

An Integrated Spatial Model for Selecting Regional Clusters of Photovoltaic Distributed Generation

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Abstract: This paper presents a methodology that integrates spatial methods for decision-making support based on technical criteria to expand participation of Photovoltaic Distributed Generation (PVDG) in electric power systems of a geographical region. The methodology starts with punctual environmental information, for example from a set of Data Collection Platforms (DCP), that were used as Decision Making Units (DMU) in a Data Envelopment Analysis (DEA) for ranking their efficiency. The DEA makes use of meteorological data such as temperature, wind speed, and cloudiness, as input, and solar irradiation, elevation, and insulation as output data. For the better-ranked, the Fuzzy TOPSIS multi-criteria method was applied to refine the DEA results. Then, for the best DMU, a classified Photovoltaic Power Potential (PPP) map was generated by the integration of the Normalized Difference Vegetation Index (NDVI) with slope and aspect maps using a Geographical Information System (GIS). Subsequently, utilizing the Analytic Hierarchy Process (AHP), the best of 8 sectors of a circular region centered of chosen DMU was selected, using the following criteria: distance to electric transmission lines and substations, solar irradiation of the region, and the PPP map. Within this sector, the PPP map was reclassified keeping only micro-regions with excellent and good classes. One of the main contributions of the research is related to the innovation in the use and integration of the

Voronoi diagram and the Delaunay triangulation for identification and connection of clusters of micro-regions with the potential for PVDG. Moreover, production values of these grouped regions were estimated using a production ratio value of the worst-case scenario of a set of solar plants currently in operation. The methodology of this work is illustrated by a case study in Brazil is considered useful for better cost-effective investment decision makings and can be applied in any region where there is potential for using solar energy.

Keywords: Renewable energy, Solar energy, Fuzzy TOPSIS, Geographic Information System, Photovoltaic Distributed Generation, Multicriteria decision-making

I. INTRODUCTION

The current dependence on fossil fuels such as oil, natural gas, and coal is responsible for the emission of polluting gases in the atmosphere, promoting climate changes with negative consequences for the next generations of human beings.

The rational and conscious exploration of natural resources from the sun, wind, water, and even the Earth's internal heat to produce energy is a very important subject.

Renewable energies are sources of clean, inexhaustible, and increasingly competitive energy, whose exploitation causes lower environmental impact than conventional energy technologies. The use of natural resources is an important factor in reducing the consumption of fossil fuels, considered the main factor for climatic change due to the emission of carbon dioxide (CO₂) in the atmosphere.

The United Nations Climate Change Conferences (COP25), a formal meeting to assess progress in dealing with climate change, discussed the climate and energy scenarios that will help to keep global temperatures from rising more than 1.5°C. This is the equivalent of achieving global net-zero CO₂ emissions by the mid-21st century [1].

According to the latest report commissioned by the UNFCCC [2], representing 197 member countries of the Paris Agreement, it is necessary to present more urgent and ambitious targets for the reduction of carbon emissions, aiming to limit the rise in global temperature above preindustrial levels by 2100.

According to the [3], despite the negative developments in climate policy and emissions regarding the forestry sector, Brazil has made progress in the energy sector. Market developments between June 2015 and September 2019 seem to favor renewable energy over fossil fuels. Although fossil capacity was eligible in the latest auctions, no coal and only 4 GW of gas-fired power generation have been contracted since 2015 in comparison to 10 GW of renewable percent.

The installed energy matrix in Brazil is composed of 60% hydro power, 15% thermal power, 1% nuclear power, and 24% renewable energy. Renewable energy is composed of 9% Biofuel, 9% Wind, 4% Small Hydro Plants (SHP), and 2% Solar Photovoltaic (SPV). Figure 1 presents the composition of the Brazilian energy matrix with its installed capacity for the year 2019 [4].

These values differ slightly from the data pre-

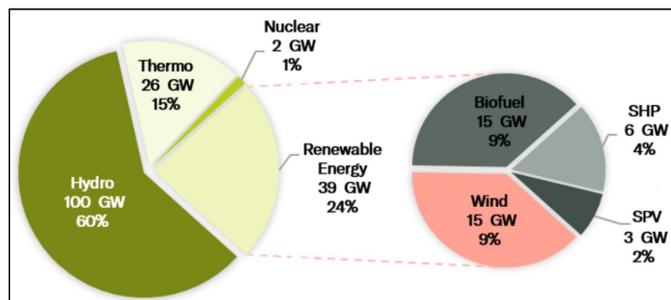


Figure 1: Composition of the Brazilian Electric Matrix, 2009.

sented by [5] in the previous year, with small advances in renewable energies. In this scenario, it is necessary to consider the positive aspects of Distributed Generation (DG) for the traditional Centralized Generation (CG), such as energy stability, reduction of losses in transmission lines, mitigation of the consequences caused by emergency or scheduled shutdowns, and minimization of environmental impacts.

The Normative Resolution 482/2012 [6], implemented by the Brazilian Electricity Regulatory Agency (ANEEL), and by the Distributed Generation Development Program for Energy - ProGD, made it possible for DG to make significant advances in establishing the general conditions for the access of micro generation and distributed mini generation to electric energy systems.

According to [7] The NR 482 came into force and established the initial rules for the development of electricity distributed generation in Brazil. From that moment, Brazilian consumers have been able to produce electricity from renewable sources and offset the surplus with their local distribution company (DISCO).

The research developed by [8] shows an increase in DG participation in the electrical system after the establishment of this resolution, with an emphasis on the state of Minas Gerais-MG.

The work developed by [9] presents an interesting study on the impacts of the dissemination of distributed renewable generation and energy efficiency on pricing to residential consumers.

The share of Photovoltaic Distributed Generation (PVDG) in the Brazilian electrical system is small, even though the country has one of the

highest annual solar irradiation rates in the world. The publication by [10] shows that Brazil has great solar potential for the generation of unexploited energy in the so-called Solar Belt, an area that goes from the Northeast to the Pantanal, including the north of Minas Gerais, the south of Bahia, and the north and northeast of São Paulo state.

The identification and classification of regions with potential for the installation of a solar power plant is a complex task with many factors to be considered (environmental, social, legal, political, technical-economic, etc.), which present site selection models do not address efficiently. In addition to mathematical models for decision-making, the process requires the use of Geographic Information Systems (GIS) algorithms, georeferenced satellite images, and integration with decision support methods, such as the Analytical Hierarchical Process (AHP).

Interesting and similar works were developed by [11], [12] and [13] used GIS and MCDM to select regions with potential for installing a solar plant that is close to the electricity infrastructure and in full harmony with the local environment.

This research is related to the location of georeferenced regions that have the potential for transforming solar energy into electrical energy and its integration with the DG systems. It is a complex problem that does not depend exclusively on the solar irradiation criterion. There is a need for both quantitative data analysis related to the environment, such as temperature, wind speed, cloudiness, insulation, altitude, and solar radiation. There is also the need of a qualitative data analysis with interviews related to the Fuzzy logic and AHP decision-making, where the specialist is consulted on the importance of technical parameters associated with the proximity of transmission lines, substations, and the renewable energy potential of the region.

The objective of this work is to locate regions with potential for the installation of photovoltaic panels (PV), for the capture, transformation of solar energy, and distribution of electric energy in the lines and transmission already installed. The continental dimension of Brazil and the high lev-

els of daily solar irradiation enable many regions to be candidates for the construction of a solar farm. As a result, clusters of georeferenced micro-regions were identified and classified as excellent and good for the installation of a solar plant.

The main objective of this work is to locate regions with potential for the installation of photovoltaic panels (PV), for the capture and transformation of solar energy, as well as the distribution of electric energy in the transmission lines already installed. To achieve that objective, this work explores the use of decision-making techniques based on multi-criteria analysis, DEA, Fuzzy TOPSIS, and AHP, integrating environmental information through a Geographic Information System-GIS, for the selection of spatial locations with potential for the implementation of solar plants. Furthermore, the article proposes, as innovation, the use of clustering procedures of predetermined micro-regions, supported by Voronoi diagram and Delaunay triangulation, to define larger areas with adequate distances for the implantation of a solar plant. Also, a case study for the Brazilian country, using only public data, is presented. The continental dimension of Brazil and the high levels of daily solar irradiation enable many regions to be candidates for the construction of a solar farm. As a result, clusters of georeferenced micro-regions were identified and classified as excellent and good for the installation of a solar plant to act collaboratively in the growth of the PVDG.

The remainder of this paper is organized as follows: Section 2 presents the main general concepts used in the research. Section 3 describes in detail the three stages of the methodology proposed in this research for implementation of solar plants. Section 4 presents results and discussions of a case study applied to the proposed methodology in the Brazil country as the geographic region of interest. Finally, section 5 reports the conclusions and points out to future work suggestions related to the subject of this research.

II. MATERIAL AND METHODS

A. Multi-criteria Method in "Fcv'Gpxgrqro gpv'Cpcr'uku"

The Data Envelopment Analysis (DEA) was so named because of the way it "envelops" observations to identify a "frontier" that is used to evaluate observations representing the performances of all of the entities that are to be evaluated. A decision-making unit-DMU is the entity under analysis. In the DEA model, each object to be evaluated uses the DMU concept, in which the inputs and outputs are used to determine the efficiency of each DMU in relation to the set.

These evaluations result in a performance score that ranges between zero and one and represents the "degree of efficiency" obtained by this evaluated entity. Arriving at these scores, DEA also identifies the sources and amounts of inefficiency in each input and output for every DMU. It also identifies the DMUs (located on the "efficiency frontier") that entered actively in arriving at these results. These evaluating entities are all efficient DMUs and hence it can serve as benchmark routes to effective improvements in future performances of the evaluated DMUs [14].

The definition of a DMU is generic and flexible. In recent years people have seen a great variety of applications of DEA for the use in evaluating the performances of many kinds of entities engaged in many different activities, in many different contexts, and in many different countries [15]. DEA is a performance measurement technique that can be used to evaluate the relative efficiency of DMUs. Here a DMU is a distinct unit within an organization with flexibility concerning some of the decisions it makes, but not necessarily complete freedom concerning these decisions [16].

The first DEA model, proposed by [17] named DEA-CCR in honor of their authors had an input orientation and it was supposed that there were constant returns to scale (CRS). The formulation of multipliers the DEA CCR model establishes that weights or multipliers of the variables must be calculated in order to maximize the efficiency of each DMU.

The CCR is one of the most popular DEA

models. The DEA ratio form is designed to measure the DEA efficiency of a specific DMU k' can be expressed by equations Equation (1) to Equation (4) :

$$Max \frac{\sum_{r=1}^R u_r Y_{rk'}}{\sum_{q=1}^Q v_q X_{qk'}} \tag{1}$$

$$s.t. \frac{\sum_{r=1}^R u_r Y_{rk'}}{\sum_{q=1}^Q v_q X_{qk'}} \leq 1 \tag{2}$$

$$\frac{u_r}{\sum_{q=1}^Q v_q X_{qk}} \geq \varepsilon, q = 1, \dots, r', \dots, R \tag{3}$$

$$\frac{v_q}{\sum_{q=1}^Q v_q X_{qk'}} \geq \varepsilon, q = 1, \dots, q', \dots, Q \tag{4}$$

where $X_{qk'}$ is the amount of the q-th input ($q=1, \dots, q', \dots, Q$) of the k'-th DMU, $Y_{rk'}$ is the amount of the r-th output ($r=1, \dots, r', \dots, R$) of the k'-th DMU v_q is the weight given to the q-th input. u_r is the weight given to the r-th output, ε is a non-Archimedean (infinitesimal) constant, Q is the number of inputs, R is the number of outputs and K is the number of DMUs. The ratio form can yield an infinite number of optimal solutions. For instance, if (u^*, v^*) is an optimal solution, then $(\gamma u^*, \gamma v^*)$ is also optimal for $\gamma > 0$.

A range of DEA models has been developed to measure efficiency and capacity in different ways. These largely fall into the categories of being either output-oriented or input-oriented models. In an input orientation, DEA minimizes input for a given level of output. It indicates how much a DMU can decrease its input for a given level of

output. In an output orientation, DEA maximizes output for a given level of input. It indicates how much a DMU can increase its output for a given level of input.

With input-oriented DEA, the linear programming model is configured to determine how much the input used could contract if it is used efficiently to achieve the same output level. For the measurement of capacity, the only variables used in the analysis are the fixed factors of production. As these cannot be reduced, the input-oriented DEA approach is less relevant in the estimation of capacity utilization. Modifications to the traditional input-oriented DEA model, however it could be done such that it would be possible to determine the reduction in the levels of the variable inputs conditional on fixed outputs and the desired output level.

For any linear program (LP) it is possible to formulate the equations in LP using the same data, and the solution to either the original LP (the primal) or the partner (the dual) providing the same information about the problem being modeled.

The transformation developed by Charnes and Cooper [17] for linear fractional programming was utilized in the DEA study to define an equivalence relation that partitioned the set of feasible solutions into equivalence classes. The transformed DEA model can be expressed as the following linear programming (LP) problem [18] – [19]:

$$Max \sum_{r=1}^R u_r Y_{rk'} \tag{5}$$

$$s.t. \sum_{q=1}^Q v_q X_{qk'} = 1 \tag{6}$$

$$\sum_{r=1}^R u_r Y_{rk} - \sum_{q=1}^Q v_q X_{qk} \leq 0, \tag{7}$$

$$k = 1, \dots, k' \dots, K$$

$$u_r \geq \varepsilon, r = 1, \dots, r' \dots, R. \tag{8}$$

$$v_q \geq \varepsilon, q = 1, \dots, q' \dots, Q. \tag{9}$$

The above primal model is difficult to solve, and the dual problem of the LP is proposed [18] - [19]:

$$Min h_k = \theta_k - \varepsilon \left(\sum_{q=1}^Q S_q^- + \sum_{r=1}^R S_r^+ \right) \tag{10}$$

$$s.t. \sum_{k=1}^K \lambda_k X_{qk} - \theta_k X_{qk} + S_q^- = 0, \tag{11}$$

$$q = 1, \dots, q' \dots, Q$$

$$\sum_{k=1}^K \lambda_k Y_{rk} - S_r^+ = Y_{rk'}, r = 1, \dots, r' \dots, R. \tag{12}$$

$$\lambda_k \geq 0, k = 1, \dots, k' \dots, K. \tag{13}$$

$$S_q^- \geq 0, q = 1, \dots, q' \dots, Q. \tag{14}$$

$$S_r^+ \geq 0, r = 1, \dots, r' \dots, R. \tag{15}$$

$$\theta_k, \text{ unconstrained}, k = 1, \dots, k' \dots, K \tag{16}$$

where S_q^- , S_q^+ are the slack variables of inputs and outputs, respectively. λ_k is the weight DMU_k and θ_k is the relative efficiency indicator of the k'-th DMU.

In Equation (10), the optimal h_k^* indicates a DEA efficiency score in a manner that $h_k^* = 1$ indicates the state of DEA efficiency, while $h_k^* < 1$ represents DEA inefficiency. For the optimal solution to the CCR model, the values of objective functions should be inverted, i.e., $f^* = \frac{1}{h_k^*}$.

The first thing noted is that the primal model has $k + t + m + 1$ constraining while the dual model has $m + t$ constrained. The primal model will have many more constraints than the dual model. For linear programs in general, the more constraints the more difficult a problem is to solve. Hence, for this reason it is usual to solve the dual DEA model rather than the primal.

DEA is a new approach to relative efficiency measurement where there are multiple incommensurate inputs and outputs. If a suitable set of

measures can be defined, DEA provides an efficiency measure not relying on the application of a common weighting of the inputs and outputs. Additionally, the method identifies peer units and targets for inefficient units.

The work developed by [20] uses two for evaluating the suitability of renewable energy plant site alternatives. In the first stage, a fuzzy analytic hierarchy process (FAHP) is adopted to set the assurance region (AR) of the quantitative factors, and the AR is incorporated into data development analysis (DEA) to assess the efficiencies of plant site candidates.

B. Fuzzy Set and Fuzzy TOPSIS

The fuzzy sets' theory was originated in the work of Lotfi Zadeh and was used to deal with problems in which a source of vagueness is involved. The word fuzzy refers to things that are not clear. Any event, process, or function that is changing continuously cannot always be defined as either true or false, which presents the need to define such activities in a Fuzzy manner. According to [21] - [22] "The theory of fuzzy sets is, in effect, a step toward a rapprochement between the precision of classical mathematics and the pervasive imprecision of the real world - a rapprochement born of the incessant human quest for a better understanding of mental processes and cognition".

Unlike crisp sets, in which an element is either a member of the set or not, a fuzzy set allows partial belonging to a set, that is defined by a degree of membership, denoted by μ , that can take any value from 0 (element does not belong at all in the set) to 1 (element belongs fully to the set).

Fuzzy set and crisp set are the part of the distinct set theories, where the fuzzy set implements infinite-valued logic while crisp set employs bi-valued logic. Previously, expert system principles were formulated with the premise on Boolean logic where crisp sets are used. But then scientists argued that human thinking does not always follow crisp "yes"/"no" logic, and it could be vague, qualitative, uncertain, imprecise, or fuzzy in nature. This gave commencement to the development of the fuzzy set theory to imitate human

thinking.

A fuzzy set \tilde{A} can be defined mathematically by a membership function $\mu_{\tilde{A}}(x)$, which assigns each element x in the universe of discourse X a real number in the interval $[0,1]$. The fuzzy set \tilde{A} in x is a set of ordered pairs:

$$\tilde{A} = \{(x, \mu_{\tilde{A}}(x) \mid x \in X \} \tag{17}$$

where $\mu_{\tilde{A}}(x)$ is a mapping from X to a membership space M , called the "membership function," that specifies the grade of membership (or degree of compatibility or degree of truth) of x in \tilde{A} . M is usually taken to be the closed real interval $[0, 1]$. In case M is taken to be $\{0, 1\}$, then \tilde{A} reduces to a regular crisp set A in X .

A Triangular Fuzzy Number (TFN) is used to represent uncertain and incomplete information in decision-making, risk evaluation, and expert systems. A TFN \tilde{A} can be defined by a triplet (a, b, c) as illustrated in Figure 2 (a), this figure shows the three types of widely-used fuzzy number. The membership $\mu_{\tilde{A}}(x)$ is defined in Equation (18).

$$\mu_{\tilde{A}}(x) = \begin{cases} \left(\frac{x-a}{b-a}\right) & a < x \leq b \\ \left(\frac{x-b}{c-b}\right) & b < x \leq c \\ 0 & \text{otherwise} \end{cases} \tag{18}$$

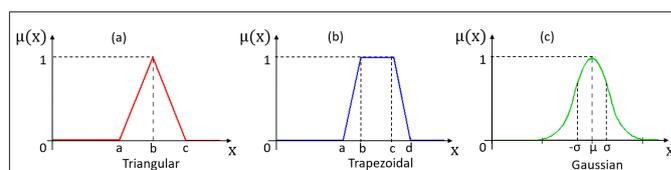


Figure 2: Three types of widely-used fuzzy number.

Basic arithmetic operations on triangular fuzzy numbers $A_1=(a_1, b_1, c_1)$, where $a_1 \leq b_1 \leq c_1$, and $A_2=(a_2, b_2, c_2)$, where $a_2 \leq b_2 \leq c_2$, can be show as follows:

$$Add : A_1 \oplus A_2 = (a_1 + a_2, b_1 + b_2, c_1 + c_2) \tag{19}$$

$$Sub : A_1 \ominus A_2 = (a_1 - a_2, b_1 - b_2, c_1 - c_2) \tag{20}$$

Mult. : if k is a scalar

$$k A1 = \begin{cases} (ka_1, kb_1, kc_1) & k > 0 \\ (kc_1, kb_1, ka_1) & k < 0 \end{cases} \quad (21)$$

$$A1 \otimes A2 = (a_1a_2, b_1b_2, c_1c_2)$$

Division :

$$A_1 A_2 = \left(\frac{a_1}{a_2}, \frac{b_1}{b_2}, \frac{c_1}{c_2} \right) \text{ if } a_2, b_2, c_2 > 0 \quad (22)$$

Multi-Criteria Decision Making (MCDM) methods have received much attention from researchers and practitioners in evaluating, assessing, and ranking alternatives across diverse industries. The Technique for Order Performance by Similarity to Ideal Solution (TOPSIS) was proposed by [23] and it is the most known technique for solving MCDM problems.

This method is based on the concept that the chosen alternative should have the shortest distance to Positive Ideal Solution (PIS), a solution that minimizes the cost criteria and maximizes the benefit criteria, and the farthest distance to Negative Ideal Solution (NIS).

The Fuzzy MCDM can be concisely expressed in matrix format as Equations .

$$\tilde{D} = \begin{bmatrix} \tilde{x}_{11} & \tilde{x}_{12} & \dots & \tilde{x}_{1n} \\ \tilde{x}_{21} & \tilde{x}_{22} & \dots & \tilde{x}_{2n} \\ \dots & \dots & \dots & \dots \\ \tilde{x}_{m1} & \tilde{x}_{m2} & \dots & \tilde{x}_{mn} \end{bmatrix} \quad (23)$$

$$\tilde{w} = [\tilde{w}_1 \quad \tilde{w}_2 \quad \dots \quad \tilde{w}_n] \quad (24)$$

where $\tilde{x}_{ij} = \frac{1}{k}(\tilde{x}_{ij}^1 + \tilde{x}_{ij}^2 + \dots + \tilde{x}_{ij}^k)$

The term \tilde{x}_{ij}^k is the rating of alternatives A_i with respect to criterion C_j evaluated by k expert and $\tilde{x}_{ij}^k = (a_{ij}^k, b_{ij}^k, c_{ij}^k)$.

The use of Fuzzy TOPSIS (FTOPSIS) is then carried out using the following steps:

Step 1: Normalize the fuzzy decision matrix.

The normalized fuzzy decision matrix denoted by \tilde{R} is shown as following formula:

$$\tilde{R} = [\tilde{r}_{ij}]_{m \times n} \quad i = 1, 2, \dots, m; \quad j = 1, 2, \dots, n. \quad (25)$$

Then the normalization process can be performed by following equation:

$$\tilde{r}_{ij} = \left(\frac{a_{ij}}{c_j^+}, \frac{b_{ij}}{c_j^+}, \frac{c_{ij}}{c_j^+} \right) \quad (26)$$

where $c_j^+ = \max_i c_{ij}$

The normalized \tilde{r}_{ij} are still triangular fuzzy numbers. The weighted fuzzy normalized decision matrix is shown as following matrix \tilde{V} :

$$\tilde{V} = [\tilde{v}_{ij}]_{m \times n} \quad i = 1, 2, \dots, m; \quad j = 1, 2, \dots, n. \quad (27)$$

$$\tilde{v}_{ij} = \tilde{r}_{ij} \otimes \tilde{w}_j \quad (28)$$

Step 2: Determine the fuzzy positive-ideal solution (FPIS) and fuzzy negative-ideal solution (FNIS).

According to the weighted normalized fuzzy decision matrix, the elements \tilde{V}_{ij} are normalized positive TFNs and their ranges belong to the closed interval $[0, 1]$. It is possible to define the FPIS A^+ and FNIS A^- as following equations:

$$A^+ = \tilde{V}_1^+, \tilde{V}_2^+, \dots, \tilde{V}_n^+ \quad (29)$$

$$A^- = \tilde{V}_1^-, \tilde{V}_2^-, \dots, \tilde{V}_n^- \quad (30)$$

where $\tilde{V}_1^+ = (1, 1, 1)$ and $\tilde{V}_1^- = (0, 0, 0)$ $j=1, 2, \dots, n$.

Step 3: Calculate the distance of each alternative from FPIS and FNIS.

The distances (\tilde{d}_i^+ and \tilde{d}_i^-) of each alternative A^+ and A^- can be currently calculated by the area compensation method.

$$d_i^+ = \sum_{j=1}^n d(\tilde{V}_{ij}, \tilde{V}_j^+), 1, 2, \dots, m \quad (31)$$

$$d_i^- = \sum_{j=1}^n d(\tilde{V}_{ij}, \tilde{V}_j^-), 1, 2, \dots, m \quad (32)$$

Step 4: Obtain the closeness coefficient (CC) and rank the order of alternatives.

The CC_i is defined to determine the ranking order of all alternatives once the \tilde{d}_i^+ and \tilde{d}_i^- of

each alternative have been calculated. Calculate similarities is the ideal solution. This step solves the similarities to an ideal solution by formula:

$$CC_i = \frac{d_i^-}{d_i^+ + d_i^-} \quad i = 1, 2, \dots, m. \quad (33)$$

According to the CC_i , it is possible to determine the ranking order of all alternatives and select the best one from among a set of feasible alternatives. Among numerous MCDM methods developed to solve real-world decision problems, the TOPSIS continues to work satisfactorily across different application areas [24].

The works developed by [25] and [26] present the mathematical formulation and the real applications of FTOPSIS. The work developed by [27] presents an analytical framework with fuzzy logic to identify locations for implementation of hybrid wind-solar farms on a complex topography terrain. The results showed that the fuzzy logic method yields better accuracy as compared with linear models.

The research [28] presents a hybrid methodology that combines the data envelopment analysis (DEA) window model, and fuzzy technique for order of preference FTOPSIS to evaluate the capabilities of 42 countries in terms of renewable energy production potential.

C. Geographical Information System (GIS)

A Geographic Information System (GIS) is a computer system for capturing, storing, checking, and displaying data related to positions on Earth's surface. By relating seemingly unrelated data, GIS can help individuals and organizations to better understand spatial patterns and relationships. In recent years, the GIS has become increasingly popular for various selection studies sites, particularly for energy planning [29], [30], [31], [32], and [33].

The research developed [34] presents the integration between GIS-based approach combined with a Multi-Criteria Evaluation methodology to create a map that shows a ranking of areas with high potential for solar farm development.

The work developed in [35] presented the integration between multi-criteria decision-making

methods named analytical hierarchy process (AHP) and GIS to be used to determine suitable site selection for solar-wind energy.

There are many Open Source GIS Software programs. This work used SPRING. Spring is a GIS and a Remote Sensing Image Processing system with an object-oriented data model which provides the integration of raster and vector data representations in a single environment. It has Windows and Linux versions and provides a comprehensive set of functions, including tools for Satellite Image Processing, Digital Terrain Modeling, Spatial Analysis, Geostatistics, Spatial Statistics, Spatial Databases, and Map Management. SPRING is a product of Brazil's National Institute for Space Research - INPE [36].

D. Analytical Hierarchical Process (AHP)

The Analytic Hierarchy Process (AHP) is a method for organizing and analyzing complex decisions, using math and psychology. It was developed by Thomas L. Saaty in the 1970s and it has been refined since then. It contains three parts: the ultimate goal or the problem you're trying to solve; all of the possible solutions, called alternative; and the criteria a person judges as alternatives. AHP provides a rational framework for a needed decision by quantifying its criteria and alternative options, and it relates those elements to the overall goal.

The AHP is a multi-objective, multi-criterion decision-making approach that employs a pairwise comparison procedure to arrive at a scale of preferences among some sets of alternatives. To apply this technique, it is necessary to break down a complex unstructured problem into its parts; arraying these parts, or variables, into a hierarchic order; assigning numerical values to subjective judgments on the relative importance of each variable; and synthesizing the judgments to determine which variables have the highest priority and which one should be acted upon to influence the outcome of the situation [37].

According to [38] to make a decision in an organized way to generate priorities, it is necessary to break the decision down into the following sequences:

1. Define the problem and determine the kind of knowledge sought.
2. Structure the decision hierarchy from the top with the goal of the decision, then the objectives from a broad perspective, through the intermediate levels (criteria on which subsequent elements depend on) to the lowest level (which usually it is a set of alternatives).
3. Construct a set of pairwise comparison matrices. Each element in which an upper level is used to compare the elements in the level immediately below concerning to it.
4. Use the priorities obtained from the comparisons to weigh the priorities in the level immediately below. Doing this with all elements. Then for each element in the level below it is added its weighted values to obtain its overall or global priority. Continuing this process of weighing and adding until the final priorities of the alternatives in the most bottom level are obtained.

E. Voronoi Diagram and Delaunay Triangulation

Voronoi diagrams are a method of spatial data interpolation into polygons around each point in such a way, that each location from the area surrounding a given point is closer to it than to any other point [39].

The Voronoi considers a set of point, $S = P_1, P_2, \dots, P_n$ for a limited integer n ($n > 1$), embedded in the R^2 Euclidean space such that no two points coincide. The ordinary Voronoi diagram, V_n , partitions the planing into Voronoi regions:

$$V_n = \bigcap_{i \neq j} \{ p \mid d(p, p_i) < d(p, p_j) \} \quad (34)$$

where $d(p, p_i)$ denotes the Euclidean distance from p to p_i [40].

The investigation of graph Voronoi diagrams is motivated by many applications and problems on networks that it can be easily solved with their help. This includes the computation of the nearest facilities, all the nearest neighbors and the closest pairs, some kind of collision-free moving, anti-centers and the closest points [41].

Voronoi also considered the geometrical dual of this structure, where any two points sites are connected to regions that have a boundary in common. Later, Boris Delaunay obtained the same structure by defining that two sites are connected if they lie on a circle in which the interior contains no other sites [42].

A Delaunay triangulation $D(\{p_i\})$ of $\{p_i\}$ is a triangulation where every point p_i is outside or on the boundary of the circumcircle of each triangle $T \in D(\{p_i\})$. The important properties related to the Delaunay triangulation and used in this work are: a) Delaunay triangulation maximizes the minimum angle among all possible triangles and b) Minimum Euclidean spanning tree of a point set is a subset of edges of its Delaunay triangulation.

The Delaunay triangulation is a triangulation which is equivalent to the nerve of the cells in a Voronoi diagram, i.e., where triangulation of the convex hull of the points in the diagram in which every circumcircle of a triangle is an empty circle [43]. The Voronoi diagram of a collection of geometric objects is a partition of space into cells, in each of them consist of the points closer to one particular object than to any others. Figure 3 illustrates the Voronoi diagram and the Delaunay triangulation of the same 2D space from centroids.

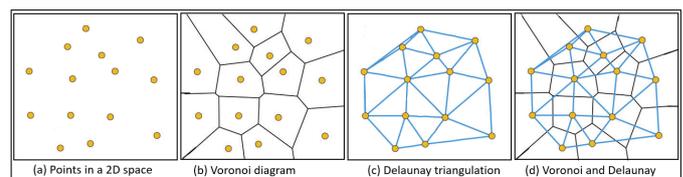


Figure 3: Examples of Voronoi and Delaunay Diagram

It is important to note also the aspects related to the duality. Suppose that p_i is not collinear and among p_i no four points lie on one circle. Then $V(\{p_i\})$ and $D(\{p_i\})$ are dual. When you get one of them, you can get the other one in $O(n)$.

When this is not the case, the collinear case may be processed. Otherwise, V and D' are dual, where D' is obtained by removing all the edges such that the two triangles on this edge share the circumcircle.

The work developed in [44] presents the basic

algorithms for the Voronoi diagram and Delaunay triangulation. For this work, it was implemented the Voronoi diagram and the Delaunay triangulation in Python language with the IDE Spyder (Anaconda 3).

F. Remote sensing of environment

Georeferenced data related to land use and occupation, and altimeter in the region are essential, as they can make investments unfeasible related to the implementation of the solar plant. The Normalized Difference Vegetation Index (NDVI) is the most common index to calculate given information related to the primary production of vegetation.

The land use and the health of the region vegetation are used to protect the environment from the process. Vegetation parameters, such as the description of phenomenological pattern can be estimated from time series of vegetation indexes derived from remote sensing and, among them, the NDVI has been widely used to monitor vegetation dynamics [45].

The Normalized Difference Vegetation Index-NDVI is a versatile vegetation index to evaluate the vegetation and dynamic of the vegetation coverage changes. The generic NDVI is calculated using the equation:

$$NDVI = \frac{(NIR - VIS)}{(NIR + VIS)} \quad (35)$$

where VIS = Visible Red and NIR = Near Infrared, both obtained through satellite images.

NDVI values + 1 represent that vegetation is available similarly the class closer to - 1 illustrate that no vegetation cover. It may be a water body or bare soil area [46].

Land use needs to be identified to define the constraints that must be taken into account in energy potential mapping. This information can be derived from satellite image, aerial photogrammetric or thematic cartographic bases. Altimeter data can be extracted from Digital Elevation Model (DEM) is necessary to produce information about slope and aspect [47].

In this topic, the following information was used: a)

Shuttle Radar Topography Mission (SRTM) DEM with 90 m pixel and b) Landsat 8/OLI images with 30 m pixels. Both data can be obtained from the website "United States Geological Survey (USGS)" [48].

G. Solar Irradiation

The available solar resource is typically measured as a combination of several components of the solar radiation that reaches the ground [49].

According to the literature, the amount of radiant energy emitted by the sun is called solar radiation and solar irradiation refers to the amount of solar radiation received from the Sun per unit area which is expressed in (kW/m²). Solar irradiation is one of the important parameters that should be taken into consideration for the design and utilization of a photovoltaic system.

Extra-terrestrial radiation can be transmitted, absorbed, or scattered by an intervening medium in varying amounts depending on the wavelength and interactions of the Earth's atmosphere. For purposes of usefulness with solar energy conversion techniques, solar radiation measurements result in three fundamental components of interest. Direct normal radiance (DNI) that it is the direct or beam radiation available from the solar disk that reaches the surface with no change in direction. Diffuse horizontal radiance (DHI) that it is the scattered diffuse radiation from the sky-dome, and Global horizontal radiance (GHI) that it is the total hemispheric radiance reaching the ground which it can be determined from the geometric sum of the DNI and DHI [50]. The formula to calculate the global horizontal irradiance (GHI) is as follows:

$$GHI = DNI * (\cos(\theta_z)) + DHI \quad (36)$$

In Equation (36) GHI is in $\frac{w}{m^2}$ and θ_z is the topocentric solar zenith angle measured in degrees.

Figure 4 shows the components of the solar irradiation.

Solar irradiation is an essential criterion for large-scale PV solar power projects. High amounts of solar energy play a major role in producing more electrical power from available resources [11].

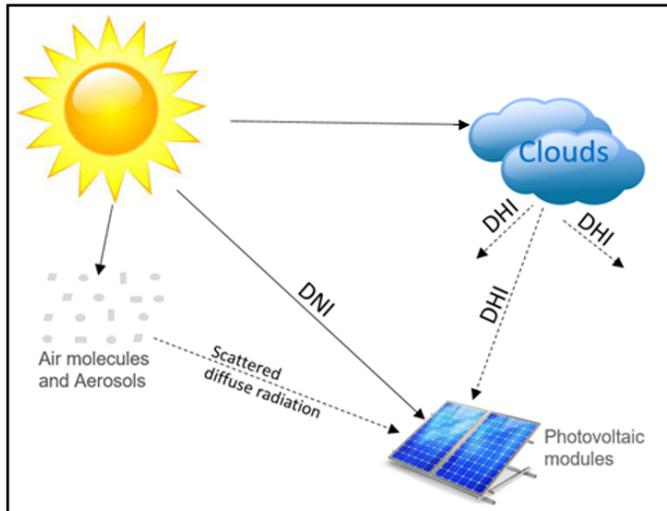


Figure 4: Solar radiation components.

III. METHODOLOGY

Figure 5 presents a flowchart with the three basic stages of this research methodology. Initially, a geographic region of interest is considered with the availability of specific punctual information, from Data Collection Platforms (DCP) for example, on climatic data and related to the transformation of solar energy into electrical energy, through photovoltaic panels.

Stage 1: "the selection of the best DMU for Solar Power Plant" is an MCDM process and it begins with the assignment of the punctual information to DMUs. For each DMU it is associated inputs, such as temperature, wind speed, etc., and outputs, such as terrain elevation, solar irradiation, etc. The DMUs are then ranked according to DEA Input Oriented, minimizing inputs and maximizing outputs, as described in Section II-A. This initial stage defines the scope of the research and served as a basis for refining the search for the most suitable regions for solar power plants.

A set of better-ranked DMUs, the FTOPSIS method is used to refine the DEA results. It is based on the proximity score, Euclidean distance of each candidate concerning their positive and negative ideals. The best candidate is the one that it is as close as possible to the positive ideal and as far as possible from the negative ideal, as presented in Section II-B.

The application of FTOPSIS requires litera-

ture review or participation of specialists in the area who consider the importance of relevant factors in the DMU: a) solar irradiation, b) transmission lines and substations, c) presence of small solar, wind, hydroelectric, and therm electric power plants, etc. The fuzzy sets and membership functions were presented in section II-B. From the FTOPSIS results, the best DMU or the better ones are considered as the input for Stage 2.

Stage 2: "Generation of PV Power Potential map" aims to generate the most efficient DMU solar potential map identified in Stage 1. The generation of the solar map is conditioned by the cross between the NDVI, which informs the conditions of the vegetation cover of the region soil, the slope of the terrain, and the aspect of sun exposure. The NDVI index was calculated using the Equation (35) .

The arrangement of photovoltaic panels must be configured on solar trackers, racks or sloping terrain to help maximize the ideal position of the sun. The digital elevation models (DEM) and solar aspect data can be obtained via radar system.

After generating the solar map from the best DMU neighborhood, a circular region centered in the best DMU location is classified as a Photovoltaic Power Potential (PPP) map that it is generated in a GIS environment. This approach was used due to the need to find facilities related to the electricity distribution system infrastructure already installed in the region. Geo-referenced information from this circular region is necessary to generate the PPP map.

The classes of the PPP map can be excellent, good, regular, bad, and prohibitive following rules define by literature review or specialists. The optimum class, for example, is assigned to regions with low NDVI value, excluding urban and water areas, low slope value, and aspect-oriented to the north direction. Thus, the PPP map is created by spatial integration of the NDVI map from remote sensing multi spectral bands, and the slope and aspect maps from Digital DEM Model.

Following, using the AHP, it is chosen the best of the 8 sectors of the circular region. These sectors follow the directions of the four cardinal directions of the north, south, east, and west and

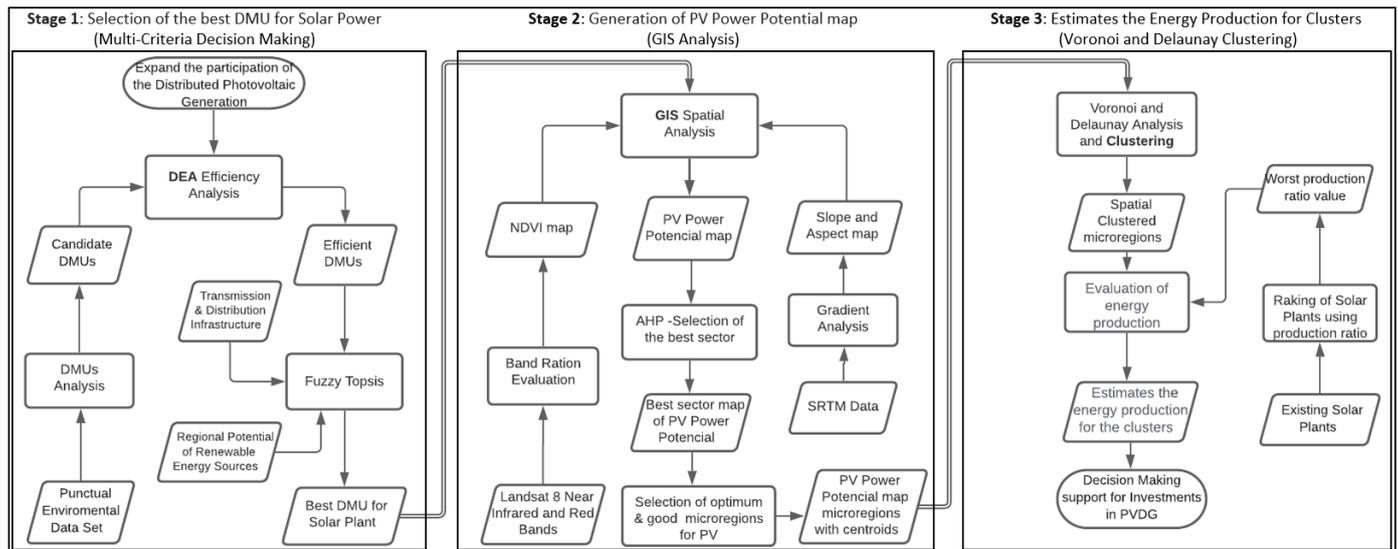


Figure 5: Methodology of the research.

compass with their intermediate positions: NNE, NEE, ESE, SES, SSW, SWW, WNW, and NWN. The criteria used in AHP are the proximity of electric transmission lines and substations, high solar irradiation, and excellent and good classes of the PPP map. Inside this best sector, the PPP map was reclassified creating micro-regions with its excellent and good classes. For this study, only the micro-regions whose areas have at least 75% in their classification of excellent and good were considered for the implementation of a solar plant.

Stage 3: “Estimates the Energy Production for Clusters“ - at this stage the micro-regions are grouped, supported by the Voronoi diagram and the Delaunay triangulation methods applied to their centroids, determining spatial clustered regions. The estimate of energy production (MW) for each of the micro-regions belonging to the clusters can be carried out based on the worst-case scenario of the current set of solar plants in operation in the country. The proposal is to make use of the excellent and good classification, and their respective areas, observed in the PV Power Potential map generated in Stage 2. The ranked values of energy production of the clustered micro-regions are important for better cost-effective investment decision makings.

IV. RESULTS AND DISCUSSION

This section presents a case study applying the proposed methodology in the Brazil country as the geographic region of interest. Also, the case study results are analyzed and discussed.

A. Case Study

Brazil has continental dimensions with a territorial extension of $8.514,876 \text{ Km}^2$ and great variation among different regions. Thus, it is important that decision makers, public and private, have a base of scientific support for selecting the most suitable regions to implement solar power plants.

The case study started by collecting a set of meteorological data from DCPs stations, spread over the Brazil territory and monitored by its National Institute of Meteorology (INMET) [51]. The Brazil DCPs provide important information on climatic conditions for the installation of solar power plants in the region. Therefore, the primary data from the survey was associated to environmental data from DCPs. Initially 112 DCPs were considered but 12 were excluded because they did not have all the data necessary for this research.

Figure 6 shows the spatial distribution of the DCPs used as a source of primary data for this research [52].

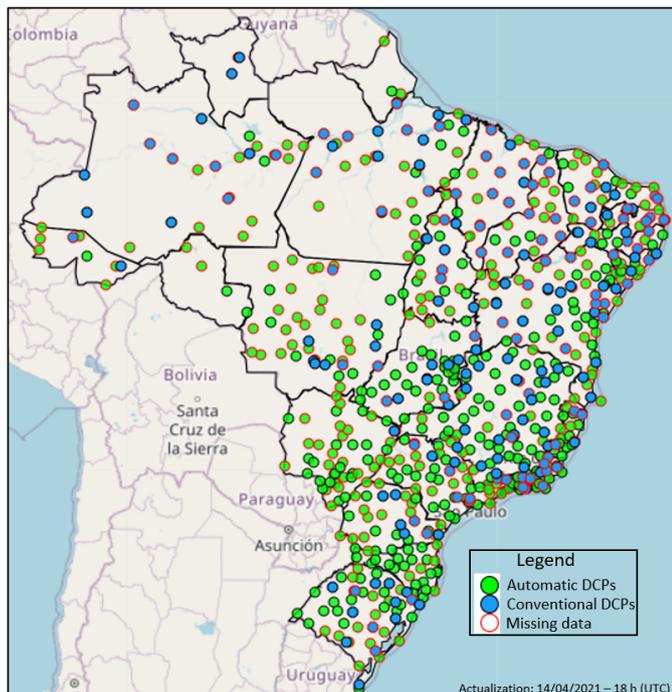


Figure 6: Primary data from DCPs used in the research.

Once having the DCPs' data, this case study followed the three sequential stages of the proposed methodology to locate suitable geographic regions according to this research objectives. Figure 7 presents in detail the three stages of the methodology used in this article.

In stage 1, initially, the DCPs were considered as DMUs whose input and output parameters were obtained from the DCPs' meteorological information. Temperature ($^{\circ}\text{C}$), wind speed (m/s) and cloudiness (Okta) inputs were utilized as negative aspects of the solar energy transformation in PV panels. Insolation (h), altitude (m) and solar irradiation ($\text{kWh}/\text{m}^2/\text{day}$) were the positive aspects, which favor the production of electricity in PV panels. Data related to irradiation on inclined plane were gotten from the Reference Center of Solar and Wind Energy Sérgio Brito (CRESESB) online database [53].

The DMUs were then used in a DEA process for ranking their efficiencies according to Equation (10) to Equation (16). These equations were implemented in Scilab-6.0.2 (64-bit) [54] and Python 3.8 Language [55]. The DMUs whose efficiency reached a DEA value $h_k = 1$ were used.

Table 1 presents the 14 most efficient DMUs

resulting from the DEA process where the second column reports the results of the DEA-AR (Assurance Regions). DEA-AR was applied here to restrict some weights to reasonable ranges, which are derived from a literature review with the impreciseness in the input/output data using classical fuzzy sets [56].

Table 1: The most efficient DMUs DEA Input Oriented

DMUName	DEA ($1/h_k$)	DEA-AR ($1/h_k$)
1 Arcoverde-PE	1.0	1.0
2 Bom Jesus da Lapa-BA	1.0	1.0
3 Caparaó-MG	1.0	1.0
4 Juramento-MG	1.0	1.0
5 Bom Jesus-RS	1.0	0.9926
6 Belo Horizonte-MG	1.0	0.9903
7 Brasília-DF	1.0	0.9865
8 Taguatinga-TO	1.0	0.9570
9 Morro do Chapéu-BA	1.0	0.9356
10 Franca-SP	1.0	0.9280
11 Paulistana-PI	1.0	0.9181
12 Carinhanha-BA	1.0	0.8964
13 Sta Rita de Cássia-BA	1.0	0.8876
14 Canarana-MT	1.0	0.8400

In sequence, the FTOPSIS multi-criteria method was utilized to refine the DEA results of Table 1 using new regional criteria related to infrastructure of transmission lines and substations, potential for distributed renewable energy generation positive aspects (photovoltaics, aerogenerators, use hydroelectric power plant, small hydroelectric power plants) and negative aspects (thermal power plants). These information were obtained from the Brazilian National System Operator (ONS), responsible for the coordination and control of the generation and transmission installations in the National Inter-Connected System (SIN) [57].

The FTOPSIS importance weights of various above criteria and their ratings considered as a

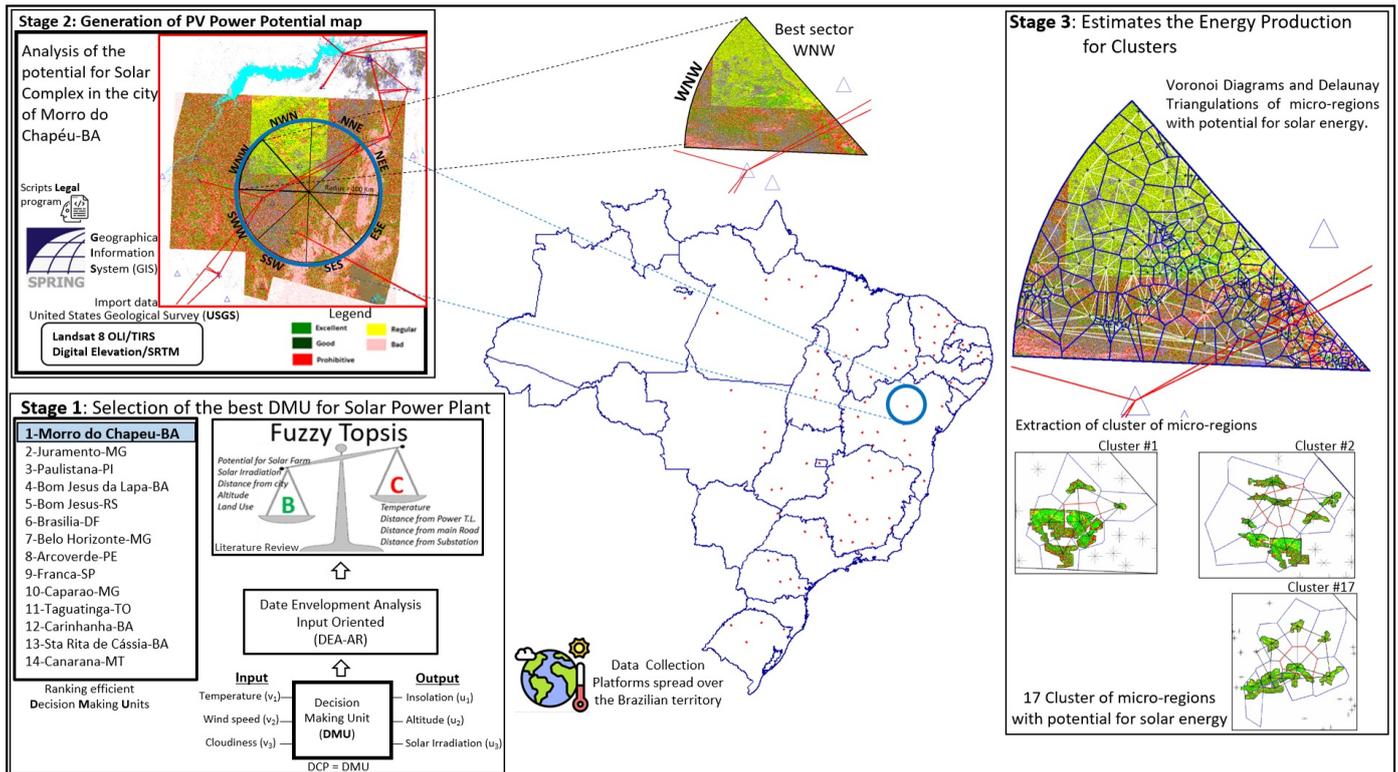


Figure 7: Study Case applied to Brazil.

linguistic variable are reported in Table 2. The triangular membership functions of the linguistic variables are showed in Figure 8. The linguistic variable values and the membership functions were determined by participation of experts.

Table 2: Linguistic Fuzzy Variable

Linguistic variable	TFN
1 Very low (VL)	(1, 2, 3)
2 Low (L)	(2, 3, 4)
3 Medium low (ML)	(3, 4, 5)
4 Medium (M)	(4, 5, 6)
5 Medium high (MH)	(5, 6, 7)
6 High (H)	(6, 7, 8)
7 Very high (VH)	(7, 8, 9)

The evaluations of the FTOPSIS approach were performed through the elaboration of the matrix presented in Equation (23) and the equations Equation (24) to Equation (33) following the linguistic concepts of the literature review. The new DMU ranking is determined by the Closeness

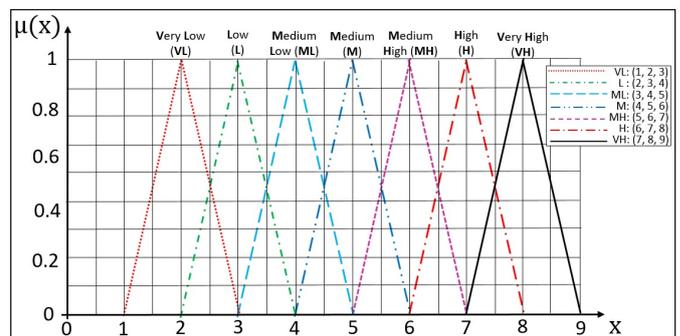


Figure 8: Triangular fuzzy membership functions.

Coefficient (CC_i). Table 3 reports the new reclassification of DMUs after the FTOPSIS application.

In stage 2 of this case study, the best DMU, located in Morro do Chapéu city, Bahia state, with geographic coordinates (11°21'00"S, 41°21'00"W), was selected as the center of a circular region with radius of 100 km to be explored. For this region, a classified Photovoltaic Power Potential (PPP) map was generated by integration of NDVI and slope and aspect maps, represented as regular grids, using a GIS.

The NDVI map was assessed from Land-

Table 3: Efficient DMUs with Fuzzy TOPSIS

DMU	d_i^+	d_i^-	CC_i
1 Morro do Chapéu-BA	71.10	72.30	0.50
2 Juramento-MG	72.36	71.05	0.49
3 Paulistana-PI	72.20	70.86	0.49
4 Bom Jesus Lapa-BA	72.64	72.64	0.49
5 Bom Jesus-RS	75.28	68.45	0.47
6 Brasília-DF	77.71	65.36	0.45
7 Belo Horizonte-MG	80.08	62.41	0.43
8 Arcoverde-PE	81.31	61.98	0.43
9 Franca-SP	83.82	59.58	0.41
10 Caparaó-MG	87.03	55.99	0.39
11 Taguatinga-TO	88.76	54.19	0.37
12 Carinhanha-BA	97.92	44.81	0.31
13 Sta R. de Cássia-BA	116.25	26.28	0.18
14 Canarana-MT	120.06	23.16	0.16

sat 8/OLI scenes and the slope and the aspect maps from SRTM Data, both available free of charge from the USGS website. Four Landsat 8 OLI/TIRS C1 level-2 images and eight SRTM images also from the USGS were used. The Landsat 8/OLI image scenes were 218067, 217067, 218068, and 217068 of the 2020-10-15 acquisition date. The SRTM images were S11W043V3, S11W042V3, S11W041V3, S12W043V3, S12W042V3, S11W041V3, S13W042V3, and S13W041V3 of the 2014-09-23 publication date.

The slope and aspect maps were evaluated and classified by the slope and slicing functions, respectively, available in the Digital Terrain Model menu of the SPRING GIS.

The data integration for generating the PPP map was performed by an algebraic spatial language of the SPRING GIS, known as LEGAL. It could be another GIS package as well. For example, the work [58] presents an algebra for spatiotemporal data in which Algebras give formal specifications at a high-level abstraction, independently of programming languages.

The best resulting class of the PPP map was obtained for low values of NDVI, low values of slope and surrounds of north direction of aspect input information. The integration of the input data was made by the AND operation of the Boolean logic applied to the values and classes presented in Figure 9.

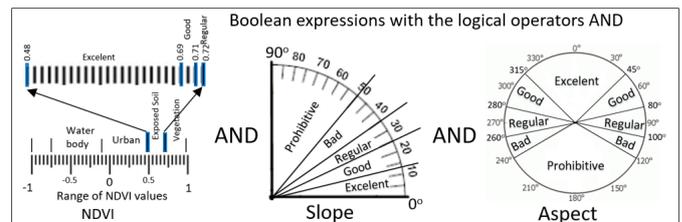


Figure 9: The algebraic GIS for generating PPP map.

The resulting PPP information is a classified map presenting the classes: Excellent, Good, Regular, Bad and Prohibitive. Figure 10 illustrates the integration concepts reported above and depicts the resulting PPP map and the circular region of interest superimposed on it and divided in 8 sectors.

Applying the AHP in all the sectors, the best one was selected considering the following information: shorter distance to electric transmission lines and to substations (buffer maps), higher solar irradiation and higher potential in the PPP map. As the result, the WNW, highlighted in Figure 7, was chosen as the best sector and its PPP map information was reclassified keeping only the excellent and good classes.

In Stage 3, the reclassified PPP map was transformed from a raster to a vector representation and only micro-regions with useful area above 75% were kept. As a primary result, the WNW sector of the solar map provided 166 micro-regions with potential for implementation solar plant.

The micro-region centroids were then used by a Voronoi diagram to find out clusters and by a Delaunay triangulation to provide the interconnection between nearby micro-regions in order to create final clustered regions. Thus, 17 clusters were identified, as showed in Figure 11, for implementation of solar plants which can produce energy independently and collaboratively.

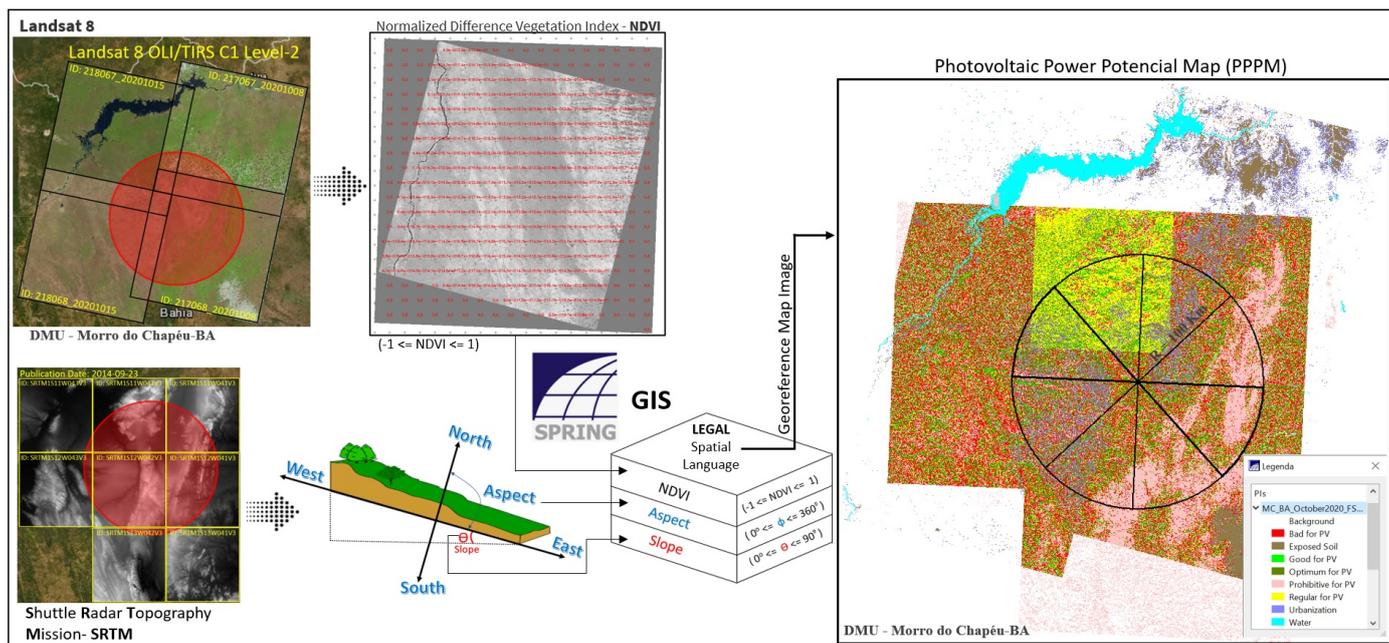


Figure 10: Photovoltaic Power Potential (PPP) map

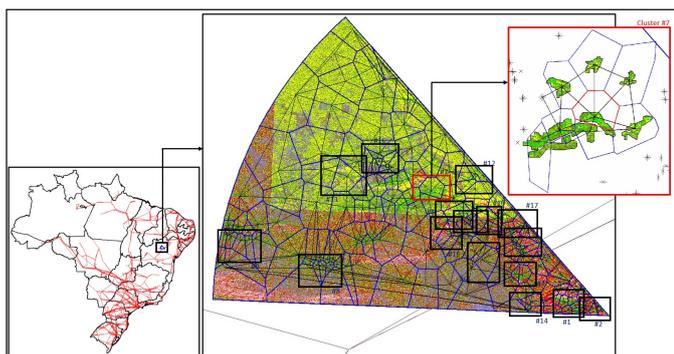


Figure 11: Selected sector WNW with Clusters of micro-regions.

B. Assessment to energy production

In this work, a survey of the main solar plants currently operating in Brazil was carried out and their real production ratios, in $\frac{MW}{Km^2}$, were evaluated. From these ratios, the most pessimistic scenario, low production by area, was used to estimate the energy production for each clustered region. Table 4 shows the production of the major solar plants in Brazil reporting their energy production, area and production ratio.

From this table it can be seen that Ituverava-BA plant, highlighted in Figure 12 [59], has the lowest production ratio. Thus, this lowest ratio was chosen for pessimistic production estimation

Table 4: Production of major solar power plants

Solar plant	Production (MW)	Area (Km^2)	Ratio ($\frac{MW}{Km^2}$)
Guaimbé-SP	150.00	1.89	79.46
São João PiauÍ-PI	210.00	3.67	57.21
Sol do Futuro-CE	81.00	1.49	54.49
Coremas-PB	54.00	1.02	52.90
Paracatu-MG	132.00	2.93	45.03
Bom J. Lapa-BA	214.00	5.42	39.47
Pirapora-MG	321.00	8.23	39.00
Juazeiro-BA	120.00	3.55	33.78
Ituverava-BA	196.00	6.75	29.03

for each of the 17 clusters found in the WMW sector. Also, it is important to note that the Ituverava-BA solar plant is close to the WNW sector having similar solar irradiation.

Table 5 shows the estimated production for clusters, considering the worst-case scenario, taking as reference the production/area ratio of the Ituverava-BA solar plant. In addition, the table reports the values of areas and distances of line transmissions of the clusters which can be important for better cost-effective investments in renew-



Figure 12: Solar plant installed in Ituverava-BA

able photovoltaic energy for the Brazilian decision makers.

Table 5: Pessimistic production for clusters.

Cluster number	Area (Km^2)	Production (MW)	Distance from L.T. (Km)
1	7.44	215.91	14.54
2	5.17	150.09	18.70
3	10.08	292.60	2.18
4	6.90	200.39	9.95
5	8.36	242.60	3.06
6	4.28	124.15	3.21
7	24.99	725.50	24.79
8	12.55	364.30	18.41
9	26.87	780.11	19.65
10	7.15	207.45	9.48
11	17.65	512.38	39.00
12	7.77	225.63	24.40
13	4.06	117.92	13.71
14	3.06	87.54	14.97
15	3.42	99.27	13.10
16	4.61	133.92	39.58
17	3.82	110.79	5.87
Total	158.11	4590.55	

V. CONCLUSIONS

This work presented a methodology for identifying clusters of micro-regions with potential for implementation of solar power plants in distributed electricity systems. The methodology was illustrated, along with resulting analyses, by a case study applied in Brazil country. All the steps of the methodology were explored in the case study: obtaining input data from DCPs and transformation in DMUs; ranking their efficiency through DEA Input Oriented approach; reclassification of the DMUs through FTOPSIS method; exploration of the region best ranked, "Morro do Chapéu-BA" region, with the generation of PPP map by integration of NDVI, slope and aspect maps in a GIS; election of one best sector with the greatest potential for PV using AHP method; identification and clustering of micro-regions, with a useful area above 75% and excellent and good classes, via Voronoi diagram and Delaunay triangulation and; assessment to energy production in MW of the clustered regions ranking them to improve decision makings in solar power plan implementations in Brazil. In this study it is considered that the ranked energy production of the respective clustered regions are important for better cost-effective investments in renewable photovoltaic energy for the Brazilian decision makers.

Particularly the case study here presented was carried out with official public databases, often available free of charge on the internet. Moreover, it can be replicated by one or several groups of investors interested in exploring solar energy and its use in distributed electric energy systems through official transmission lines.

For future research works, it is suggested to apply the Analytic Network Process (ANP) method with the BOCR (Benefits, Opportunities, Costs and Risks) to the sector selection of this methodology. In this case, the participation of specialists in the environmental, social, energy, and investors areas, is fundamental. It is also important to integrate this methodology with a much larger databases containing information about connections with currently distributed

energy generations that are not yet officially registered.

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