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Multi-Criteria Decision Support System for Automatically Selecting Photovoltaic Sets to Maximise Micro Solar Generation

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Abstract: Technological advancements have improved solar energy generation and reduced the cost of installing photovoltaic (PV) systems. However, challenges such as low energy-conversion efficiency and the unpredictability of electricity generation due to shading or climate conditions persist. Despite decreasing costs, access to solar energy generation technologies remains limited. This paper proposes a multi-criteria decision support system (MCDSS) for selecting the most suitable PV set (comprising PV modules, inverters, and batteries) for microgrid installations. The MCDSS employs two multi-criteria decision-making methods (MCDM) for analysis and decision-making: AHP and TOPSIS. The system was tested in two case studies: Barreiras, with a global efficiency of 14.4% and an internal rate of return (IRR) of 56.0%, and Curitiba, with a worldwide efficiency of 14.8% and an IRR of 52.0%. The research provided a framework for assessing and selecting PV sets based on efficiency, cost, and return on investment. Methodologically, it integrates multiple MCDM techniques, demonstrating their applicability in renewable energy. Managerially, it offers a practical tool for decision-makers in the energy sector to enhance the feasibility and attractiveness of microgeneration projects. This research highlights the potential of MCDSS to improve the efficiency and accessibility of solar energy generation.

Keywords: photovoltaic sets; multi-criteria decision making; micro solar generation; generation optimisation

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1. Introduction

Solar generation has seen significant development since 2010 and has become a low-cost source of energy [1]. Solar energy usage has increased mainly because of the drop in investment costs [2,3]. In this way, the microgeneration market has expanded and gradually attracted more attention, according to the database of the U.S. Energy Information Administration (EIA), due to the gradual reduction in the cost of photovoltaic (PV) modules [4]. However, some issues persist with the low efficiency of energy conversion and the uncertainty of electricity generation due to the adverse effects on the modules when they are partially or totally shaded [5]. Despite the reduction in the costs of PV equipment, solar energy generation technologies are not accessible to everyone [1,6].

Recent related works, such as [7–12], have been carried out to increase the energy efficiency of PV components, such as cooling systems, PV cell materials, PV modules and inverters. Identifying a low efficiency or total inefficiency in some microgeneration is possible. This fact occurs when the low-power photovoltaic set is acquired without prior analysis by a specialist to assess the user's consumption, the installation location of the PV set, and the energy generation potential [13]. In addition, some related works [14–16] explore different methods for real-time statistical analysis and forecasting of factors that impact end users' energy and economic performance. However, these studies do not focus on maximising the performance of PV systems based on detailed data and information about installation requirements and constraints.

Although it exists everywhere in the world, solar irradiation has particularities that vary according to geographical position, such as the average amount of irradiation that reaches the Earth in one year, cloudiness index, clearness index, temperature, and so on [17]. This gap highlights the need for a more comprehensive approach considering specific installation conditions to optimise PV system efficiency and effectiveness. Therefore, multiple variables (climatic and geographical data, technical specifications, economic factors, regulatory and policy frameworks) must be simultaneously considered while defining the most suitable PV set (PV modules, inverter and batteries) [18].

This article proposes a multi-criteria decision support system to identify the most suitable PV set (PV modules, inverter, and batteries) for a microgrid installation, considering the maximum potential energy generation and global efficiency system as well as minimum acquisition and installation costs. The main expected contributions of the research presented in this paper are as follows:

- It improves the PV set selection and application to extract the maximum installed energy potential and the maximum efficiency of technologies available based on specific implementation requirements.
- It encourages the use of renewable energy sources, since this tool analyses the available budget versus implementation costs and energy generation capacity.
- It supports the decision of specialists or not in the PV set selection according to the implementation requirements.
- The remainder of the paper is structured as follows: Section 2 presents the materials and methods of the research, including (i) a review to improve the understanding of PV set definition requirements, (ii) MCDM methods available to support this research and (iii) the conceptualising of a multi-criteria decision support system for a solar microgeneration installation. Section 3 discusses the results of applying the system in two specific experimental cases. Section 4 discusses the research's conclusion, main advantages and limitations, and finally, Section 5 presents the future perspectives for this research.

2. Material and Methods

2.1. Photovoltaic (PV) Set Definitions

A photovoltaic (PV) set comprises multiple devices: PV modules, inverter, batteries, cabling, hardware, and protection devices. From these devices, two are the main components for the generation of photovoltaic energy: PV modules and inverters.

PV modules convert the solar radiation focused on its surface into heat and electrical energy [19]. When PV modules are exposed to irradiation, they produce changes in electrical properties, generating a potential difference between their terminals and, consequently, electrical current when applied to a circuit [20].

Many types of PV modules are made mainly from crystalline or amorphous materials. The crystalline ones are commonly more expensive than the amorphous ones, but they have higher efficiencies, especially those of monocrystalline materials [21]. Efficiency mainly reflects the percentage of electrical power over the total photon power received from the incident irradiation [22]. Table 1 explores an efficiency comparison among multiple PV cell types, focusing on composition characteristics such as thin film, rigid film, organic sell, etc., and PV efficiency. With commercial cells, there are three different types: monocrystalline silicon, polycrystalline silicon and thin film.

The solar inverter is the second most crucial piece of equipment for solar energy generation. Solar inverters or PV inverters are responsible for converting the DC output of a PV solar panel into a DC or AC that can be fed into a commercial electrical grid (on-grid) or used by a local electrical network (off-grid). There are two solar inverters: (i) central and (ii) micro-inverter.

- The central inverter is the most common commercially, and its name is derived from the installation method since it needs two or more PV modules to work correctly. It is a central and standard part of all modules of the PV system.

- The micro-inverter is integrated with PV modules due to its small size. Typically, the PV panels + inverter set is named the AC module. This equipment has two types of converters in operation to supply energy to the electric network: a CC-DC and a CC-AC.

  Table 2 compares inverters based on the technologies used and their respective efficiencies.

Table 1. Comparison of PV cells: technology vs. efficiency.

PV Material	Status	Efficiency	Characteristics
CdTe (Cadmium Telluride)	Commercial	7%	Thin film on rigid substrates
a-Se:H (Amorphous Silicon)	Commercial	5–10%	Thin film on rigid substrates
Mono-Si (Monocrystalline Silicon)	Commercial	12–18%	Rigid cell
Multi-Si (Polycrystalline Silicon)	Commercial	11–15%	Rigid cell
Ti3C2Tx	Research	17%	Organic cell
c-Si	Special	20%	Rigid cell
In2O3:SnO2	Research	24–26%	Thin film on rigid substrates
GaAs (Gallium Arsenite)	Special	24–28%	Thin film on rigid substrates
Multi-junction PV Cell	Special	39–46%	Thin film on flexible substrates

Source: Based on [23,24].

Table 2. Comparison of solar inverters: technology vs. efficiency.

Author	Characteristics	Efficiency	Specification
SASIDHARAN and SINGH [25]	Full-bridge inverter Single-stage inverter CC-CA isolated Micro-inverter	90.0%	Converter: CC-CA Input: 80 Vdc Output: 220 Vac Potency: 500 W Switching: 4 kHz
WU and CHOU [26]	Multistage inverter (7 stages) Non-isolated Micro-inverter	94.9%	Converter: CC-CA Input: 70 Vdc Output: 110 Vac Potency: 500 W Switching: 15.3 kHz
XUEWEI et al. [27]	Full-bridge inverter Isolated Micro-inverter	95.0%	Converter: DC-DC Input: 21–41 Vdc Output: 200 Vdc Potency: 200 W Switching: 100 kHz
WU et al. [28]	Buck–boost converter Non-isolated Central inverter	95.5%	Converter: DC-DC Input: 0–600 Vdc Output: 380 Vdc Potency: 5000 W Switching: 25 kHz
CHOI e LEE [29]	Fly back Isolated Micro-inverter	96.0%	Converter: DC-DC Input: 24 Vdc Output: 380 Vdc Potency: 180 W Switching: 50 kHz
ARSHADI et al. [30]	Half-bridge inverter Non-isolated Micro-inverter	96.2%	Converter: DC-AC Input: 700 Vdc Output: 220 Vac Potency: 149.5 W Switching: 20 kHz
ZHAO et al. [31]	Half-bridge inverter Non-isolated Micro-inverter	96.5%	Converter: DC-DC Input: 48 Vdc Output: 800 Vdc Potency: 500 W Switching: 100 kHz
CHA et al. [32]	Resonator converter Isolated Micro-inverter	97.5%	Converter: DC-DC Input: 40–80 Vdc Output: 350 Vdc Potency: 370 W Switching: 50 kHz
ARSHADI et al. [30]	Half-bridge inverter Non-isolated Micro-inverter	96.2%	Converter: DC-AC Input: 700 Vdc Output: 220 Vac Potency: 149.5 W Switching: 20 kHz

According to [33], several factors negatively influence the generation of PV energy. Among the identified factors, it is possible to divide them into three categories: (i) geographic, (ii) constructive parameter and installation mistakes. Table 3 presents the impact of each factor on power generation.

Table 3. Impact of external issues in PV.

Category	External Issue	Impact on Power Generation
Geographic position	Temperature	1–10%
	Dust Deposition	0–15%
	Snow	Determined by the Local Installation
	Shading	Determined by the Local Installation
	Spectral distribution	0–5%
Constructive Parameters	Lifetime	0–5%
	Uncertainty of construction parameters	0–5%
Installations Mistakes	Cabling	0–3%
	Installation angle	1–5%

Source: Based on [33].

These factors are relevant for selecting the most suitable set of PV panels, inverters, and other devices for a solar microgrid. Additionally, it is essential to establish how this system will be installed and the maintenance guidelines to be provided to the end user to extract the maximum performance throughout the entire life cycle of the PV system.

2.2. Multi-Criteria Decision-Making: Foundations

Multi-criteria decision-making (MCDM) techniques have emerged to aid decision-making processes involving numerous variables that cannot be easily considered simultaneously to find the optimal solution [34]. These techniques standardise decision-making through mathematical modelling, facilitating the resolution of problems with multiple objectives. Some notable MCDM techniques include PROMETHEE [35], ELECTRE [36], TOPSIS [37], and AHP [38].

- PROMETHEE (Preference Ranking Organization Method for Enrichment Evaluation)—This aids in identifying the most suitable solution when decision-makers have predetermined criteria and alternatives [39]. It prioritises alternatives based on pre-established criteria, providing decision-makers with a comprehensive view of the business and enabling multifunctional decision-making strategies. However, it may encounter ranking issues.
- ELECTRE—This method constructs an over-classification relationship based on decision-makers' preferences towards available alternatives [40]. ELECTRE uses a binary over classification relationship to classify alternatives, employing either a pessimistic or optimistic approach.
- TOPSIS (Technique for Order of Preference by Similarity)—This method is primarily used to rank alternatives based on preference [41]. It selects alternatives closest to the ideal positive solution and farthest from the ideal negative solution, formed using the best and worst values achieved by alternatives across evaluation criteria. Its advantages lie in its simplicity, ability to compare ideal and undesirable scenarios, and quick identification of the best alternative [37].
- AHP (Analytic Hierarchy Process)—This structured decision-making tool helps individuals and organisations solve complex problems by breaking them down into simpler, more manageable components [42]. AHP is especially valuable in scenarios where decisions involve multiple criteria, both qualitative and quantitative. AHP has been extensively utilised across different domains. Studies [43,44] have applied AHP to develop collaborative supplier performance indices, select cleaning systems for parts, choose IoT platforms, assess disaster-response management systems, analyse interoperability, and prioritise software risks [45].

According to [41], the AHP and the TOPSIS are recognised as two of the most effective multi-criteria decision-making (MCDM) methods [46]. Both methods offer unique advantages that make them well-suited for complex decision-making scenarios involving multiple criteria and alternatives.

In this context, AHP enables using qualitative or quantitative data for criterion analysis in various health, industrial, technical, and strategic applications [47,48]. The first step of AHP involves decomposing the decision problem into a hierarchy with several levels, starting from the overall goal at the top, followed by criteria and sub-criteria, and finally, the alternatives at the bottom [38]. This hierarchical structure allows decision makers to focus on smaller, related sets of decision elements, simplifying the analysis.

The core of AHP lies in making pairwise comparisons between elements at each level of the hierarchy. Decision- makers compare the relative importance of criteria, sub-criteria, or alternatives two at a time, using a scale of 1 to 9, where 1 indicates equal significance and 9 indicates extreme importance of one element over the other [49]. These comparisons are used to construct a comparison matrix for each level of the hierarchy. A priority vector is calculated from these matrices, representing each element's relative weight. Additionally, AHP includes a consistency check to ensure that the judgments made in the pairwise comparisons are logically consistent. A consistency index (CI) is calculated, and if the value is less than 0.1, the consistency is considered acceptable; otherwise, the judgments should be reviewed and adjusted. Finally, the priority weights are combined to calculate the overall score for each alternative, helping to identify the best option based on the defined criteria [38].

In parallel, TOPSIS operates on the principle that the chosen alternative should have the shortest distance from the positive ideal solution (PIS), which represents the best possible scenario, and the farthest distance from the negative ideal solution (NIS), representing the worst possible scenario [41]. This dual consideration of the ideal and anti-ideal solutions makes TOPSIS particularly effective in handling trade-offs among multiple conflicting criteria, providing a balanced evaluation of each alternative. The method is straightforward and intuitive, normalising data, calculating distance measures, and ranking other options based on their relative closeness to the ideal solution.

The calculation process of TOPSIS involves different steps, according to [37,50]. First, the decision matrix lists all alternatives and their performance scores across various criteria. Each criterion's values are then normalised to transform them into dimensionless numbers, facilitating comparison. This normalisation is typically performed using the Euclidean distance formula. Next, the weighted normalised decision matrix is formed by multiplying the normalised values by their corresponding criterion weights, reflecting each criterion's relative importance. The positive ideal solution (PIS) and negative ideal solution (NIS) are then determined. The PIS consists of the best values for each criterion (maximum for benefits and minimum for costs), while the NIS consists of the worst values (minimum for benefits and maximum for costs). The Euclidean distances to the PIS and NIS are calculated for each alternative. Finally, the relative closeness of each alternative to the ideal solution is computed, and the other options are ranked accordingly. The alternative with the highest relative closeness to the PIS is considered the best choice.

Therefore, the MCDSS for identifying the most suitable PV sets employs both AHP and TOPSIS methods in parallel to enhance the overall reliability and effectiveness of the decision-making process. Utilising these methods simultaneously allows for a comprehensive evaluation of their performance, helping to identify which method best determines the optimal photovoltaic system according to the criteria specified by the user. The following section explores the steps in developing and implementing this decision support system.

2.3. Multi-Criteria Decision Support System (MCDSS) for Photovoltaic Set Identification

For the correct functioning of the method to be developed, specific data must be inputted as the calculation basis for determining the customised photovoltaic plant for the installation site. Calculating the energy potential estimate of a region requires integrating solar irradiation factors and temperature factors to assess system losses. Since temperature interference varies throughout the day, it is necessary to calculate the behaviour of the photovoltaic system hour by hour for a year to apply temperature losses accurately. Therefore, the system's response will be more precise if the information is more detailed. In addition, monthly averages of solar irradiation data provide better detail than just an annual average.

Based on this context, the multi-criteria decision support system (MCDSS) for photovoltaic set definition was structured in (i) mapped input data, (ii) data pre-processing, (iii) MCDM application, and (iv) output data. Figure 1 presents the MCDSS for photovoltaic set definition architecture.

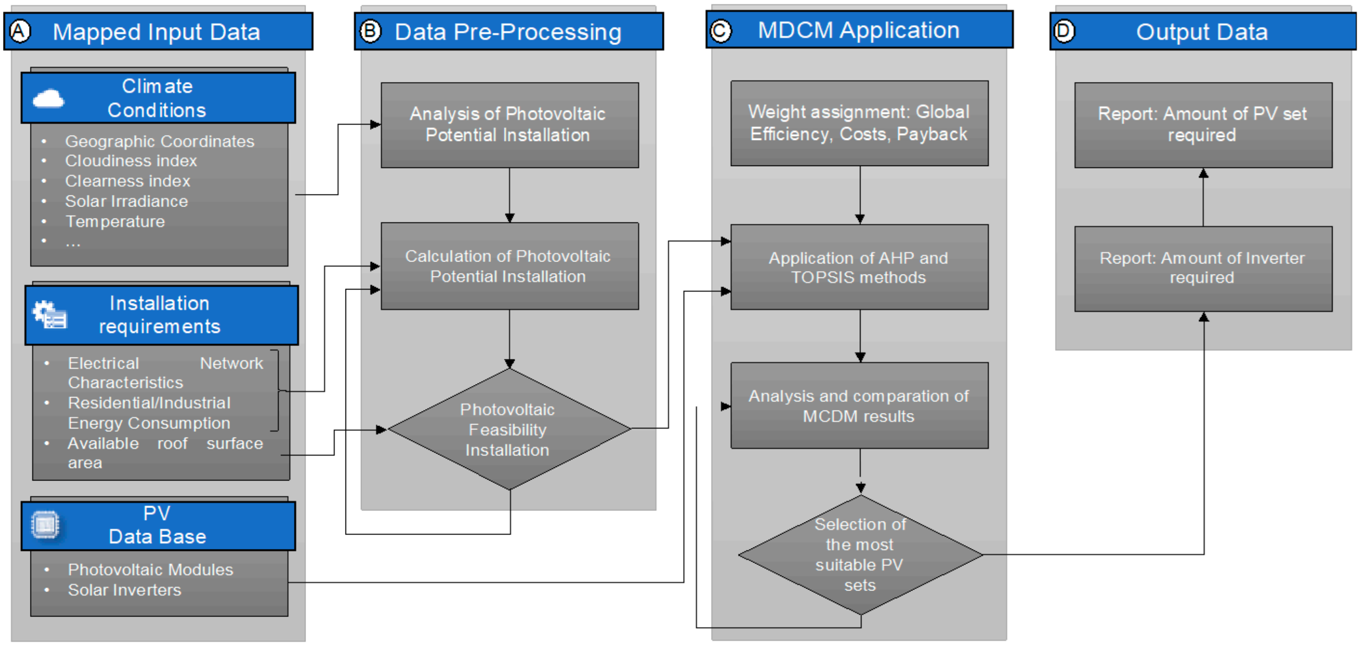

Figure 1. MCDSS for photovoltaic set definition architecture.

- Mapped Input Data (Detail A of Figure 1)—In this section, input data are mapped and collected. These data include crucial information such as climate conditions, installation requirements, and a photovoltaic database. Climate conditions provide insights into solar irradiation patterns and temperature, while installation requirements encompass practical considerations such as available physical space and ideal orientation of solar panels. The photovoltaic database contains details on products and technologies available in the market, essential for comparison and proper equipment selection.
- Data Pre-Processing (Detail B of Figure 1)—Data pre-processing plays a fundamental role in treating and preparing the mapped input data for analysis. This process is divided into sub-steps, including the analysis of available photovoltaic potential, calculation of demanded photovoltaic potential, and evaluation of the feasibility of photovoltaic system installation. These steps help determine the maximum amount of solar energy that can be generated, the system's required capacity to meet electricity demand, and whether installation is viable in each location.
- MCMD Application (Detail C of Figure 1)—The application of multi-criteria decision methods (MCMD) is the heart of the system, where processed data are analysed and used to make decisions. AHP and TOPSIS are applied to determine the best photovoltaic set configuration. Evaluated criteria typically include system efficiency, installation cost, and return on investment time.
- Output Data (Detail D of Figure 1)—The system produces outputs that include specific recommendations for PV sets based on defined criteria. These criteria may include selecting photovoltaic module models, inverters, and other relevant considerations.

These results are presented clearly and comprehensively, providing users with essential information for making informed decisions about implementing photovoltaic systems.

2.3.1. Mapped Input Data

The mapped input data consist of three essential components: (i) climate conditions, (ii) installation requirements, and (iii) PV database. These elements provide information to support the next steps of the MCDSS, allowing the selection and sizing of photovoltaic systems in different contexts and locations.

The first essential component is Climate Conditions, which offer definitions of geographic coordinates, cloudiness index, clearness index, solar irradiation patterns, ambient temperature, and other relevant environmental factors. These data are fundamental for calculating the energy generation capacity of photovoltaic systems at different times of the year and under various weather conditions. The geographic coordinates are obtained directly from the global positioning system (GPS), which provides precise information about the specific location of a given place. These data are essential for analysing and planning photovoltaic systems, as they help determine solar exposure and the ideal angle of solar panels. Information about cloudiness, clarity, and temperature indices is also obtained from reliable meteorological sources, such as national weather websites. In the case of Brazil, for example, these data can be extracted from the National Institute of Meteorology (INMET) [51]. These indices provide valuable insights into local weather conditions, including cloud presence, atmospheric transparency, and temperature variations throughout the day and seasons.

Solar irradiance, measured in units of W/m^2 (watt per square metre), represents the instantaneous amount of energy received from the Sun in a specific region. Accurately sizing a photovoltaic (PV) system for electricity generation requires calculating the maximum, minimum, and average annual solar irradiance throughout the day and the average annual solar irradiance during peak hours. This assessment is crucial for optimising system performance, since these factors collectively impact the availability and intensity of solar energy, highlighting the importance of comprehensive analysis and consideration during system design and implementation.

The amount of solar irradiance reaching the Earth's surface is influenced by various factors, including geographical features, cloud cover, clearness index, temperature, and other atmospheric conditions. Therefore, Equation (1) estimates the irradiation received at the top of the atmosphere in a specific region in each period [52].

$$I_{\Delta t} = \frac{W_0}{r^2}\left\{(t_2 - t_1)\cdot sin\delta\cdot sin\phi + \frac{12}{\pi}\cdot cos\delta\cdot cos\phi\cdot[sin(\tau_2) - sin(\tau_1)]\right\}, \quad (1)$$

where $I_{\Delta t}$ is the average intensity of local irradiation during the interval (Δ_t), which is measured in W/m^2 (watt per square metre); W_0 is a solar constant whose value is 1380 W/m^2; r is the ratio between the current distance of the Sun in relation to Earth and the average distance from the Sun to Earth; t_1 and t_2 are the beginning and end times of the interval Δ_t; δ is the Sun's declination; ϕ is the latitude of the studied location and τ is the hourly angle of the Sun; τ_1 is the hourly angle of the Sun corresponding to t_1 and τ_2 is the hourly angle of the Sun corresponding to t_2. Equation (2) simplifies Equation (1) for a given period, keeping the variable δ and ϕ.

$$I_0 = \frac{W_0}{r^2}\cdot sin\alpha, \quad (2)$$

where I_0 is the instantaneous intensity of irradiation at the location, α is the solar elevation angle, and r is the ratio of the current distance from the Sun to the Earth. r is determined by Equation (3), and α is determined by Equation (4).

$$r = 1.0 + 0.017\cdot cos\left[\frac{2\pi}{365}\cdot(186 - D)\right] \quad (3)$$

$$sin\alpha = sin\delta\cdot\ sin\phi + cos\delta\cdot cos\phi\cdot cos\tau \quad (4)$$

where D is the Julian day in sequential count; α is the solar elevation angle; δ is the Sun's declination; ϕ is the latitude of the studied location, and τ is the hourly angle of the Sun. Based on the equations above, it is possible to estimate the solar irradiance at the top of the atmosphere for any location on planet Earth.

It is important to calculate the maximum, minimum, and average annual solar irradiance throughout the day and the average solar yearly irradiance during peak hours to size the PV set correctly for electricity generation. The amount of solar irradiance received from the Sun on the Earth's surface is directly impacted by multiple factors such as geographical factors, cloudiness and clearness index, temperature, and so on.

The second element is Installation Requirements, which encompass a variety of practical considerations, including the availability of physical space, optimal orientation and angle of solar panels, safety requirements, and local regulations. These data help determine the feasibility and logistics of installing photovoltaic systems in different locations and environments.

Additionally, residential or industrial energy consumption data are fundamental variables across the process to determine the optimal configuration of the photovoltaic system. This information provides crucial insights into energy consumption patterns over time, enabling a precise analysis of the site's energy needs. Additionally, these data help identify peak consumption times, which are essential for properly sizing the system and determining the required energy storage capacity, such as batteries. Therefore, the information needed is the average consumption, the amount charged by the concessionaire for the kW consumed, the installation type, the annual tariff adjustment amount and the available roof surface.

The values entered in the installation requirements are used to calculate the potential to be installed, the investment payback time, and the possibility of installation according to the value entered for the available area. If the area is insufficient, the system will not find any option for a PV module that meets the power required to meet the user's demand.

The last essential component is Photovoltaic Database, which contains detailed information about a wide range of products and technologies available in the market. These data include technical specifications of solar panels, inverters, and other components and performance and efficiency data. This information is essential for comparing and selecting the most suitable equipment to meet the specific needs of each photovoltaic project. Table 4 shows an example of the PV database variables.

Table 4. Example of the data for a PV database.

Brand		Model	Area (m^2)	Weight (kg)	V_{oc} (V)	I_{sc} (A)	V_{mp} (V)	I_{mp} (A)	Power (W)	Eff (%)	Price (USD)
RENESOLA	[53]	RS6535ME3	2.58	29.0	49.5	13.78	41.5	12.90	535	21	116.20
UP SOLAR	[54]	UPM375MH	1.82	19.0	41.5	11.57	34.6	10.93	375	21	128.77
UP SOLAR	[54]	UPB450P	2.17	28.0	49.5	11.60	41.3	10.88	450	22	115.28
CANADIAN	[55]	CS6W535MS	2.56	27.6	49.0	13.85	41.1	13.02	535	21	125.27
CANADIAN	[55]	CS6W550MS	2.56	27.6	49.6	14.00	41.7	13.20	550	21	127.28
CANADIAN	[55]	CS6W560MS	2.56	27.6	50.0	14.10	42.1	13.31	560	22	128.78
SCHUTEN	[56]	STM365/120	1.81	20.5	41.2	11.29	33.9	10.75	365	20	127.27
SCHUTEN	[56]	STM395/120	1.81	20.5	42.0	11.65	35.6	11.05	395	22	137.57

2.3.2. Data Pre-Processing

Data pre-processing handles the mapped input data and supports the multi-criteria decision-making models with structured information. Data pre-processing is divided into sub-steps, which are (i) analysis of available photovoltaic potential, (ii) calculation of demanded photovoltaic potential, and (iii) assessment of the feasibility of photovoltaic system installation.

The analysis of installed photovoltaic potential is the first step of data pre-processing. It focuses on two fundamental analyses for determining the best photovoltaic set, which are (i) defining solar irradiation at the location on the ground where the photovoltaic system will be installed and (ii) determining the average temperature at the location where the photovoltaic system will be installed. The definition of solar irradiation at the location on the ground where the photovoltaic system will be installed is based on Equations (1)–(4), which are available on different platforms such as Weather Spark [57] and Solar Electricity Handbook [58]. Figure 2 demonstrates the potential solar irradiation on the inclined plane of the São Paulo region, Brazil, throughout April 2024. For this report, the geographical coordinates of São Paulo are −23.548 degrees latitude, −46.636 degrees longitude, and 2523 ft elevation.

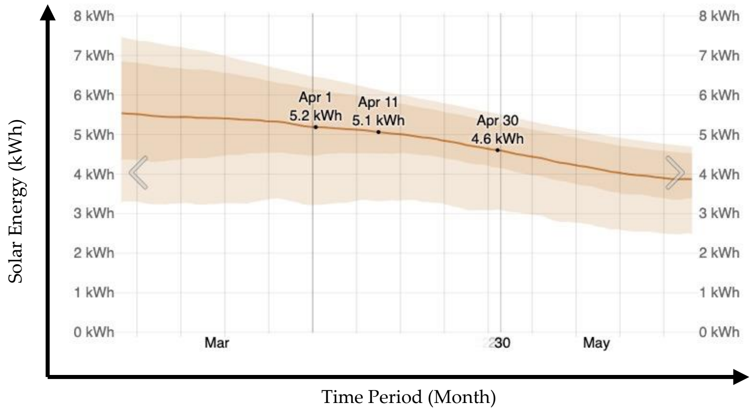

Figure 2. The average daily shortwave solar energy reaches the ground per square metre (orange line), with 25th to 75th and 10th to 90th percentile bands. Source: [57].

With the determination of the irradiation potential, it is necessary to obtain the average temperature of the region. The temperature of the area where the system will be installed strongly influences photovoltaic energy generation, so it must be calculated before estimating the photovoltaic potential of the region. In addition to ambient temperature, it is necessary to assess the temperature of the photovoltaic module, as the higher the temperature of the solar system, the lower its efficiency. The average temperature can be obtained from the Weather Spark and Fabhabs platforms, and the photovoltaic module temperature can be obtained from Equation (5). Figure 3 shows the average temperature of the São Paulo region, Brazil, throughout April 2024.

$$T_{cel} = T_a + \left(\frac{T_{NOCT} - 20}{0.8}\right) \cdot \; I_{\%} \tag{5}$$

where T_{cel} is the operating temperature of the photovoltaic cell, T_α is the ambient temperature, T_{NOCT} is the value of the operating temperature of the photovoltaic cell provided by the module datasheets, and $I_{\%}$ is the percentage obtained from the behaviour of irradiation at the top of the atmosphere relative to its maximum value. After estimating the operating temperature of the modules, it is possible to calculate the percentage of losses due to temperature, which has a value of −0.40% in power for each °C above 25 °C. Therefore, the photovoltaic potential of the region is given by Equation (6).

$$P_{PV} = I_{\Delta t} \cdot TL_{\%} \tag{6}$$

where P_{PV} is the available photovoltaic potential; $I_{\Delta t}$ is the irradiance reaching the ground; $TL_{\%}$ is the temperature loss expressed as a percentage relative to energy production, which can be directly applied to the value of the irradiance reaching the ground.

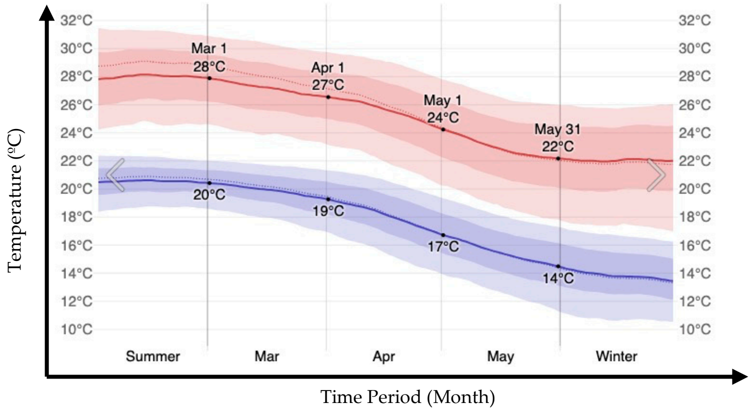

Figure 3. The daily average high (red line) and low (blue line) temperature, with 25th to 75th and 10th to 90th percentile bands. The thin dotted lines are the corresponding average perceived temperatures. Source: [57].

After the analysis of the available photovoltaic potential (Stage 1), which determines the maximum amount of solar energy that the photovoltaic system can generate at a given location, it is necessary to calculate the installed potential (Stage 2) for the photovoltaic system. To calculate the installed photovoltaic potential, it is necessary to consider (i) the historical energy consumption of the residence or industry and (ii) the availability of usable area for the installation of the photovoltaic system.

The local energy consumption history analysis considers consumption patterns over time, seasonality, and daily variations. These data are essential to estimate the amount of electrical energy the photovoltaic system will need to generate to meet consumer demand. On the other hand, the availability of roof area for the installation of solar panels involves evaluating the usable area of the roof, its orientation and tilt relative to the Sun, the presence of shading from nearby trees or buildings, and other possible physical constraints. Based on this information, it is possible to calculate the demanded photovoltaic potential, determining the necessary capacity of the photovoltaic system to meet the electrical energy demand of the location. This calculation is essential to properly size the photovoltaic system and ensure it can efficiently and economically meet the consumer's energy needs. If the available area is insufficient, the user will be informed of the maximum capacity to be installed.

Finally, the feasibility of installing the photovoltaic system is assessed, considering various factors such as installation costs, return on investment, government incentives, regulatory and environmental restrictions, and technical feasibility. This assessment is crucial to determine whether the photovoltaic system installation is viable and economical at a given location. These data pre-processing steps provide a solid foundation for successful planning and implementation of photovoltaic systems, ensuring that they are correctly sized, optimised for maximum utilisation of available solar energy, and economically viable for the customer.

2.3.3. MCDM Application and Output Data

The equipment selection will be carried out using multi-criteria decision support methods, AHP and TOPSIS, to provide a customised installation proposal for each region, as well as the energy demand and specific requirements the user demands. Therefore, combining methods will assist users interested in generating their own energy, aiming to minimise installation costs and reduce energy demand so that only installation availability costs are charged.

The methods allow and provide for the inclusion of qualitative parameters to indicate the preference of one criterion over another. Therefore, the user will be asked to determine the weights for the criteria evaluated by the decision methods, which must meet the consistency index. The criteria assessed by the multi-criteria decision support methods will be (i) system efficiency, (ii) installation cost, and (iii) payback period. All criteria have a direct relationship; for example, the most efficient system may have a higher initial investment, while a cheaper system may not guarantee a shorter payback period for the installed photovoltaic system.

- System efficiency evaluation criterion—the method will indicate the equipment with the best energy utilisation. Priority will be given to photovoltaic modules that can obtain higher electrical power for a certain amount of solar irradiation.
- Installation cost evaluation criterion—the decision will be to select equipment with the lowest cost.
- Financial analysis and evaluation criteria will lead the method to prioritise a balanced installation, aiming to reduce the investment payback time. To conduct an economic analysis of the photovoltaic system to be installed, factors such as payback period, net present value (NPV), and internal rate of return (IRR) will be evaluated. To achieve this, it is necessary to verify the kilowatt-hour rate charged by the local utility company where the equipment will be installed.

Due to the many alternatives, decision support methods will facilitate the decision-making process regarding which photovoltaic module and inverter model will be installed according to the user's needs regarding the evaluated criteria. Therefore, the first recommendation will be the quantity and model of photovoltaic modules that best match the user-entered criteria. Based on the power generated by the photovoltaic modules, the method will exclude some inverter models to avoid errors during selection. Inverters will be excluded if the energy generated by the selected modules is less than 80% of the nominal inverter power or 20% higher. This result prevents an improper choice by the method, such as recommending an oversized inverter based on the "cost" criterion when actual values are input.

For the selection of a photovoltaic module alternative, various factors will be analysed, such as open-circuit voltage (V_{oc}), maximum power (P_{Max}), maximum power current (I_{Max}), area (a), efficiency (η), and cost (C), which will be compared to determine the best alternative. The exact process will be carried out to determine the best inverter alternative, where the analysed factors will include maximum power (P_{Max}), efficiency (η), maximum DC voltage (Vdc), and cost (C). The PV equipment selected by each decision support method will be presented and compared to verify if the chosen alternatives correspond to the trends provided by the user. Two comparisons will be made: first, the photovoltaic modules and inverters will be separately compared, and finally, the components will be integrated to generate the complete system for the final comparison.

Each evaluated criterion's maximum and minimum values will be used for these comparisons, generating a range of values. Subsequently, the value of the respective analysed criterion for the selected alternative will correspond to a percentage within this previously established range, providing a better visualisation of the selected alternative. For example, assuming the global maximum and minimum values for the efficiency criterion of the modules are, respectively, 15% and 18%, and the alternative selected by the multi-criteria decision support method has an efficiency of 17.5%, according to the previous values, the selected module corresponds to 83.33% of the value range of the alternatives. By checking this result, it is possible to observe that there are more efficient modules among the options, but they were not selected due to some other criterion, which could be the high cost. After verifying the comparisons of the alternatives selected by each multi-criteria decision support method, it will be up to the user to choose the most suitable option.

Finally, the method will present which photovoltaic module model and quantity are necessary for the installation to have an average annual capacity equivalent to that established by the user when determining the energy demand of the location where the system will be installed, according to the photovoltaic module models entered in the method's database. The same will be performed with the inverters, but considering the equipment's construction factors, especially the maximum photovoltaic voltage, which could damage the equipment if it exceeds the manufacturer's specification.

3. Results and Discussion

The MCDSS-PV was applied in two scenarios with different locations: (i) Curitiba, Brazil, and (ii) Barreiras, Brazil. Table 5 presents monthly irradiation and temperatures for these regions.

Table 5. Monthly averages of irradiation and temperatures for the cities of Curitiba and Barreiras.

Mapped Data	January 2023	February 2023	March 2023	April 2023	May 2023	June 2023	July 2023	August 2023	September 2023	October 2023	November 2023	December 2023
						Curitiba						
$I_{\Delta t}$ (W/m^2)	6400	6000	5800	4900	3900	3400	3600	4400	5400	5900	6600	6800
T_{max} (°C)	28	28	28	23	21	20	19	21	21	23	25	25
T_{min} (°C)	16	16	15	13	10	8	8	9	11	13	14	15
						Barreiras						
$I_{\Delta t}$ (W/m^2)	6000	6000	5800	5700	5500	5400	5800	6400	6800	6500	6000	6000
T_{max} (°C)	30	31	31	31	33	32	32	34	36	35	32	31
T_{min} (°C)	21	21	21	21	20	19	18	19	22	23	22	21

Source: [57].

For the study of this scenario, a demand of 350 kWh/month will be considered in a three-phase installation, with an available power to be deducted of 100 kWh/month. In other words, the installed capacity must supply 3000 kWh/year, which the PV installation must supply.

3.1. Case Study of Barreiras City, Brazil

Barreiras' City of Bahia state in Brazil, according to [57], is the region with the highest irradiation potential in the northeast of the country, reaching daily average values of 5995 Wh/m^2, as shown in Table 5. This city is located at the following coordinates: latitude: −12.142939, longitude: −45.0089385, altitude: 454 m, and GMT −3. Figure 4 presents the annual irradiance map of northeast Brazil and highlights Barreiras' City in Bahia. Figure 5 demonstrates the average high and low temperatures.

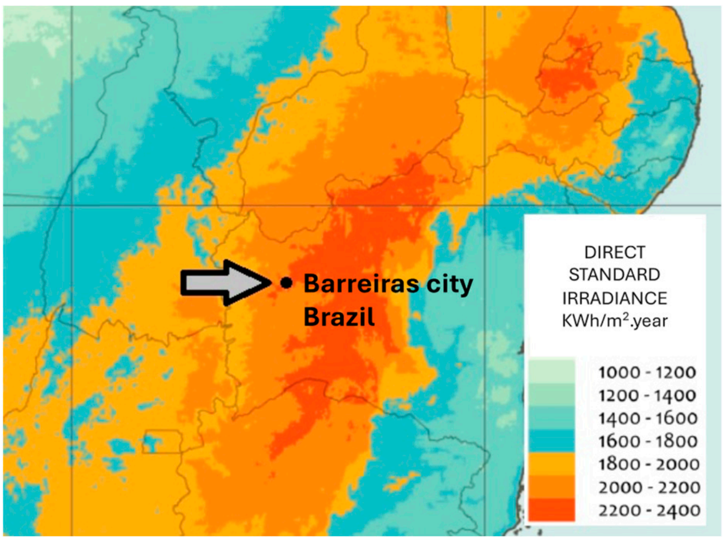

Figure 4. Average annual irradiation in Barreiras' City, Brazil. Source: [57].

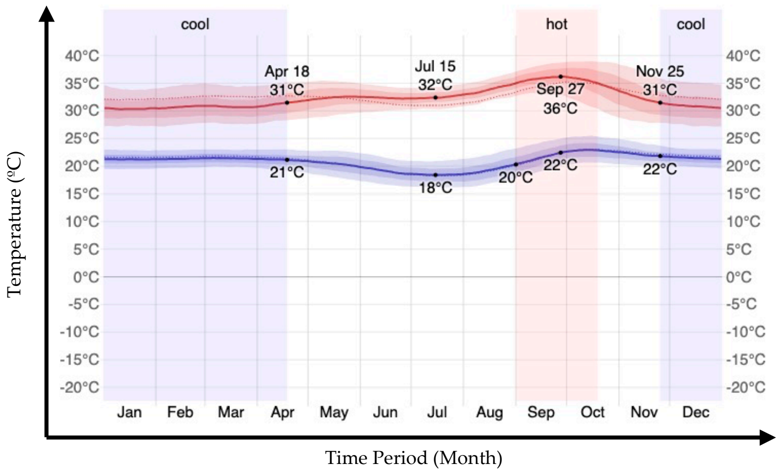

Figure 5. The average temperature highs and lows in Barreiras City. Source: [57].

After verifying the geographical conditions of the region of Barreiras City, it was defined that for this installation, the evaluation criterion to be maximised was the installation cost. Therefore, both decision support methods should select alternatives with lower fees. The other criteria were determined considering the coherence ratio, whose value must be less than 10%. Therefore, if the weight for the installation cost is 100, the other criteria have weights of 75. When applying the expert method for determining the PV set, a proposal was obtained, as shown in Figures 6 and 7.

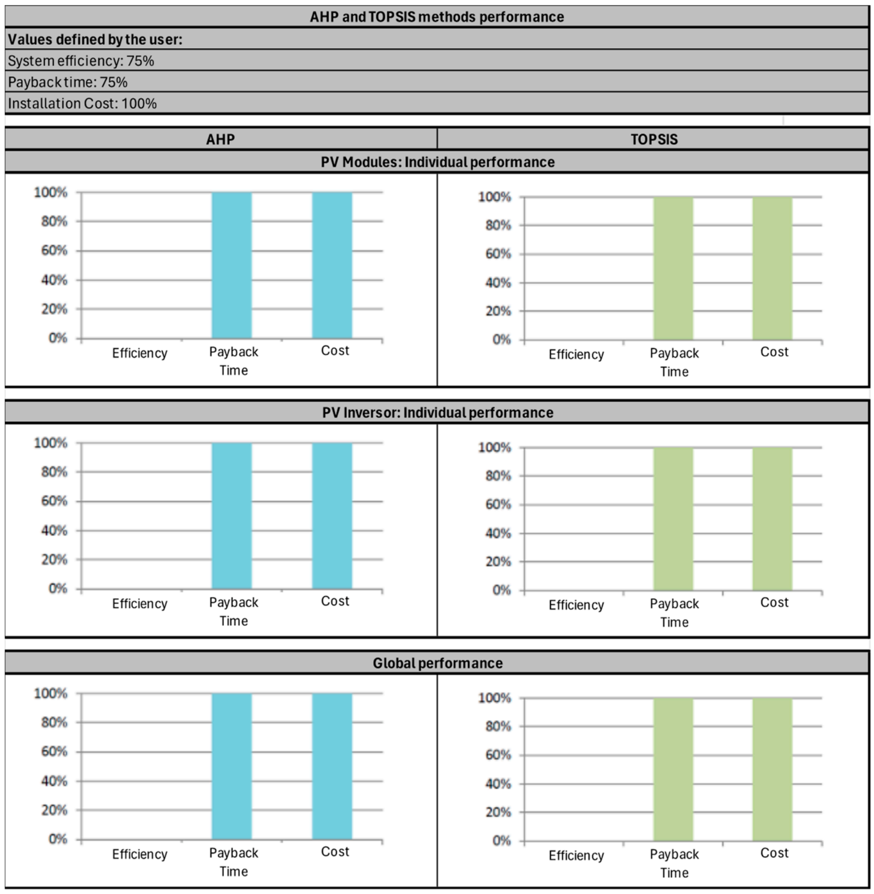

Figure 6. Comparison of the alternatives selected by the MCDSS for photovoltaic set definition concerning the global range of criteria for the case study of Barreiras City.

AHP	TOPSIS
PV modules	
PV Module selected: TEST MOD285W_15	**PV Module selected: TEST MOD285W_15**
Quantity: 6	Quantity: 6
Installed power: 1710.0W	Installed power: 1710.0W
Payback: 0.92 years	Payback: 0.92 years
Cost: USD 585.69	Cost: USD 585.69
Efficiency: 15.0%	Efficiency: 15.0%
Surface: 11.4 m^2	Surface: 11.4 m^2
PV Inversor	
PV Inversor selected: TEST 2KW_96	**PV Inversor selected: TEST 2KW_96**
Quantity: 1	Quantity: 1
Installed power: 2000W	Installed power: 2000W
Payback: 1.75 years	Payback: 1.75 years
Cost: USD 698.79	Cost: USD 698.79
Efficiency: 96.0%	Efficiency: 96.0%
Global Information	
Power output: 3322 KWh.year	Power output: 3322 KWh.year
Average annual demand: 4200 KWh.year	Average annual demand: 4200 KWh.year
Availability demand: 1200 KWh.year	Availability demand: 1200 KWh.year
Energy balance: 322 KWh.year	Energy balance: 322 KWh.year
Overall method performance	**Overall method performance**
Energy efficiency rate: 0.0%	Energy efficiency rate: 0.0%
Payback time rate: 100.0%	Payback time rate: 100.0%
Investment cost rate: 100.0%	Investment cost rate: 100.0%
System payback time: 2.67 years	System payback time: 2.67 years
System cost: USD 1 284.50	System cost: USD 1 284.50
System Efficiency: 14.4%	System Efficiency: 14.4%
Net Present Value: USD 10,338.27	Net Present Value: USD 10,338.27
Internal Rate of Return: 49.0%	Internal Rate of Return: 49.0%
Energy savings over 25 years: USD 28,289.03	**Energy savings over 25 years: USD 28,289.03**

Figure 7. Analysis of the alternatives selected by the MCDSS for photovoltaic set definition of the City of Barreiras.

After examining the proposals generated by both methods, it became evident that the selected photovoltaic equipment was identical. As anticipated, both methods prioritised equipment with the lowest cost, aligning with the user's requirements. Given these case study findings, it is impossible to determine the method that demonstrates the most suitable performance because both methods choose the same PV set for a micro-generation.

3.2. Case Study of Curitiba City, Brazil

The second city to be analysed is Curitiba of Paraná state in Brazil. According to Pereira et al. (2017), the estimated average daily irradiation for the country's Southern region is 4.53 kWh/m^2·day. The Southern region presents an average daily irradiation 17.48% lower than the Northeast region. Curitiba has the following coordinates: latitude: −25.401; longitude: −49.249; altitude: 935 m; and GMT −3. Figure 8 presents the annual irradiance map of Brazil's south and highlights Curitiba city in Parana. Figure 9 demonstrates the average high and low temperatures.

Due to the first case study prioritising installation cost, the weight of the investment payback time was maximised for the case study in Curitiba. Therefore, the MCDSS for photovoltaic set definition tended to have a balanced value between efficiency and cost for determining the system to be installed. The weight assigned to "payback time" was 100%, and for the other criteria, the weight was 75%. The proposal generated by the MCDSS can be seen in Figures 10 and 11.

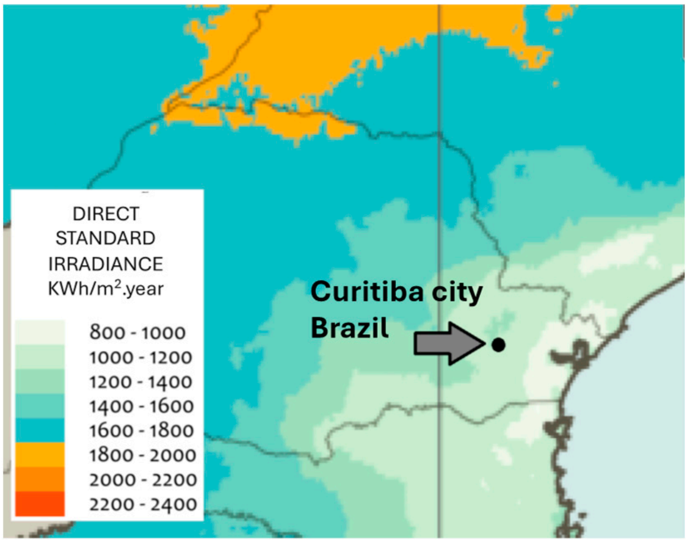

Figure 8. Average annual irradiation in Curitiba city, Brazil. Source: [57].

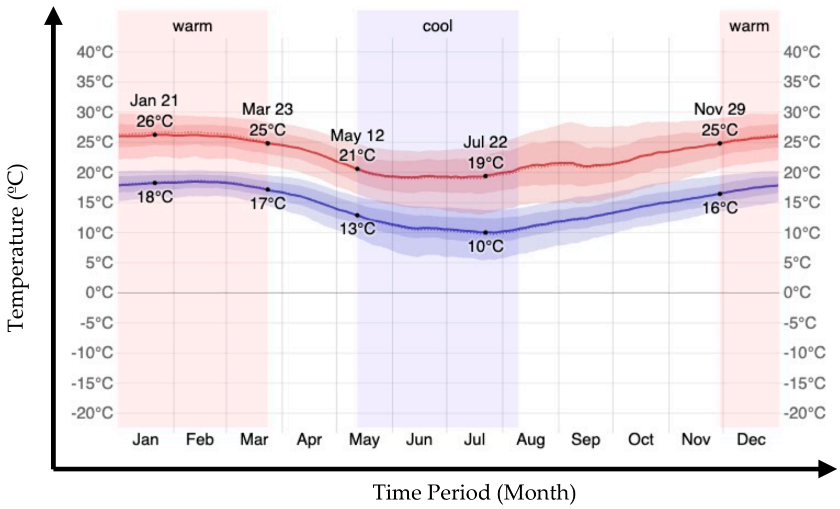

Figure 9. Average high and low temperature in Curitiba city, Brazil. Source: [57].

As observed in Figures 10 and 11, the methods selected divergent alternatives. For the selection of photovoltaic modules, the AHP method sought the equipment with the shortest payback time among the options, as desired by the user. This photovoltaic module model had the lowest cost among the possible options. On the other hand, the TOPSIS method selected a photovoltaic module model that was quite similar but had slightly higher efficiency than the one AHP selected. The methods used to determine inverters had completely divergent responses. The AHP method selected an inverter model with the shortest payback time possible, like when choosing photovoltaic modules. However, the TOPSIS method selected the most efficient inverter model among the available options, ignoring models with shorter payback times and lower costs. Upon analysing the system, it was possible to verify that the photovoltaic system selected by the AHP method minimised the investment payback time and selected the cheapest possible system within the range offered by the alternatives. The TOPSIS method determined a slightly more efficient system than the proposal provided by AHP. Still, it did not achieve a satisfactory result for the payback time criterion as required by the user.

Figure 10. Comparison of the alternatives selected by the MCDSS for photovoltaic set definition concerning the global range of criteria for the Curitiba case study.

Upon analysing the systems proposed by the decision methods, it is possible to verify that despite the evaluation graphs of the selected alternatives being completely different, the photovoltaic systems determined by AHP and TOPSIS are similar due to the restricted range of options for choosing the inverters. The annual power generated by the systems is 3036 kWh/year for the installation selected by the AHP method and 3056 kWh/year for the system chosen by the TOPSIS method, generating a positive energy balance of 36.0 kWh and 56.0 kWh, respectively. For the analysis of the maximised criterion, the investment payback time, the AHP method selected a system with a payback time value of 2.76 years. On the other hand, the TOPSIS method selected photovoltaic component alternatives so that the payback time was 2.95 years. When analysing the different criteria for efficiency, the TOPSIS method selected alternatives whose overall efficiency was higher than the proposal of the AHP method, reaching a global efficiency value of 14.8% compared to the 14.4% chosen by the AHP method. For the installation cost criterion, the AHP method selected an installation that was 6.1% cheaper than the system proposed by the TOPSIS method, whose total cost was USD 1284.49.

When analysing the economic viability, the system proposed by the AHP method obtained a better IRR value, reaching 52.0%. The NPV value was also higher for the system determined by the AHP method, which was USD 9336.15. Analysing the amount saved on electricity at the end of the photovoltaic system's life, the installation proposed by the TOPSIS method presented a higher value compared to the system proposed by the AHP method, where the resulting value was USD 26,021.92, 0.7% higher than the value determined by the photovoltaic installation by the AHP method.

AHP	TOPSIS
PV modules	
PV Module selected: TEST MOD285W_15	**PV Module selected: TEST_mod286,9W_15,1**
Quantity: 6	Quantity: 6
Installed power: 1710.0W	Installed power: 1721.4W
Payback: 1.01 years	Payback: 1.02 years
Cost: USD 585.69	Cost: USD 595.00
Efficiency: 15.0%	Efficiency: 15.1%
Surface: 11.4 m^2	Surface: 11.4 m^2
PV inversor	
PV Inversor selected: TEST 2KW_96	**PV Inversor selected: TEST 2KW_98**
Quantity: 1	Quantity: 1
Installed power: 2000W	Installed power: 2000W
Payback: 1.75 years	Payback: 1.93 years
Cost: USD 698.79	Cost: USD 772.35
Efficiency: 96.0%	Efficiency: 98.0%
Global Information	
Power output: 3036 KWh.year	Power output: 3056 KWh.year
Average annual demand: 4200 KWh.year	Average annual demand: 4200 KWh.year
Availability demand: 1200 KWh.year	Availability demand: 1200 KWh.year
Energy balance: 36 KWh.year	Energy balance: 56 KWh.year
Overall method performance	**Overall method performance**
Energy efficiency rate: 0.0%	Energy efficiency rate: 11.0%
Payback time rate: 100.0%	Payback time rate: 77.0%
Investment cost rate: 100.0%	Investment cost rate: 84.0%
System payback time: 2.76 years	System payback time: 2.95 years
System cost: USD 1 284.49	System cost: USD 1 367.35
System Efficiency: 14.4%	System Efficiency: 14.8%
Net Present Value: USD 9336.15	Net Present Value: USD 9324.03
Internal Rate of Return: 52.0%	Internal Rate of Return: 49.0%
Energy savings over 25 years: USD 25,849.61	**Energy savings over 25 years: USD 26,021.92**

Figure 11. Analysis of the alternatives selected by the MCDSS for photovoltaic set definition of Curitiba City.

4. Conclusions

This research presents a multi-criteria decision support system (MCDSS) designed to optimise the selection of photovoltaic (PV) sets for microgrid installations. By integrating two robust multi-criteria decision-making (MCDM) methods, AHP and TOPSIS, the MCDSS provides a comprehensive framework for evaluating PV sets based on efficiency, cost, and return on investment. Applying this system in case studies from Barreiras and Curitiba demonstrates its effectiveness, yielding global efficiencies of 14.4% and 14.8% and internal rates of return (IRR) of 56.0% and 52.0%, respectively.

The findings highlight significant analytical, methodological, and managerial contributions. Analytically, the study offers a detailed assessment model for PV set selection, addressing the critical factors impacting energy generation. Methodologically, it showcases the integration of AHP and TOPSIS in renewable energy applications, enhancing decision-making processes. Managerially, the MCDSS serves as a practical tool for decision-makers, improving the feasibility and attractiveness of microgeneration projects.

Challenges like low energy conversion efficiency and shading effects remain despite technological advancements and reduced costs. The proposed MCDSS addresses these issues, facilitating more efficient and accessible solar energy generation. This research underscores the potential of MCDSSs to support the broader adoption of renewable energy sources, contributing to a sustainable energy future.

Implementing this system can reduce the complexity of selecting the most appropriate PV components, making it easier for experts and non-experts to make informed decisions. The MCDSS ensures that the selected PV sets are tailored to maximise energy output and economic viability by considering various factors such as climatic conditions, geographic location, and specific installation requirements. Additionally, the research highlights the importance of considering local environmental factors and specific installation conditions in the selection process. By incorporating these variables into the MCDSS, the system can provide more accurate and context-sensitive recommendations, ultimately leading to better performance and higher satisfaction for end-users.

Therefore, the MCDSS is a method for assessing and selecting PV sets based on efficiency, cost, and return on investment. Methodologically, it integrates multiple MCDM techniques, demonstrating their applicability in renewable energy. Managerially, it offers a practical tool for decision-makers in the energy sector to enhance the feasibility and attractiveness of microgeneration projects. The MCDSS can potentially improve the efficiency and accessibility of solar energy generation, promoting the adoption of renewable energy sources and supporting a transition to a sustainable energy infrastructure.

5. Future Works

Future research could expand the applicability of the MCDSS to other renewable energy sources, such as wind or hydropower, and explore the integration of additional decision-making criteria. Further validation of the system in diverse geographical locations and varying climatic conditions would also strengthen its utility and robustness. Moreover, incorporating real-time data and advanced forecasting techniques could enhance the system's predictive capabilities, providing even more precise and dynamic recommendations.

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