represented by the following first-order model [38].

$$y(x) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_k x_k + \varepsilon_i = \beta_0 + \sum_{i=1}^{k} \beta_i x_i + \varepsilon_i \qquad (6)$$

where: $y(x)$ is the answer of interest; x_i are the independent variables; β_i are the coefficients to be estimated; k is the number of independent variables; ε_i is the experimental error.

If the answer locus has curvature, then a higher-order polynomial shall be adopted:

$$y(x) = \beta_0 + \sum_{i=1}^{k} \beta_i x_i + \sum_{i=1}^{k} \beta_{ii} x_i^2 + \sum_{i<j}\sum \beta_{ij} x_i x_j + \varepsilon_i \qquad (7)$$

Most problems with answer-surfaces employ one or both models shown and, even though it is not likely the polynomial model will perform as a suitable approximation for all experimental space covered by the independent variables, those models have been proven efficient for at least a specific part of the region [38].

Since one of the objectives of RSM entails optimizing the answers, it is recommended, whenever possible; to represent them by means of second-order models, since the curvature of those models define the location of a stationery point. In order to adjust a second-order model, the design of experiment design shall have some properties. Since Eq. (5) model has $1 + 2k + k(k-1)/2$ parameters, the design of experiment shall have at least this same number of different points and at least three levels for each variable or factor.

It is often convenient, while applying the RSM method, to transform the problem variables into encoded variables. Encoded variables are defined as dimensionless variables with zero average and the same standard deviation. The following coding scheme may be used, in accordance with Myers et al. [39]:

$$X_{coded} = \frac{X_{uncoded} - (Hi + Lo)/2}{(Hi - Lo)/2} \qquad (8)$$

where: Hi is the value for the decision variable equivalent to level $+1$; and Lo, for the level -1; X_{coded} is a standardized value with reference to the maximum and minimum values of the DOE; $X_{uncoded}$ is the real value of response variables.

Similarly, if the conversion back to uncoded values is planned, it suffices to rewrite (8) in the following manner [40,41]:

$$X_{undecoded} = \frac{Hi + Lo}{2} + X_{coded}\frac{Hi - Lo}{2} \qquad (9)$$

where: Hi is the value for the decision variable equivalent to level $+1$; and Lo, for the level -1; X_{coded} is a standardized value with reference to the maximum and minimum values of the DOE; $X_{uncoded}$ is the real value of response variables.

Typically, the estimation of the coefficients defined in Equations (6) and (7) models is done by applying the method of the Ordinary Least Squares (OLS). The method is based on choosing values for β_i, so that the sum of the squared errors is minimized [39]:

$$L = \sum_{i=1}^{k} \varepsilon_i^2 = \sum_{i=1}^{k} \left(y_i - \beta_0 - \sum_{i=1}^{k} \beta_i x_i \right)^2 \qquad (10)$$

where: y_i is the response of interest; x_i are independent variables; β_i are the coefficients to be estimated; k is the number of independent variable; ε_i is the experimental error.

In matrix notation, Eq. (7) may be rewriten as:

$$\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon} \qquad (11)$$

where:

$$\mathbf{y} = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix},\ \mathbf{X} = \begin{bmatrix} 1 & x_{11} & x_{12} & \cdots & x_{1k} \\ 1 & x_{21} & x_{22} & \cdots & x_{2k} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & x_{n1} & x_{n2} & \cdots & x_{nk} \end{bmatrix},\ \boldsymbol{\beta} = \begin{bmatrix} \beta_0 \\ \beta_1 \\ \vdots \\ \beta_k \end{bmatrix},\ \boldsymbol{\varepsilon} = \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_n \end{bmatrix} \qquad (12)$$

and solving for L:

$$\begin{aligned} L &= (\mathbf{y} - \mathbf{X}\boldsymbol{\beta})^T \left(\mathbf{y} - \mathbf{X}\boldsymbol{\beta}\right) = \mathbf{y}^T\mathbf{y} - \boldsymbol{\beta}^T\mathbf{X}^T\mathbf{y} - \mathbf{y}^T\mathbf{X}\boldsymbol{\beta} + \boldsymbol{\beta}^T\mathbf{X}^T\mathbf{X}\boldsymbol{\beta} \\ &= \mathbf{y}^T\mathbf{y} - 2\boldsymbol{\beta}^T\mathbf{X}^T\mathbf{y} + \boldsymbol{\beta}^T\mathbf{X}^T\mathbf{X}\boldsymbol{\beta} \end{aligned} \qquad (13)$$

provided $\boldsymbol{\beta}^T\mathbf{X}^T\mathbf{y}$ is a 1x1 matrix, i.e a scalar, and the transposed matrix $(\boldsymbol{\beta}^T\mathbf{X}^T\mathbf{y})^T = \mathbf{y}^T\mathbf{X}\boldsymbol{\beta}$ is the same scalar. The least-square estimation should satisfy:

$$\frac{\partial L}{\partial \boldsymbol{\beta}} = -2\mathbf{X}^T\mathbf{y} + 2\mathbf{X}^T\mathbf{X}\widehat{\boldsymbol{\beta}} = 0 \qquad (14)$$

which may in turn be simplified into:

$$\mathbf{X}^T\mathbf{X}\widehat{\boldsymbol{\beta}} = \mathbf{X}^T\mathbf{y} \qquad (15)$$

Eq. (15) represents the set of least squares normal equations in matrix notation. By multiplying both sides of Eq. (15) by the inverse of $\mathbf{X}^T\mathbf{X}$, results:

$$\widehat{\boldsymbol{\beta}} = \left(\mathbf{X}^T\mathbf{X}\right)^{-1}\mathbf{X}^T\mathbf{y} \qquad (16)$$

Eq. (16) is the approximate function which relates the answer of interest with the process variables, that is, since the real functional relation among x and y is unknown, it is estimated by means of a regression model, which is suitable within a certain range of variation of the independent variables [38].

3. Problem and data presentation

3.1. Input variables of the problem

Concerning wind farm investments, it is noticeable that the most sensitive variables for the NPV result are the (i) energy selling price, (ii) the level of electricity production, and (iii) the initial investment for the enterprise, especially on wind turbines [42]. Variables (ii) and (iii) grow with the wind farm installed power. Also, the social and environmental issues grow with the installed power, since larger projects demand more land and usually result in more negative impact, especially during site construction. Accordingly, the installed power was selected as one of the input variables of the problem.

Another variable selected is the specific type wind turbine considered. Two sets of 5 equipment each with different diameters, from two distinct manufacturers (A and B), where selected with large diameters characteristic of current utility-size wind turbines, in the range of 2–3.5 MW of nominal power output. Each physical equipment was represented in the calculations by its characteristic power production curve as a function of the wind speed, as provided by the manufactures. It is noticed that the choice of the wind turbine regarding its fabrication, impacts not only the produced energy as also the area occupied by the wind farm. That said, the company that produces the wind turbine is a categoric variable which is included in the analysis.

The energy selling price is both a key variable for the level of return on a wind farm investment, also is the main impact factor on the final consumer [23]. This imposes an important tradeoff to the problem and confirms the relevance of this input variable considered.

After determination of the input variables, i.e., (i) installed power and (ii) energy selling price as the continuous variables and the type of equipment, and the type of equipment as the category variable, it is possible to devise the experiment arrangement from the RSM.

In the current problem, four experiment arrangements were generated, two for the calculation of the output variables to be considered in the context of each of the two manufactures of turbines at for the city of Macau, at Rio Grande do Norte (RN) state, and two others at the city of Santa Vitória do Palmar, at Rio Grande do Sul (RS) state.

3.2. Response variables to be optimized

3.2.1. Energy density

The energy density produced by a wind farm corresponds to the amount of energy produced in a unity of area over a given period and can be considered as a variable that contributes to the electric sector well-being when optimized. The energy density calculation can be mathematically described as in Eq. (17):

$$\rho_e = \frac{AEP}{A} \tag{17}$$

with: ρ_e = energy density (MWh/m^2); AEP = annual energy production (MWh); A = used area (m^2).

For the AEP estimate for the four power levels and five central points, equations for the wind turbines power curves were used together with a Monte Carlo Simulation (MCS). For estimating the energy production of each turbine a regression model was estimated, using the wind speed as the independent term. Thus, a polynomial interpolation of fifth degree was chosen for the turbines power curves, as pictured in Figs. 3 and 4, because this model presented the best fit (R^2 above 98%). Then the result for the power is multiplied by 8.76 (8,760 h/1000) to obtain the annual energy production of each turbine, as in Eq. (18):

$$AEP = 8,76\left(\beta_0 + \beta_1 v + \beta_2 v^2 + \beta_3 v^3 + \beta_4 v^4 + \beta_5 v^5\right) \tag{18}$$

with: AEP = annual energy production (MWh); v = wind speed (m/s); β_i = regression coefficients.

As there are five central points in the experimental setting, it was opted to estimate the AEP through a MCS. According to Jiang et al. [43], a MCS is characterized by numerous executions with different values for the uncertain inputs which are randomly determined by predefined probability distributions in each simulation round. With the input samples, many simulation rounds are carried for an output.

The AEP's uncertainty resides on the annual average wind speed and its stochastic calculation can be mathematically described by Eq. (19):

$$AEP = 8.76 \int_{v_{min}}^{v_{máx}} P(v) f(v) dv \tag{19}$$

with: $v_{\max}$ = maximum wind speed; $v_{\min}$ = minimum wind speed; $P(v)$ = average wind speed probability; $f(v)$ = wind probability distribution function.

For the purpose of modeling uncertainties of the annual average wind speed behavior, a Weibull distribution is considered, usually used in studies about wind energy production [44–46]. In Eq. (20) it is depicted the Weibull distribution probability density function:

$$f(v) = \frac{k}{C}\left(\frac{v}{C}\right)^{k-1} e^{-\left(\frac{v}{C}\right)^k} \tag{20}$$

with: v = wind speed; C = scale parameter (m/s); k = shape parameter (dimensionless).

Given that wind speed behavior is different in each place, the appropriate parameters for the Weibull distributions were used for the cities of Santa Vitória do Palmar-RS (C = 7.7; k = 2.32) and Macau-RN (C = 8.26; k = 2.66), based on Brazilian Wind Atlas [47].

In the calculation of the territorial area, the sum of the area used by the total amount of turbines of each kind needed to meet each considered power level was evaluated. Eq. (21) contains the mathematical formula for the estimate of the territorial area, according to Custodio [48]:

$$A = \frac{45}{2} D^2 (n+2) \tag{21}$$

with: D = turbine diameter (m); n = amount of the analysed turbine.

In Table 1 there is the diameter and used area for one unity of turbine of each kind for the two considered brands:

3.2.2. Net Present Value

The reason for doing a financial viability analysis is to help the decision making of whether to consider an opportunity for investment. For that, one of the most used criteria for supporting this decision is the Net Present Value (NPV) [45,49]. The NPV basically corresponds to the cash flow due to the difference between the income and outcome in each period, which are discounted with a rate, representing by the capital cost [50,51]. Eq. (22) describes the formula for calculating the NPV.

$$NPV = \sum_{t=0}^{n} \frac{CF_t}{(1+i)^t} \tag{22}$$

with: i = discount rate; t = considered period; CF_t = net cash flow in period t.

Literature on financial administration says that an investment must be considered when the NPV is greater or equal to zero. This also means that the Internal Rate of Return (IRR) is superior to the minimum capital cost considered, as a function of the investment risk [52]. Therefore, estimating an investment's capital cost is a fundamental step for performing a financial viability analysis.

Regarding the capital cost estimate, a tax of 6,19% was used as benchmarking, as it was calculated in Aquila et al. [23] by the Weighted Average Cost of Capital (WACC) method, which is considered in many studies about analysis of investments in renewable energy generation projects, as in Ondracek et al. [53] e Ertürk [49], and is also recommended by the Clean Mechanism's Executive Board, in annex to Guidelines on the Assessment of Investment Analysis [54].

About NPV optimization, it is known higher prices contribute to higher NPV values but also make the energy cost less affordable for the final consumer. This way, it follows that the idea is to meet the lowest energy selling price which still makes the project viable (NPV $\geq$ 0). So, in this study the NPV will be an output variable to be minimized with the intention of getting a positive NPV with the

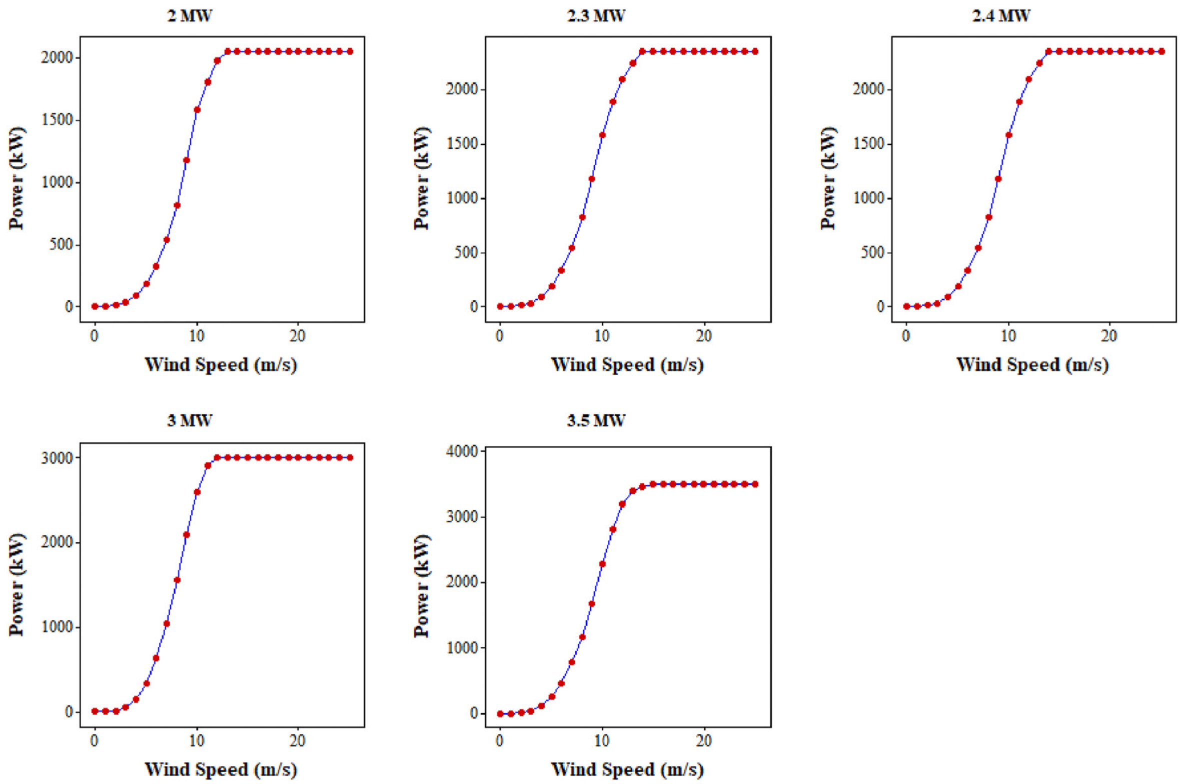


Fig. 3. Curve power for Brand A turbines.

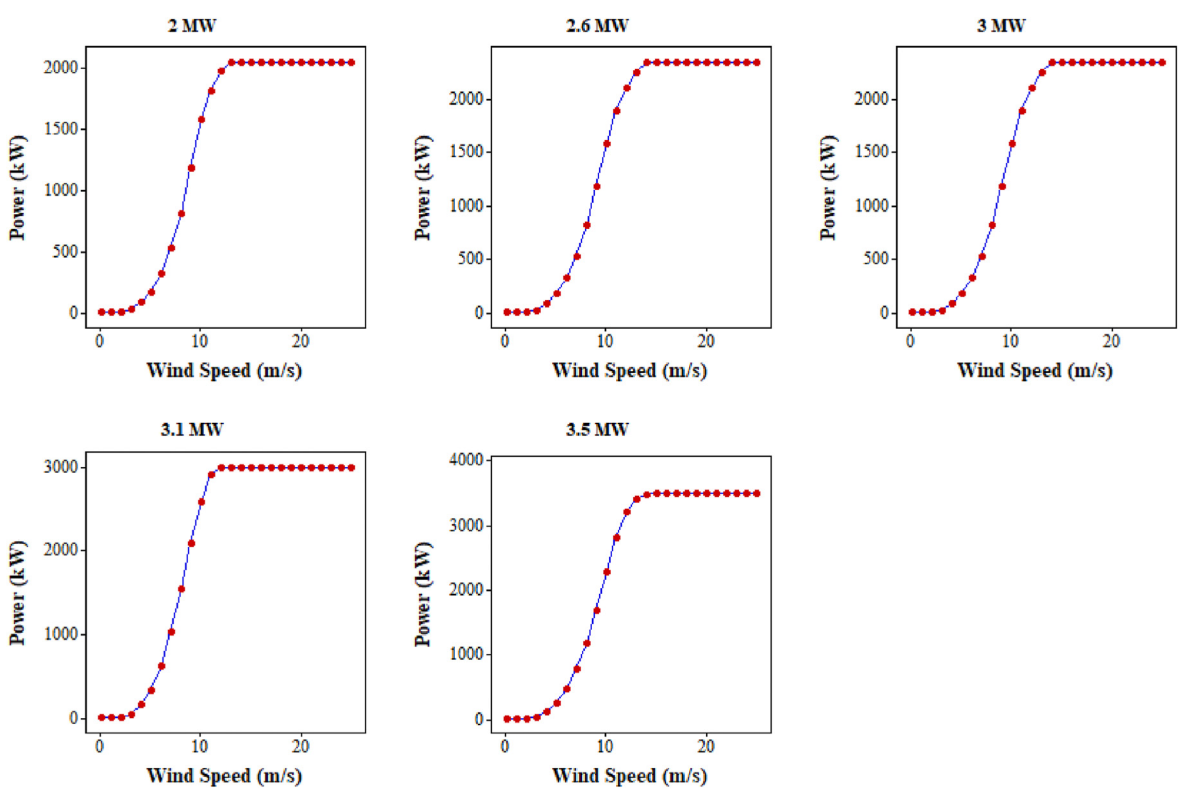


Fig. 4. Curve power for Brand B turbines.

Table 1
Data on wind turbines.

Turbine type	D (m)	A (m^2)
A (2 MW)	82.0	302,580.0
A (2.3 MW)	82.0	302,580.0
A (2.4 MW)	82.0	302,580.0
A (3 MW)	115.7	602,392.5
A (3.5 MW)	101.0	459,045.0
B (2 MW)	80.0	288,000.0
B (2.6 MW)	100.0	450,000.0
B (3 MW)	112.0	564,580.0
B (3.1 MW)	112.0	564,580.0
B (3.3 MW)	126.0	714,420.0

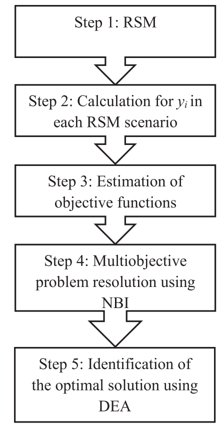


Fig. 5. Step by step methodology for wind farm configuration.

lowest possible energy selling price. Table 2 shows the cash flow structure for calculating the NPV and Annex 1 contains the hypothesis assumed for calculating each parameter in the cash flow.

4. Results and discussion

The economic planning of wind farms using the NBI-RSM-DEA method consists of the following steps: 1. RSM is used to produce experimental scenarios; 2. Energy density and NPV are estimated for each RSM experimental scenario; 3. Estimation of objective functions by quadratic regressions; 4. The objective functions obtained are used to construct the problem solution frontier from the NBI method; 5. The best Pareto-optimal solution of the problem is identified from the DEA. Fig. 5 illustrates the step-by-step of the proposed planning for setting up a wind farm.

The experimental setting produced thirteen scenarios, five corresponding to central points of the setting and two to axial points. In this problem, the axial points correspond to 5 MW and 30 MW, which are actually the minimum power (x_1) that characterizes a large scale wind farm and the maximum power for which a wind farm can get tax discount on the use of the distribution system in Brazil, respectively.

Regarding the price (x_2), to the axial points are given the values R$/MWh 100.00 to the lower and R$/MWh 200.00 to the higher. These have been the values between which wind energy varied between 2016 and 2017, the period in which data for the wind farm financial analysis was collected. It is valid to point that the possible values for the categorical variable which refers to the turbines brands are addressed as “Brand A″ and “Brand B”. In Table 3 the uncoded values for the power levels and adopted prices in the experimental setting are described.

In the second step the output of the variables to be optimized are evaluated for the four analysed cases. The cases outlined in Fig. 6 correspond to the possible wind farm configuration in the cities of Vitória do Palmar-RS and Macau-RN, with wind turbines of brand A or B.

For each of the four cases the outputs for energy density (y_1) and NPV (y_2) were calculated. It is important to note that estimating AEP is fundamental for both y_1 and y_2 calculations. For this estimate, the average over the 5,000 values provided by SMC in each scenario was considered. Because of it, the central points of the setting show different values for each output.

In this step it is possible to note the difference in output over the scenarios due to different input levels, different generation curves profiles for each kind of turbine and distinct wind potential in each city considered for the wind farm. Table 4 contains the calculated results for each scenario in each analysed case (see Table 5).

Afterwards, in the third step all objective functions were taken to have a good determination coefficient ($R^2 > 70\%$) [55]. In Figs. 7 and 8 the output surfaces for y_1 and y_2 for each turbine brand in the cities of Santa Vitória do Palmar-RS and Macau-RN are shown graphically, respectively.

With the objective functions modelled, the next step is to solve the multiobjective problem by formulating the NBI described in Eq. (3), with the additional constraint referent to a RSM for a problem with two inputs ($x_1^2+x_2^2 \leq \sqrt{2}$). For that, 21 optimization rounds were carried varying w_i by 0.05 in each round. As noted in section 3.2, in constructing the payoff matrices, the individual optimization of the objective referent to energy density was done in the sense of maximizing energy density and minimizing NPV.

However, the criteria used for determining the best Pareto-optimal solution was to identify the solution with a positive NPV

Table 3
Factors and their levels.

Factors	Symbol	Levels				
		−1.414	−1	0	1	1.414
Power (MW)	*Pw*	5.0	8.7	17.5	26.3	30.0
Price (R$)	*Pr*	100.0	114.6	150.0	185.4	200.0

Table 2
Wind farm Project cash flow.

Gross revenue
(−) Tax collected on gross revenue
(−) Sector charges
(−) O&M costs
(−) Administrative and insurance expenses
(−) Financial expenses and debt amortization
(−) Income tax and social contribution
(−) Investments
(+) Funding release
(=) Cash flow

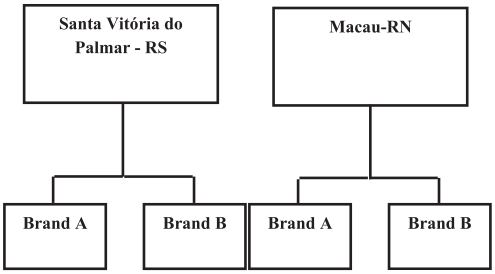


Fig. 6. Diagram with the four possibilities analysed.

(safeguarding the project's viability to the investor) which has the lowest energy selling price. This way, the best Pareto-optimal solution would be the one that guarantees a financial return to the investment and carries the lowest possible energy cost to the electricity customer.

In Table 6 there are the x_1 and x_2 values for each Pareto-optimal solution of the analysed cases, with the values for the best solution highlighted and in Table 7 the same for y_1 and y_2. In Fig. 9 the Pareto boundaries are illustrated with the best solutions for each analysed case, also with the best Pareto-optimal solution in highlight.

With the purpose of identifying which Pareto-optimal solution is the best among the analysed cases, DEA was applied to verify in which context the wind farm can be the most efficient when producing the results y_1 and y_2 while using the inputs x_1 and x_2. DEA was applied in its classic formulation as described in Eq. (4), with the obtained results described in Table 8 and the efficiency boundaries illustrated in Fig. 9. It is noted that the DMU in which the wind farm can be the most efficient is with it being in the city of Macau-RN and using the turbine of brand A.

The second best context is in the city of Santa Vitória do Palmar-RS with turbines of brand B, the third in the city of Santa Vitória do Palmar-RS with turbines of brand A and the worst one in the city of Macau-RN with turbines of brand B. It is possible to note that the best case scenarios for each of the cities were with different brands of turbines, what asserts for the relevance of identifying the location as well as the wind turbine model for the planning of a wind farm.

Considering the proposed methodology, it was capable of achieving the objective of helping with the planning of a wind farm in a way compatible with the maximization of the electric sector well-being. It can also be said the methodology meet the interests of regulators, investors and consumers of electric energy.

For the regulators the methodology could be implemented as a standard requirement for projects taking part in bids. As for the investors, by exploring the landscape in the most productive way and assuring rentability, an option for future expansion of the project is preserved. Moreover, by meeting the important requirement of mitigating the socio-environmental impact, the project becomes more attractive for certificate programs that authorize the commercialization of Renewable Energy Certificates (REC), what would make possible for the investor to obtain new increments in the NPV in the future.

Nonetheless, on considering that the best optimal solution is the one which makes the project rentable with the lowest energy selling price, the final customer is also being benefited. A lower energy selling price favors a cheaper energy cost for the final customer. Moreover, a socio-environmental benefit in the project setting favors society as a whole. That is, the customers pays a lower price for the energy they consume and the project which produces

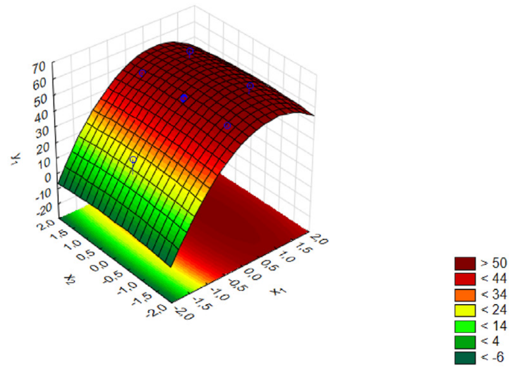
Table 4
Design of experiments for Density and NPV.

N	*Pw* (MW)	*Pr* (R$)	*Santa Vitória do Palmar-RS*				*Macau-RN*			
			Brand A		*Brand B*		*Brand A*		*Brand B*	
			Density	*NPV*	*Density*	*NPV*	*Density*	*NPV*	*Density*	*NPV*
1	−1	−1	23.727	2.02	22.482	−0.20	28.094	9.80	23.425	1.48
2	+1	−1	61.534	22.03	66.657	33.89	61.696	22.40	60.182	22.40
3	−1	+1	23.757	28.19	22.625	24.93	28.094	40.68	23.694	28.01
4	+1	+1	61.229	108.83	66.561	128.80	62.583	113.90	60.998	107.96
5	−1.414	−1	28.431	9.99	26.499	7.74	33.507	15.90	27.468	8.87
6	+1.414	−1	47.573	51.06	61.231	105.19	66.456	125.89	53.478	74.46
7	0	−1.414	52.208	−7.08	62.607	7.46	68.612	15.86	58.658	1.94
8	0	+1.414	51.879	65.05	62.935	95.98	68.652	111.98	59.918	87.55
9	0	0	52.559	30.18	62.398	50.82	68.236	63.07	59.084	43.87
10	0	0	51.371	27.69	63.417	52.96	67.778	62.11	59.691	43.87
11	0	0	52.352	29.75	63.124	52.35	68.862	64.39	59.410	44.56
12	0	0	52.166	29.36	61.932	49.85	67.821	62.20	59.481	44.70
13	0	0	52.292	29.62	63.425	52.98	69.156	65.00	59.771	45.31

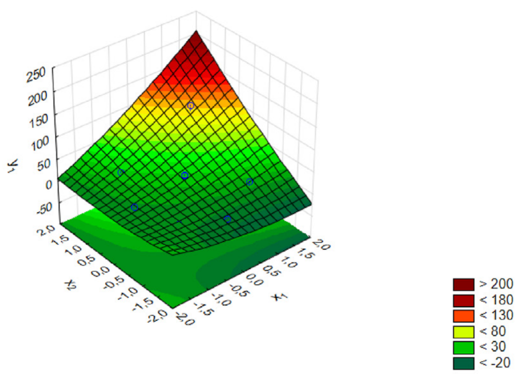
Table 5
Coefficients for the estimated objective functions.

Terms	*Santa Vitória do Palmar-RS*				*Macau-RN*			
	Brand A		Brand B		Brand A		Brand B	
	Density	NPV	Density	NPV	Density	NPV	Density	NPV
Constant	**52.1482**	**29.3213**	**62.8592**	**51.7925**	**68.3705**	**63.3551**	**59.4873**	**44.4634**
Pw	**12.7936**	**19.8418**	**17.1536**	**34.4720**	**14.3359**	**30.1712**	**13.8556**	**24.2061**
Pr	−0.0925	**26.8738**	0.0637	**30.6535**	0.1180	**32.2907**	0.3584	**29.1449**
Pw^2	**−7.6885**	3.2293	**−11.6815**	0.5247	**−12.7419**	−1.4063	**−11.4585**	**−2.2090**
Pr^2	−0.6677	2.4600	−2.2282	−1.8443	−3.4167	−4.8964	−2.0510	−0.6708
Pw x *Pr*	−0.0839	**15.1574**	−0.0599	**17.4445**	0.2219	15.1535	0.1364	**14.7581**
R^2 (%)	85.01%	95.52%	90.56%	99.37%	85.82%	91.79%	89.23%	99.67%
R^2adj. (%)	74.31%	92.33%	83.82%	98.92%	75.68%	85.92%	81.54%	99.44%

Bold values represent significant terms in the models (*p-value*$<$ 5%).

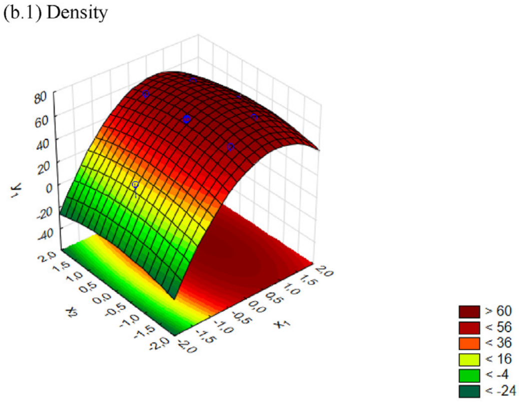


(a.2) NPV



(b) Brand B

(b.1) Density



(b.2) NPV

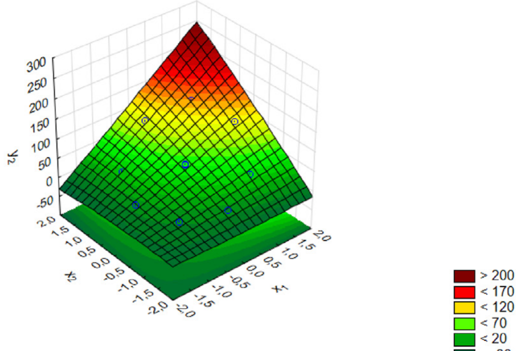
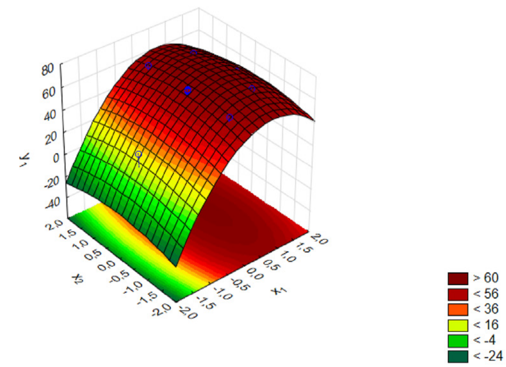
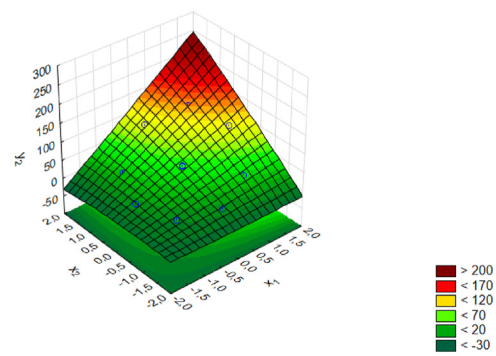


Fig. 7. Response surfaces for Density and NPV - Santa Vitória do Palmar-RS.

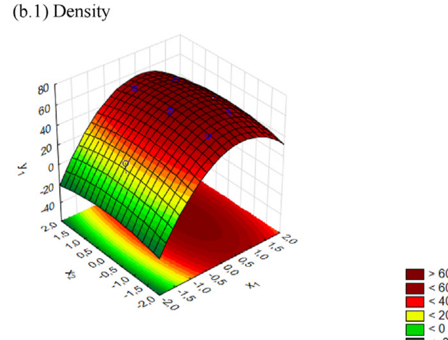


(a.2) NPV



(b) Brand B

(b.1) Density



(b.2) NPV

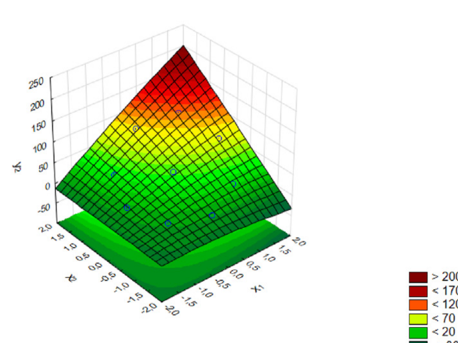


Fig. 8. Response surfaces for Density and NPV - Macau-RN.

Table 6
x_1 and x_2 results for multiobjective optimization.

Weights		Santa Vitória do Palmar-RS				Macau-RN			
w_1	w_2	Brand A		Brand B		Brand A		Brand B	
		Power (x_1)	Price (x_2)	Power (x_1)	Price (x_2)	Power (x_1)	Price (x_2)	Power (x_1)	Price (x_2)
1.00	0.00	24.860	145.701	23.990	150.157	22.475	151.257	22.850	153.801
0.95	0.05	24.814	141.553	23.801	144.787	22.229	145.813	22.714	148.649
0.90	0.10	24.776	137.434	23.650	139.556	22.048	140.826	22.610	143.767
0.85	0.15	24.746	133.346	23.533	134.464	21.917	136.200	22.532	139.120
0.80	0.20	24.723	129.289	23.448	129.510	21.825	131.870	22.477	134.681
0.75	0.25	24.708	125.266	23.392	124.693	21.763	127.794	22.444	130.429
0.70	0.30	24.700	121.278	23.363	120.015	21.726	123.937	22.429	126.348
0.65	0.35	24.701	117.327	23.357	115.474	21.710	120.272	22.430	122.424
0.60	0.40	24.710	113.415	23.372	111.070	21.710	116.778	22.445	118.646
0.55	0.45	24.727	109.546	23.405	106.799	21.723	113.438	22.474	115.003
0.50	0.50	23.835	106.897	22.410	104.019	21.747	110.237	22.514	111.487
0.45	0.55	**22.944**	**104.990**	21.162	102.194	21.780	107.161	22.564	108.089
0.40	0.60	22.137	103.568	19.955	100.974	21.822	104.199	22.622	104.804
0.35	0.65	21.402	102.499	18.805	100.273	21.035	102.042	21.388	102.481
0.30	0.70	20.727	101.695	**17.718**	**100.008**	19.835	100.880	20.199	101.179
0.25	0.75	20.102	101.095	16.695	100.104	18.740	100.246	19.179	100.453
0.20	0.80	19.519	100.657	15.731	100.503	**17.735**	**100.009**	18.279	100.097
0.15	0.85	18.972	100.348	14.822	101.161	16.807	100.077	**17.470**	**100.000**
0.10	0.90	18.455	100.146	13.964	102.043	15.945	100.388	16.732	100.095
0.05	0.95	17.966	100.035	13.150	103.125	15.139	100.900	16.050	100.338
0.00	1.00	17.500	100.000	12.377	104.392	14.382	101.580	15.414	100.701

Table 7
y_1 and y_2 results for multiobjective optimization.

Weights		*Santa Vitória do Palmar-RS*				*Macau-RN*			
w_1	w_2	*Brand A*		*Brand B*		*Brand A*		*Brand B*	
		Density (y_1)	*NPV* (y_2)	*Density* (y_1)	*NPV* (y_2)	*Density* (y_1)	*NPV* (y_2)	*Density* (y_1)	*NPV* (y_2)
1.00	0.00	57.480	43.32	69.157	77.58	72.407	81.34	63.699	62.39
0.95	0.05	57.471	38.68	69.100	70.24	72.317	74.24	63.654	56.53
0.90	0.10	57.443	34.17	68.938	63.23	72.083	67.77	63.527	51.06
0.85	0.15	57.397	29.79	68.685	56.51	71.743	61.77	63.333	45.91
0.80	0.20	57.334	25.54	68.351	50.04	71.320	56.13	63.082	41.04
0.75	0.25	57.254	21.40	67.944	43.80	70.832	50.78	62.783	36.40
0.70	0.30	57.158	17.39	67.475	37.75	70.290	45.65	62.442	31.97
0.65	0.35	57.046	13.48	66.948	31.88	69.704	40.72	62.064	27.72
0.60	0.40	56.920	9.69	66.371	26.17	69.081	35.96	61.654	23.62
0.55	0.45	56.779	5.99	65.750	20.61	68.426	31.33	61.215	19.66
0.50	0.50	56.562	2.85	64.975	15.52	67.743	26.83	60.751	15.82
0.45	0.55	**56.213**	**0.66**	63.835	11.57	67.035	22.43	60.265	12.09
0.40	0.60	55.772	−0.87	62.372	8.64	66.307	18.12	59.758	8.46
0.35	0.65	55.267	−1.95	60.652	6.51	65.499	14.17	59.098	5.57
0.30	0.70	54.716	−2.69	**58.732**	**5.00**	64.428	11.35	58.187	3.90
0.25	0.75	54.133	−3.20	56.664	3.97	63.154	9.43	57.139	2.89
0.20	0.80	53.525	−3.52	54.485	3.27	**61.736**	**8.14**	56.011	2.27
0.15	0.85	52.898	−3.72	52.226	2.83	60.214	7.30	**54.832**	**1.89**
0.10	0.90	52.257	−3.81	49.907	2.58	58.616	6.79	53.620	1.68
0.05	0.95	51.604	−3.82	47.547	2.45	56.962	6.53	52.386	1.57
0.00	1.00	50.943	−3.76	45.158	2.42	55.265	6.45	51.136	1.54

that energy is causing a lesser socio-environmental impact. This way, a greater usefulness level is achieved for the whole society.

5. Conclusions

The present study showed that the multiobjective optimization aided by DOE and DEA is a powerful tool for establishing the ideal configuration of a wind farm taking into consideration interests objectives for all stakeholders. For that, in the proposed methodology, the wind farm planning considers objectives which converge to the maximization of the electric sector well-being.

It is noted that the optimization of the model NBI-RSM-DEA offers different levels for the optimal solution, according to the specific wind potential of each place and technology referent to the brand of the wind turbines. In the analysed case, it was also possible to note that a wind turbine brand can have a better performance in a particular place.

It is possible to say that the proposed methodology's objective was met, noting that it was possible to identify the best power level, selling price, hosting place and turbine brand to be used in the planning of a wind farm. Also valid to note is that the methodology shows a great opportunity to support bidding processes and renewable energy certification programs, given that the socio-environmental potential is enhanced and economic viability is assured.

The main advantage of the proposed method was the possibility

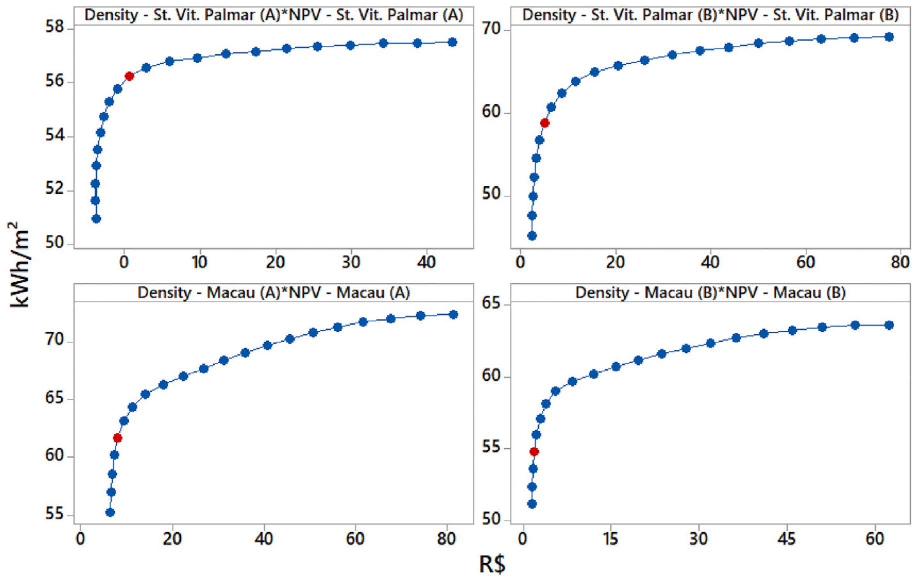


Fig. 9. Pareto frontiers for Density and NPV.

Table 8
DEA results.

DMU	x_1	x_2	y_1	y_2	Efficiency
Santa Vitória do Palmar – RS (Brand A)	22.9	104.99	56.21	0.66	0.91
Santa Vitória do Palmar – RS (Brand B)	17.7	100.01	58.73	5.00	0.95
Macau – RN (Brand A)	17.7	100.01	61.74	8.14	1.00
Macau – RN (Brand B)	17.5	100.00	54.83	5.00	0.88

of obtaining the optimal solution to a wind farm planning problem in the face of a trade-off with conflicting objectives. It is worth mentioning that each technique used in the method is extremely important to achieve this result. RSM allowed to build the objective functions for the problem. NBI routine provided a set of optimal solutions in each scenario. And DEA proved to be a subjectivity-free technique to indicate the best optimal solution. In turn, the set of these mathematical techniques involves complex concepts, which can limit the popularization of the approach for practical applications.

As for future works, it is recommended the development of new methodologies similar to the present study's, with the analysis of different input and output variables. Also as an opportunity for further research is the making of other methodologies focused in the planning of generation systems for other energy sources, aiming at maximizing the electric sector well-being.

Authors contributions section

Conceptualization: Luiz Celio Souza Rocha and Giancarlo Aquila; **Methodology**: Giancarlo Aquila, Luiz Celio Souza Rocha, Pedro Paulo Balestrassi and Paulo Rotella Junior; **Software**: Giancarlo Aquila, Luiz Celio Souza Rocha, Joao de Sá Brasil Lima and Joseph Youssif Saab Junior; **Formal Analysis**: Giancarlo Aquila, Luiz Celio Souza Rocha, Paulo Rotela Junior, Joao de Sá Brasil Lima and Joseph Youssif Saab Junior ; **Resources**: Pedro Paulo Balestrassi; **Data Curation**: Giancarlo Aquila, Luiz Celio Souza Rocha, Joao de Sá Brasil Lima and Joseph Youssif Saab Junior; **Draft Preparation**: Paulo Rotela Junior, Joao de Sá Brasil Lima and Joseph Youssif Saab Junior; **Writing-Review and Editing**: Giancarlo Aquila and Luiz Celio Souza Rocha; **Supervision**: Pedro Paulo Balestrassi; **Project Administration**: Pedro Paulo Balestrassi; **Funding Acquisition**: Pedro Paulo Balestrassi and Giancarlo Aquila.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.renene.2020.05.179.

ANNEX I Cash Flow Assumptions

Parameters	Values	Sources
Investment	R$/MW 3,918,623.32	CCEE [56]
Project life	20 years	COPEL [57]
Energy selling price	R$/MWh 164.82	CCEE [56]
Energy produced	Calculated by SMC	Calculated by Equation 19
Leasing	R$ 68.73 per km^2	Aquila et al. [42]
O&M Cost	2% of investment	Based on Aquila et al. [42]
Distribution system fee	R$ 4,580.00 by installed MW	COPEL [57]
Marketing fee	R$ 0.07 by MWh	Aquila et al. [42]
Operator fee	R$ 470.00 by MW installed	Aquila et al. [42]
ANEEL fee	R$ 2,556.24 by MW installed	ANEEL [58]
Administrative and insurance expenses	0.3% of investment	COPEL [57]
CSLL	9% over 12% of gross revenue	Aquila et al. [42]
IRPJ	25% over 8% of gross revenue	Aquila et al. [42]

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