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Multi-criteria Analysis of Brazilian Wind Farms

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Abstract- - Research with renewable energy sources, especially wind and solar energy, has been increasingly gaining the attention of researchers, development agencies and companies as a complement to traditional energy sources with finite reserves or hydropower. Although renewable sources rely on random climate conditions, their performance has rarely been evaluated adequately. Therefore, evaluating the performance of these renewable sources is essential to identify generation potentials and establish benchmarks in this sector. In this study, the aim is to evaluate the performance of Brazilian wind farms using a multi-criteria approach. In order to achieve this objective financial, technical, and operational performance criteria were evaluated, divided into nine sub-criteria, based on data survey among twenty plant managers. The modelling combined different renewable technology approaches to represent the entire system. Three methods were combined and compared: Analytic Hierarchy Process (AHP), Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE), and Data Envelopment Analysis (DEA), to evaluate the performance of five Brazilian farms. The two major results of this study are: (1) the interviewed managers had different perceptions when responding to the group of criteria and subcriteria, and (2) PROMETHEE and DEA methods achieved similar results. However, DEA is preferred method, as it indicates how and by how much an inefficient unit/farm should improve to consider efficient.

Keywords Performance evaluation, Brazilian wind farms, DEA, AHP, PROMETHEE

1. Introduction

Population growth and technological developments in all sectors of society have increased reliance on energy to generate goods and services, with consequences for energy consumption worldwide. therefore, Energy is fundamental to the world economy. Concurrently, global economy is based on an energy matrix dominated by non-renewable sources such as natural coal, natural gas and oil. These energy sources are finite in nature, indicating that these resources will begin to deplete rapidly in a few decades if the current consumption pattern continues.

Seeking solutions to the problem above described, many countries and institutions, including the European Union, have sought to prioritize strategies targeting renewable energy sources through programs, guidelines, regulations and recommendations. Addressed to different economic sectors, these media aim at alternatives to reduce excessive expenditures and increase the efficiency of these alternative sources [1]. Another motivating factor for the development of renewable energy is the long-term decarbonisation of the environment.

The European Energy Commission predicted a minimum target of 27% for the installed renewable capacity by 2030, without excluding hydroelectric power [2]. The Spanish power system had a total installed capacity of 104.056 GW at the end of 2018, of which 23.4% and 6.8% were from renewable wind power and solar power, respectively. Algeria has established the ambitious goal of deriving 40% of the electricity production from renewable energy sources (RES) by 2030, [1]. Pursuing the same objective, Brazil has proposed energy policies that incorporate renewable energies and energy efficiency [5].The gradual increase in the domestic demand for renewable energy led to a consumption of 64,281 MWh in 2018, which raised Brazil's world ranking, surpassing Canada as the eighth largest energy consumer [3]. The Brazilian electricity matrix, which features a renewable-thermal configuration, was launched in December 2018 with 8% wind energy and an installed capacity of 14.72 GW. This demonstrated a virtuous growth of the source over the years; therefore, Brazil reached the list of the ten countries with the highest installed wind power capacity. Moreover, the use of the conventional sources does not meet consumer demand. In this case, the use of renewable power will be very economical and beneficial to provide the required energy of consumers [4].

Wind energy involves the transformation of wind into electricity using wind turbines, a renewable and inexhaustible energy source, offering an alternative to fossil fuels. However, electricity generation through wind turbines requires specific time and place for implementation. Wind supply is abundant in the southern and northeaster regions of Brazil, allowing the installation of numerous wind farms [5-8].

Wind farms, also known as wind complexes, are sets of hundreds of individual wind turbines connected to an electric power transmission network. Small wind farms are used to produce energy in isolated areas. As wind turbines undergo a wide range of dynamic phenomena associated with the random nature of wind speed, accurate wind forecasting schemes can aid the operator in maximizing the power generation. The singularities of wind generation, related to the uncertainty of climatic conditions, can stimulate the establishment of performance indicators for the evaluation of individual systems and, in parallel, promote comparative analyses among various wind farms [7-9].

The renewable energy industry faces the challenge of developing a method to evaluate relative performance of different farms, or to compare each wind farm with the environment in which it is immersed. As the performance evaluation of wind farms must consider several criteria, represented by economic, environmental, social and technical indicators [8] , it is necessary to apply multi-criteria decision methods that allow the ranking, selection, and/or comparison of different alternatives, [9]. Multi-criteria decision-making (MCDM) methods constitute a family of mathematical decision approaches with the purpose of selecting the best alternative from a given set of units. It translates the performance of each alternative into a single aggregate value to ease the ranking process, which has a hierarchical structure of goals, criteria, sub criteria, and alternatives [11].

An extensive review of multi criteria decision-making (MCDM) to evaluate the performance renewable energy development is presented in [16]. The authors classified the method AHP (Analytic Hierarchy Process) as value measurement model and Promethee (Preference ranking organization method for enrichment evaluation) as outranking models.

Rakshit and Mandal [11] approached the efficiency of environmental energy projects estimation by traditional input-oriented Data Envelopment Analysis model, (DEA) while Nadimi and Tokimatsu [12] considered that heterogeneous decision-making units lead to unreasonable results, so they applied K-Mean clustering method to select homogenous sets of units and then analysed each homogenous sub-set by DEA.

The aim of this paper is to apply three alternative MCDM methods for the performance evaluation of five Brazilian wind farms based on three main criteria: financial, energy, and technical; and nine sub-criteria, using the analytic hierarchy process (AHP), preference ranking organization method for enrichment evaluation (PROMETHEE), and data envelopment analysis (DEA) methods. The major contributions of this paper were to identify that:

Experts had different perception of the macro criteria (Financial, Energy, and Technical) when considering the sub-criteria evaluation.

➢ AHP methodology contributed significantly to the establishment of the PROMETHEE criteria weight.

➢ DEA performance evaluation of wind farms is important for it determines those farms classified as inefficient and the effort that they must make to become efficient.

➢ Although the methods consider different levels of manager judgement from total to none, the results are not significantly different.

This paper is organized as follows: Section 2 discusses the concepts of a performance measurement system and the associated methods. Section 3 presents the methodology used to establish the set of indicators and details the AHP, PROMETHEE, and DEA methods. Five Brazilian wind farms are evaluated in Section 4, with final comments presented in Section 5.

2. Performance Measurement (PM)

PM is characterized by performance indicators combined with MCDM methods that translate the performance into a single aggregate value to support an organization's operational and strategic decision [13].

2.1. Performance Indicators

A measurement is a mapping from the real world onto a numerical system [13], each dimension or aspect of the process may be observed when represented by a measure. A performance measurement system represents a brief and precise set of measures (financial or non-financial) that supports the decision-making process of an organization by collecting, processing, and analysing the quantified data of performance information [14]. Performance measurement systems for management and decision support should consider the quantitative and qualitative analysis of organizations through indicators. Dizdaroglu [15] mentioned indicators as elements to measure efficiency and effectiveness within organizations, highlighting the performance of all existing production processes that require evaluations, whether by the employees, executives, and customers. According to Gimbert et al. [14], the indicators involve the internal and external environments of organizations.

An indicator is a variable that describes a characteristic or state through the observed or estimated data of the system. Performance indicators are the elements that allow control, improvement and acts as fundamental support in important decisions that involving the management of production processes, people, and organizations. It is important to observe that indicators are crucial elements for measuring the levels of efficiency and effectiveness within organizations, revealing the performance of all existing production processes that require evaluations, whether by employees, executives or clients [17].

An index is the result of aggregating multiple indicators that provides a simplified but coherent multidimensional view of the set of indicators it represents. Its function is to present the results of organizations and sectors in relation to the environment that they are inserted.

2.2. Multiple Criteria Decision-Making methods

Decision problems related to renewable energy are highly complex due to the uncertainty of the source. They involve multi-dimensional and multi-stakeholder processes, consequently with multi-criteria. The MCDM approach may be used to identify the best alternatives from a given set of criteria. It has a hierarchical structure of goal, criteria, sub-criteria, and alternatives [1, 8]. This may be formulated as an m x n matrix, where the matrix elements, for example *Hij* describes a semantic relationship between the alternative *i* criteria j. The MCDM decision matrix H can expressed as follows:

$$H = \begin{array}{c} \\ A_1 \\ \vdots \\ A_m \end{array} \begin{array}{c} \begin{array}{ccc} C_1 & \cdots & C_n \end{array} \\ \begin{bmatrix} h_{1,1} & \cdots & h_{1,j} \\ \vdots & \ddots & \vdots \\ h_{i,1} & \cdots & h_{i,j} \end{bmatrix} \end{array} \quad (1)$$

Where h_{ij} represents the performance score for alternative *i* with respect to criterion *j*. The criteria should reflect the economic, environmental, technical, social and political concerns [1]. Based on the number of alternatives under consideration, the MCDM problems related to renewable energy management are highly complex due to the uncertainty associated to the power source, involving multidimensional processes and multi-stakeholder, consequently with multi-criteria [16].

MODM methods are suitable for evaluating continuous alternatives for which parameters are predefined in the form of decision variable vectors.

MADM methods compare the relative importance of each criteria indicator of an alternative with the same criteria indicator of another alternative.

In this paper, both the MADM and MODM approaches were used to evaluate and measure the relative energy efficiency of five farms using renewable energy systems. The following three methods were evaluated:

- AHP [1, 9, 16, 17, 20].
- PROMETHEE [18, 22].
- DEA [19].

The two first methods are MADM. They assign a higher value to the alternative with best indicator.

The difference between the above methods is in the process of establishing how relevant the indicator of an alternative is in comparison with that same indicator in another alternative. AHP is a subjective method where the assignment of weights to criteria and sub-criteria is determined by the experts' choice, therefore, sometimes this method may be biased and have an effect on the decision making process, [8]. The PROMETHEE method combines the experts' choice of criteria weights with mathematical equations for assigning sub-criteria weights.

The third method is the DEAM MODM, an entropy method that calculates weights by solving mathematical equations without any influence of experts. Thus, this method may be considered as a non-biased approach. Either the classificatory or the prescriptive method allows the identification of efficient and non-efficient alternatives.

DEA prescribes how far inefficient alternatives are from the efficiency frontier. This method also prescribes the criteria which these alternatives should improve and to what extent, to achieve efficiency [19]. Due to its prescriptive characteristics, DEA was used in this study to compare results with the classificatory methods.

2.3. Analytic Hierarchy Process

The AHP comprehends a hierarchical structure of objectives, criteria, sub-criteria and alternative [17] (value tree). Subsequently, pairwise comparisons evaluate the performance of the alternatives for each criteria and sub-criteria. This seeks to portray the natural processing of the human mind, which by facing numerous elements, controllable or uncontrollable, integrates the properties into levels or groups.

The AHP approach may consider the qualitative and quantitative aspects of decision problems involving the structuring of multi-criteria for choice in the hierarchy. This method evaluates the relative importance of these criteria, compares and ranks the alternatives. The AHP methodology involves the following steps [17]:

- Step 1: identify the problem and determine the knowledge required for its resolution;
- Step 2: establish a hierarchy, based on the purpose of the decision to be taken, followed by the criteria to be evaluated and, finally, the alternatives available
- Step 3: the construction of a comparative matrix. Each element at the top is used to compare the elements immediately below (alternatives);
- Step 4: the weights established by the comparisons are used to weigh the priorities at the next lower level;
- Step 5: apply the priorities obtained through the comparative matrix among all criteria in the final analysis, after obtaining all the standardized matrices of each criteria.

The AHP is based on the priority that differentiates the importance of the criteria, as presented in Table 1, in the range of 1 to 9, where 1 indicates the indifference of importance of a criteria toward the others, and 9 signifies the extreme importance of one criterion over another, along with the intensity of importance [20].

Table 1. Scale of AHP values for paired comparison [20]

Saaty Scale	Numerical Evaluation	Reciprocal
i is extremely more important than j	9	1/9,
i is very strongly more important than j	7	1/7
i is much more important than j	5	1/5
i is moderately more important than j	3	1/3
i is equally important to j	1	1
Intermediate	2,4,6,8	1/2, 1/4 ,1/6 , 1/8

A judgment is the numerical representation of peer comparisons between the elements of two criteria. The group of all these judgments may be represented by a square matrix. Each judgment represents whether or not the element on the left column is dominant over an element of another column. It reflects on the answers of two questions: which of the two elements is most important regarding higher-level criteria and to what intensity, within the 1-9 scale, of Table 1. The diagonal positions will be *1*, as an element is equally important to itself. To fill the other elements of the matrix outside the diagonal, the judgments are made and the intensity of importance (weight) is determined in Eq. (2), which presents the scale of comparisons employed in the method. For the inverse comparisons, the reciprocal values of the upper right part of the matrix are placed in the lower left part of the matrix.

$$A = \begin{bmatrix} 1 & a_{12} & \dots & a_{1n} \\ 1/a_{21} & \cdots & \cdots & a_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ 1/a_{n1} & \cdots & \cdots & a_{nn} \end{bmatrix} \tag{2}$$

where:
$$a_{ij} > +;$$
$$a_{ij} = 1\ ;\ a_{ji} = 1;$$
$$a_{ij} = 1/a_{ji}\ ;$$
$$a_{ik} = a_{ij} * a_{jk} = 1$$

Therefore, the decision maker must perform n *(n-1) = 2* comparisons, where *n* is the number of elements of the analysed level. In the square matrix, we obtain a_{ij} for *i = 1;2...;n* and *j = 1;2; ...;n*. These matrices are always mutually positive. Peer-to-peer comparisons are performed at all hierarchical levels. Each element a_{ij} of the line vector of the dominant matrix represents the domination of the alternative a_i over the alternative a_j.

The resolution of matrix *A* results in the auto vector of priorities, which expresses the relative importance of each criterion by a weight. The nature of multi-criteria problems lies in the prioritization processes, as they involve significant trade-offs, requiring the assignment of weights for each criterion [21].

The method selected by the author can be justified considering that many research decisions are strongly based on subjective judgments.

2.4. Preference Ranking Organization Method for Enrichment Evaluations.

The PROMETHEE method originates from the French school of decision-making developed by professors J.P.Brans, B. Mareschal, and P. Vincke [23]. It belongs to a family of multi-criteria methods of analyzis, classified as overcoming methods, which help decision makers to find the best among a set of possible decision alternatives. The success of the PROMETHEE method may be attributed to its mathematical properties and, particularly, to its ease in application [23].

The implementation of the PROMETHEE method requires two types of information, namely:

➢ Information on the relative importance (i.e., weights) of the considered criteria.

➢ Information on the decision maker's preference function, employed when comparing the contribution of the alternatives in terms of each criterion.

PROMETHEE does not provide specific guidelines for determining weights; it assumes that the decision maker is able to weigh the criteria appropriately, particularly in cases where the number of criteria is not too large or AHP may be used to implement this phase [23]. The second type of information involves the preference function that translates the difference between the evaluations of two alternatives (a and b) in terms of a criterion, into a preference degree ranging from 0 to 1. One alternative is efficient when it dominates another alternative for all criteria considered. Each criterion is associated with a value ”q” for indifference, a value ”p” for explicit preference, and an intermediate value ”d” between ”p” and ”q” that represents the difference between two actions for a given criterion.

The main steps for implementing the PROMETHEE II method [22] are:

➢ **Step 1**. Determine deviation based on pair-wise comparisons:

$$d_j\,(a,b) = g_j(a) - g_j(b) \tag{3}$$

where $d_j\ (a,b)$ represents the difference between the performance $g_j(a)$ of alternative *a* and performance $g_j(b)$ of alternative b for each criterion.

➢ **Step 2**. Apply the preference function, as Eq. (4).

$$P_j\ (a,b) =\ F_j\ [dj\ (a,b)]\ j = 1 \dots k \tag{4}$$

where $P_j\ (a,b)$ indicates the preference of alternative *a* over alternative *b* in each criterion as a function of $d_j(a,b)$.

➢ **Step 3**. Calculate the preference index of the alternative compared to all other alternatives, as Eq. (5).

$$\pi\ (ab) =\ \sum_{j=1}^{k} w_j *\ P_j(a,b)\ \forall\ a,b \in A \tag{5}$$

where $\pi\ (ab)$ of *a* over *b* from *0* to *1* is defined as the weighted sum $\mathrm{p}(a,b)$ for each criterion, associated with the *j*th criterion of alternative *b* for each criterion.

➢ **Step 4**. Calculate the outranking flows based on the PROMETHEE I partial ranking according to Eqs. (6-7).

$$\emptyset_+(a) =\ \frac{1}{n-1}\ \sum_{x\ \in A}^{\pi\ (a,x)} \tag{6}$$

$$\emptyset_-(a) =\ \frac{1}{n-1}\ \sum_{x\ \in A}^{\pi\ (a,x)} \tag{7}$$

where $\emptyset_+(a)$ and $\emptyset_-(a)$represent the positive and negative overrun flows for each alternative.

➢ **Step 5.** Calculate PROMETHEE's complete ranking, according to Eq. (8).

$$\emptyset\ (a) =\ \emptyset_+(a) - \emptyset_-(a) \tag{8}$$

where $\emptyset\ (a)$ indicates the outranking for each alternative.

2.5. Data Envelopment Analysis

DEA is a nonparametric technique based on linear programming (MODM method) to determine the relative efficiency of production units. This technique relies on the measurement of relative efficiency between alternative units considering various inputs and outputs and identifying efficient units according to pre-established criteria. DEA outputs serve as an evaluation element of inefficient units, or as a focus for setting efficient targets for each inefficient production unit [19].

The use of the DEA method to measure the relative efficiency of companies and production units has been highly attractive in several application sectors. This method assists decisions of public officials and private companies by identifying sources of inefficiency and the units that may serve as a reference for best practices [26].

The DEA approach uses linear programming to estimate the efficiency frontier, a hypothetical efficiency limit of the units studied, as illustrated in Fig.1. This methodology is capable of incorporating several inputs (resources, inputs, or production factors) and outputs (products) to calculate the efficiency of decision-making units, known as DMUs or Decision Making Units [26].

DEA calculates the distance of each unit from the efficiency boundary by solving linear programming problems (PPL). All units or DMUs that meet this efficiency limit are considered efficient. However, the efficiency of the unit decreases as it moves further from the efficiency frontier. Fig. 1 illustrates the relative efficiencies of various DMUs analysed using the DEA method. Units A, B, C, and D, which lie at the limit of relative efficiency, are considered efficient by the DEA method. Units E, F, and G, which are further from the relative efficiency limit, are therefore considered inefficient.

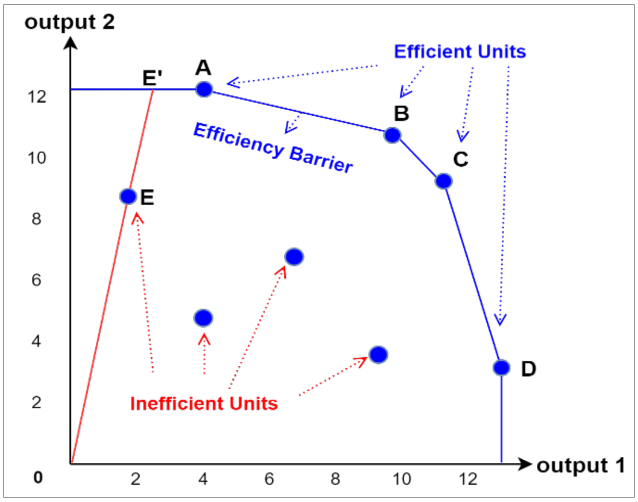

Fig. 1. DEA efficiency frontier. Adapted from [1]

The distance between points *E* (inefficient) and *E'* (efficient) is a measure of the amount by which unit E should increase to be considered efficient. Further *0E*, is the efficiency measure of the unit E. Consider a set of *n* decision units *(j = 1;…;n)* each having X_{ij} inputs *(i = 1;…;m)* and generating outputs Y_{rj} *(r = 1;….; s)*, with U_r and V_i the multipliers associated with the outputs and inputs, respectively. The weights *w* that maximize the weighted sum of the outputs for unit *j*, should be estimated. The sum calculated with these weights for remaining units should be less than or equal to 1. The efficiency E_j of unit *j* can be written as shown (9):

$$E_0 = \max \frac{\sum_{r=1}^{s} u_r\ y_{r0}}{\sum_{i=1}^{m} v_i\ x_{i0}} \tag{9}$$

subject to:

$$\sum_{r=1}^{s} u_r\ y_{rj} - \sum_{i=1}^{m} v_i\ x_{ij}\ \leq 0 j = 1,2 \dots n \tag{10}$$

$$v_i u_i\ \geq\ \varepsilon\, r = 1 \dots., s\ i = 1 \dots, m$$

where y_{rj} and x_{ij} are known outputs and inputs. Unit *j* is efficient if $E_j = 1$. However, if E_j is less than 1, unit *j* is deemed inefficient. Equation (10) shows that a priori information on the weights, which represent the importance of different aspects (variables) in the analysis, is not required in DEA method.

The solution of (10) indicates that each unit has the freedom to choose the weights through an optimization process, resulting in the best evaluation for the adopted criterion.

3. Methodology

To evaluate the Renewable Wind Energy sources, five wind farms were selected. The criteria and sub-criteria were then selected after the literature survey [7]. The research was based on secondary data and primary data. The secondary data were obtained from reports available on corporate websites and primary data were collected, representing the expert judgement, through the application of an internet questionnaire with twenty managers considering nine indicators distributed in three criteria: financial, technical and operational. After defining the decision matrix, the evaluation of the farm set was performed using multi-criteria methods (AHP, PROMETHEE and DEA) as detailed in Fig. 2 and discussed in the following subsections:

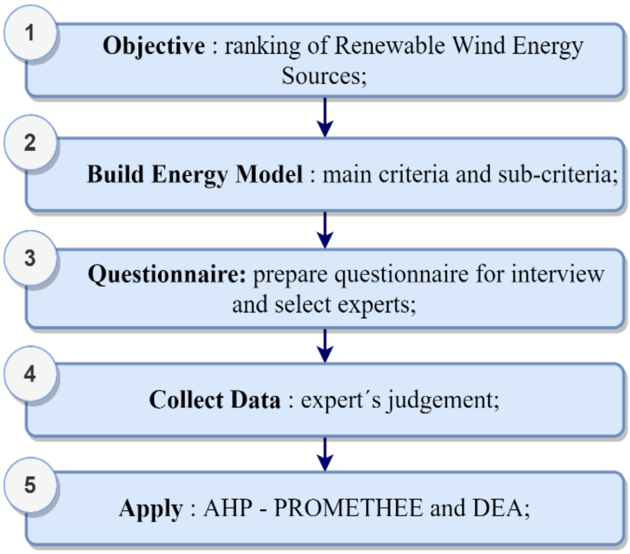

Fig 2. Working methodology.

3.1. Data Collection

Data collection was based on primary and secondary data. The primary data were obtained through a questionnaire developed using a free and secure platform offered by Google Docs. The questionnaire with multiple-choice questions was submitted to 20 expert evaluators (industry professionals). It was divided into two parts, the first section specifically covering the evaluation of the three guiding criteria: Financial, Technical, and Energy. The questionnaires developed through worksheets as in [27] were completed by the expert evaluators, exported to Excel, and inserted in the AHP method. The second part considered the nine sub-criteria, as shown in Table 2. Secondary data were obtained from Brazilian Electricity Regulatory Agency (ANEEL).

3.2. Criteria and Sub-Criteria Selection

The literature reveals that assessment studies in the renewable energy sector use multiple perspectives covering technical, economic, social, environmental, and political factors [13]. This study considered the first three performance criteria associated with sub-criteria to support the strategic decisions of the decision maker, as shown in Table 2. The aim was to evaluate the relative efficiency of each farm during their operation to evaluate the companies' returns regarding expenditures in the same period.

3.2.1. Economic Criteria

The objective was to evaluate the results of each farm during its operation in order to evaluate the return of a company in relation to the expenses in the same period. The economic criteria covers the following:

Park Gross Operating Revenue (PGOR). The total revenue generated from the activities of the organization, i.e. the activities for which the company was incorporated, according to their statutes and social contract.

Average Cost of Operation and Maintenance (ACOM). The average cost of Operation and Maintenance for the BOP (Balance of Plant) refers to all the auxiliary components and systems of a power plant in the process of energy supply (transformers, disconnectors, circuit breakers, inverters, support structure, labour, and inputs), covering the work scope between the service provider and customer.

Average Cost of Operation and Maintenance of Wind Turbines (ACOMT). The ACOMT is weighted amongst all the activities and responsibilities defined in the work scope between service provider and customer. Regarding the operation, a set of actions are performed 24 hours a day, 365 days per year. The ACOMT considers the activities of preventive maintenance, predictive maintenance, small and large corrections and regulation of different/various equipment or systems intended for operation. As this involves the highest risk and expense, maintenance activities are detailed to obtain the best understanding among the parties involved in the contracts.

3.2.2. Energy indicators

Energy Indicators reflect what is produced in a specific time interval. These identify how much a farm is capable of producing relative to the following:

Installed Active Power (IAP). The IAP of a system is the sum of installed, granted, or authorized power of the energy farm in operation in the system, defined in accordance with the specific Brazilian Electricity Regulatory Agency (ANEEL), and authorized power import capacities located in the system.

Average Capacity Factor (ACF). The ACF is a metric that determines the percentage of energy effectively captured in relation to the energy that may be captured if the wind turbines operate continuously at full capacity, which is not feasible when there is insufficient wind to generate the nominal capacity. Based on this measure, one may evaluate the wind potential or the actual or estimated use of the total installed power of a region.

Complex Availability (CA). The CA installed capacity is defined by the sum of the nominal active electrical powers of the plant generation. The power unit currently used by ANEEL is kWh (kilowatt-hour) or MWh (megawatt hour). These indexes indicate the power per unit of time that a power generation plant can produce at a specified time.

3.2.3. Technical indicators

Technical indicators estimate the quality of services provided by measuring power outages and average life of the large components of the wind farm:

Mean Time Between Failures (MTBF). The MTBF is an important indicator that calculates the average time between the end of one failure and the beginning of another (the next fault) in a repairable equipment.

Mean Time To Repair (MTTR). The MTTR indicator is the average time required to perform a repair after the failure occurred. MTTR refers to the time taken by maintenance personnel to restart the machine, restart the operation of the fault conditions until the repair is complete and the machine is in an acceptable condition to operate.

Average Life Time of Equipment (ALTE). ALTE considers the average life expectancy of a set of large components that constitute a wind farm or complex.

Table 2. Selected Criteria

Criteria	Sub-Criteria	Acronyms
Economic	Park Gross Operating Revenue	**PGOR**
	Average Cost of OM of Wind Turbines	**ACOMT**
	Average Cost of Operation and Maintenance	**ACOM**
Energetic	Installed Active Power	**IAP**
	Average Capacity Factor [19]	**ACF**
	Complex Availability (Wind turbines and BOP)	**CA**
Technical	MTBF (Mean Time Between Failures) of the Complex	**MTBF**
	Mean Time to Repair of the Complex (Average)	**MTTR**
	Life Time of Equipment	**ALTE**

4. Farms evaluation

The evaluation of the farms was performed using the steps shown bellow, Fig. 3.

4.1. Analytic Hierarchy Process

The AHP criteria weight was determined through a questionnaire provided to twenty experts. It was decomposed into two parts. In the first part economic, technical, and energetic criteria were considered, the respondents had to compare one in relation to the other based on Table 1.

The ranking position of each criterion was determined as the mean of the weights attributed by the respondents, as in Table 3.

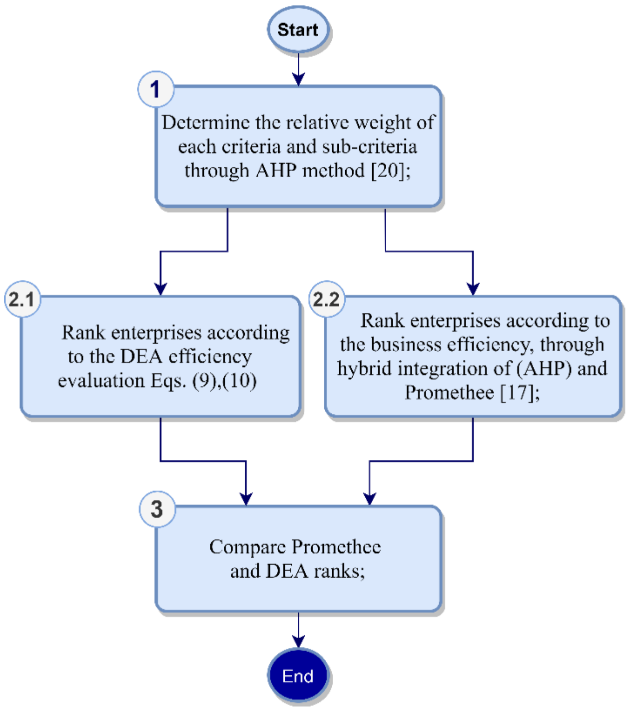

Fig. 3. Steps used to evaluate the farms.

Table 3. Consolidated results of the 20 evaluators for the criteria

Criteria	Weight	Ranking (Rkg)
Economic	54.10%	1
Energetic	28.20%	2
Technical	17.70%	3

These results indicate that the economic criterion is twice more relevant than the technical criterion and three times more important than the energy criterion.

The second part of the questionnaire was focused on analysing the individual performance of the nine sub-criteria according to Saatys scale [20]. As in the previous case, the average of the answers provided by the twenty experts was calculated. Table 4 shows the results, wherein the ranking of each sub-criterion provides its weight and position.

The Complex Availability (CA) had a weight of 24.8%, followed by Park Gross Operating Revenue (PGOR) with 15.5%. The Installed Active Power (IAP) was identified as the less important criterion, as shown in Table 4.

Table 4. Sub−Criteria Ranking

Criteria	Sub-Criteria	Weight	Rank	Criterion Weight
Economic	Park Gross Operating Revenue	15.50%	2	39.94%
	Average Cost of OM of Wind Turbines	11.20%	4	
	Average Cost of Operation and Maintenance	6.30%	8	
Energetic	Installed Active Power	3.80%	9	43.30%
	Average Capacity Factor	14.90%	3	
	Complex Availability	24.80%	1	
Technical	Mean Time Between Failures	8.40%	6	23.10%
	Mean Time to Repair of the Complex	6.70%	7	
	Life Time of Equipment	8.90%	5	

4.2. PROMETHEE

The secondary data indicators for the nine criteria in the five farms or complexes, identified here, as farms from A to E, were secondary data obtained from reports available on corporate websites and shown in Table 5. The first three are classified as financial criteria, the next three as technical criteria and the last three represent the energetic criteria. The first column of the Table 5 represents the farms; the next nine are the performance indicators for each farm. The second line represents the maximizing or minimizing objective for each criterion. For instance, the highest the gross operating revenue and the lowest cost of the average wind turbine, the better. Therefore, the PGOR criterion should be maximized and the ACOMT should be minimized when applying PROMETHEE.

This paper takes the PROMETHEE II, which provides complete ranking for analysing the performance of the five wind farms, from the best to the worst considering the objective of maximizing or minimizing the criteria, as specified in Table 5.

The PROMETHEE II implementation requires the operation data and two additional information: the weight that express the relative importance of each sub-criterion and the preference function. The weights are those obtained from AHP evaluation, Table 4. The preference function translates the difference between the evaluations of two alternatives into a preference degree ranging from zero to one, as expressed in Eq. 3 to 8. The indifference was taken as 5% from the maximum and minimum range of each normalized criterion, as shown in Table 6. From the joint application of AHP and PROMETHEE methods, Farm E was identified as the benchmarking farm, as it has the best performance when compared to each other, Table 6. The influence of the criterion weight on the farm ranking was simulated through three scenarios. The first applied the "AHP weight" (line eight, Table 6), while the second assigned equal/uniform weights *(1=9=0:111)* to the nine "Uniform Weight" criteria (line nine, Table 6). The tenth line of Table 6, "Proportional Weight" shows weight distribution similar to the one shown in Table *3 ((54:1=3) = 18:03 ; (28:2=3) = 9:4 ; (17:7=3) = 5:9)*. The results presented in Table 7 indicate that the weights do not have a significant influence on the farm ranking

4.3. DEA

Two scenarios were considered to evaluate the set of five wind farms using DEA.

4.3.1. Scenario 1:

The DEA inputs were ACOM, IAP, ACOMT, and ALTE and the outputs were PGOR, ACF, CA, and MTBF, as variables to be maximized, while MTTR was the variable to be minimized. The results of this scenario indicate that all farms are efficient on some axis (each variable corresponds to one axis), as shown in Table 8. An analysis of the second part of Table 8 indicates that the variables PGOR and DISP contribute to the efficiency of complete A in the ratio 0:3 to 0:7. The efficiency of farm B is determined by MTBF based on the data presented in Table 8, which indicates the unit B with the longest time among failures. The efficiencies of farms C, D, and E are determined by PROB, CA, and ACF, respectively. The maximum efficiency was obtained when a large number of variables (input + output) were compared with the number of units under study. This fact diminished the discriminatory power of DEA.

A situation may arise where each analysed unit (FARM) has the best performance for a given criterion, classifying the unit as efficient in this criterion. A unit can be classified as efficient in DEA when it has the highest value for an indicator in a given criterion compared with all other units, as verified in the results presented in Table 7. In this scenario, no difference in efficiency was found among the analysed units. This result motivated the proposal of a new scenario presented below.

Table 5. Operation data for five farms units.

FARM	Financial			Technical			Energetic		
	Max.	*Min.*	*Min.*	*Max.*	*Min.*	*Max.*	*Max.*	*Max.*	*Max.*
	PGOR	**ACOMT**	**ACOM**	**MTBF**	**MTTR**	**ALTE**	**CA**	**ACF**	**IAP**
A	70	390	73	1	10	2014	0.85	0.55	60
B	210	170	125	4	3	2017	0.9	0.35	220
C	180	600	54	1	8	2013	0.88	0.5	180
D	66	305	52	5	2,5	2014	0.95	0.55	70
E	205	203	65	4	2	2016	0.96	0.6	182

Table 6. Normalized Operation Data.

FARM	PGOR	ACOMT	ACOM	MTBF	MTTR	ALTE	CA	ACF	IAP
A	0.02	0.48	0.71	0	0	0.25	0	0.8	0
B	1	1	0	0.75	0.87	1	0.45	0	1
C	0.79	0	0.97	0	0.25	0	0.27	0.6	0.75
D	0	0.68	1	1	0.93	0.25	0.9	0.8	0.06
E	0.96	0.92	0.82	0.75	1	0.75	1	1	0.76
Indifference	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
% AHP Weight	15.55	11.04	6.35	8.24	6.7	8.89	24.8	14.89	3.55
% Uniform Weight	11.11	11.11	11.11	11.11	11.11	11.11	11.11	11.11	11.11
% Proportional Weight	18.03	18.03	18.03	9.4	9.4	9.4	5.9	5.9	5.9

Table 7. PROMETHEE Weight Ranking.

FARM	AHP	Uniform	Proportional
E	0.731704	0.672000	0.64600
D	0.576590	0.568040	0.55547
B	0.417662	0.460000	0.49300
C	0.343940	0.373300	0.38026
A	0.187247	0.199000	0.19800

Table 8. DEA Scenario 1, Four Inputs - Five Outputs Farm Efficiency Analysis.

Sub-Criteria	A	B	C		D	E
ACONT	0	0	0		0	0
IAP	0	0	0		0	2.1
ALTE	1	1.8	0.6		1.6	0
ACOM	0.5	0	1.2		0.3	0.7
PGOR	0.3	0	1		0	0
MTBF (H)	0	1	0		0	0
CA	0.7	0	0		1.1	0
ACF	0	0	0		0	1.1
MTTR (H)	0	0	0		0	0
Efficiency	1	1	1		1	1

Table 9. DEA Scenario 2, Annual Performance Efficiency Evaluation

Sub-Criteria	A	B	C	D	E
PGOR	1	0.830	1	1	1
ACOMT	1	0.751	1	0.578	1
ACOM	1	1	0.623	1	0.958
IAP	1	1	1.0	1	0.832
CA	1	1	1.0	1	1
ACF	1	1	0.697	1	1
MTBF	1	1	1.0	0.267	0.233
MTTR	1	1	1.0	0.628	0.409
ALTE	1	1	1.0	0.959	1
Efficiency	1	0.94	0.91	0.76	0.75

2.1.1. Scenario 2:

This scenario follows a similar procedure to the AHP and PROMETHEE methods, involving a pair-to-pair comparison of the criteria. One criterion was fixed as the output, while the other eight were considered as input. Nine models were developed: Model 1 had the output variable PGOR with all other variables as inputs. The goal was to maximize PGOR with the other variables remaining constant. In Model 2, the aim was to minimize the output variable ACOM, while all other variables were considered constant. This procedure was applied to all seven remaining simulations. Table 9 presents the results for each of the evaluations. The last row of this table represents the average performance of each farm obtained considering all nine criteria; this has been used to establish the efficiency ranking for each farm. Wind farm A achieved the maximum performance for all criteria followed by farm B, while farm E having the worst performance. In addition to the ranking of the farm units, the DEA method is prescriptive and indicated that farm B should improve the PGOR and ACOMT criteria by 17% and 24.9%, respectively, to achieve the maximum efficiency. The same analysis may be applied to the other farms. The performance of wind farm C should improve by 37.7% and 30.3% corresponding to the ACOM and ACF criteria, respectively, to achieve maximum efficiency, while farms D and E should improve the performance of all four 12 indicators.

5. Comparison of Methods

When comparing the evaluated plants, the PROMETHEE and DEA methods presented similar results and parity in the plant efficiency ranking, shown in Table 10. This result, reinforces that both multi-criteria methods, with or without attributed weights, may be applied to assist the decision-making process. It should be emphasized that the number of variables and possible correlations between the indicators may contribute negatively to the application of the DEA method. However, these aspects are not relevant to the PROMETHEE method

Table 10. Comparison of results from three PROMETHEE scenarios and one DEA

	PROMETHEE WEIGHT			DEA
	AHP	Uniform	Proportional	
E	0.731704	0.672000	0.64600	0.86400
D	0.576590	0.568040	0.55547	0.63200
B	0.417662	0.460000	0.49300	0.62780
C	0.343940	0.373300	0.38026	0.35500
A	0.187247	0.199000	0.19800	0.29910

6. Conclusion

This work evaluated the efficiency of five Brazilian wind farms considering three criteria and nine sub-criteria by three methods; AHP, PROMETHEE and DEA multi-criteria methods. The first two consider the effective participation of the decision maker. The proposed approach is useful to support the development of renewable energy policies and provides important information for planning and investment in this sector.

A significant item to note is that the experts had a different perception of the macro criteria (Financial, Energy, and Technical) from when considering the sub-criteria evaluation. When considering the macro criteria, the economic weight was 54.1%, while it was 32.94% when evaluating the individual sub-criteria. The economic criterion occupied the first position in scenario one, while it was at the second position in scenario two. The energetic criterion, which was at the second position in scenario one, moved to the first position in scenario two, as shown in Fig. 4. However, a better energetic ranking was expected, as it is the main objective of wind farms. The AHP methodology contributed significantly to establish the weights for each PROMETHEE performance

The overall results of the study corroborated the importance of AHP, PROMETHEE and DEA methods to assist decision-making. Through these methods, it was possible to model the performance indicators and compare the efficiency of the wind power plants. The DEA performance evaluation of the wind farms is important, as it identifies the inefficient farms and the effort needed to become efficient. The application of DEA, similar to the AHP and PROMETHEE methods, with pairwise criteria increases the discrimination of the method. In general, the assessment of the performance of renewable energy farms requires complex analysis, which may be defined as a multidimensional space of different indicators and objectives.

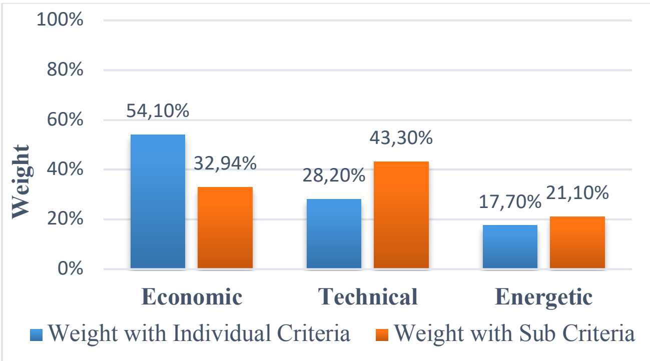

Fig. 4. Weights of the individual criteria and the nine sub-criteria

Multi-criteria decision analysis techniques provide a reliable methodology for classifying renewable energy farms, considering criteria and sub-criteria with multiple inputs and outputs. Although only five farms were evaluated in this study, the promising results indicate that performance analysis may be employed to compare the farm efficiency and suggest actions for the low-performance farms. Research with these performance indicators can help in the decision analysis in future energy contracts, which in turn could be in free contracting (ACL) and regulated (ACR) environments. These indicators should be considered in the business model, as they influence the plant's gross operating revenues.

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