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RESEARCH ARTICLE



# Selection of photovoltaic panels for floating systems: an analysis based on Entropy, CRITIC and TOPSIS

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**ABSTRACT**

In the context of sustainable energy use, multiple criteria are involved in the decision to select the best energy generation projects, as well as its installation location. However, despite the widespread use of decision-making techniques, there is a noticeable gap due to the lack of a systematic process for selecting the best projects for energy transition. This paper evaluates alternatives of photovoltaic panels for energy generation in floating systems and proposes a procedure to select the best project using a multiple-criteria decision analysis. The Entropy method was used to determine the weight of eight criteria, including cost, number of cells, efficiency, area, panel weight, and power characteristics, and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) was used to make the selection. A sensitivity analysis was conducted considering different weighing methods. Among the 20 photovoltaic panels analysed, the method proved to be effective in determining the most successful one for installation in floating systems. The chosen panel maintained the best performance in all scenarios tested. This paper provides a systematic approach for selecting the most suitable photovoltaic panel for floating energy systems, contributing to researchers to refine decision-making methodologies and practitioners to optimise project implementation in sustainable energy initiatives.

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Sustainable energy; renewable energy; floating photovoltaic systems; multicriteria decision analysis

## 1. Introduction

A variety of solar panels are available on the market, and this diversity extends to the type of project proposed for each panel arrangement, whether in onshore (land-based) or offshore (marine-based) systems. Therefore, it is crucial to include analyses of cost, panel efficiency – considering the local installation conditions – as well as the area occupied by the panels, weight, and other characteristics linked to the performance and efficiency of the photovoltaic system.

Although the cost of photovoltaic energy has been decreasing, it remains higher than that of electricity from fossil sources. As such, improvements in the design and manufacturing of solar cells are essential to increase efficiency and reduce costs. New technologies that use tracking systems, both terrestrial and floating, can significantly boost energy production, with gains ranging from 22% to 56%. However, these systems face technical challenges, particularly in floating setups (Tina and Scavo 2022).

Floating photovoltaic energy promotes the installation of panels on water surfaces, such as reservoirs and canals, offering advantages over onshore systems, including the lack of need for large occupied areas, higher energy yields due to the cooling effect of water, and synergies with existing infrastructure, such as hydroelectric power plants (Silalahi and Blakers 2023).

Floating photovoltaic systems, also known as offshore photovoltaic systems, have shown significant growth over the years, with the first installation in Japan in 2007, followed by the first commercial plant in the U.S. in the same year. Although they represented less than 1% of solar panels in 2022, the installed capacity of floating panels has grown by more than 2000% in the last decade, with large installations in bodies of water, such as coal mines and hydroelectric lakes, the majority of which located in China (Essak and Ghosh 2022).

Therefore, it is essential to consider a range of factors before choosing the most suitable option for the specific needs of each project. The use of increasingly sophisticated decision-making methods has grown significantly, with special emphasis on the TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) method, which provides an objective ranking by evaluating each alternative's performance based on specific criteria (G. Sun et al. 2018). To ensure that these criteria are accurately weighted in the analysis, complementary methods can be applied to address potential biases and enhance the robustness of the results.

The Entropy Weighted Method (EWM) helps determine criteria weights objectively, avoiding human bias and enhancing the reliability of the evaluation results (Sahoo et al. 2017). Similarly, the CRITIC (Criteria Importance Through

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Intercriteria Correlation) method has gained prominence by factoring in both the conflict between criteria and the variation in information provided by each criterion, ensuring a balanced approach to weighting (Krishnan 2024).

Thus, considering the context of sustainable energy use, in which multiple criteria are involved in the decision to select the best energy generation projects, it is crucial to rely on capable of integrating multiple factors in the decision process. In this sense, this paper evaluates alternatives of photovoltaic panels for energy generation in a floating system and proposes a procedure to select the best project using multiple-criteria decision making (MCDM) methods. The TOPSIS technique weighted by Entropy and CRITIC was used to account for the different characteristics of each panel, as well as the economic and structural criteria selected for the analysis. This research provides a systematic approach for selecting the most suitable photovoltaic panel for floating energy systems, contributing to researchers to refine decision-making methodologies and practitioners to optimise project implementation in sustainable energy initiatives.

While selection models are commonly applied in various engineering fields, this study presents a novel integration of the TOPSIS method with Entropy and CRITIC weighting techniques tailored for floating photovoltaic (FPV) systems. Unlike traditional selection models, which may not account for the specific environmental and structural constraints associated with water-based installations, this approach systematically evaluates each criterion's relevance within the unique context of FPV. The dual weighting process ensures a balanced emphasis on both economic and structural factors, addressing practical challenges such as panel stability, maintenance in aquatic environments, and performance optimisation. This methodological combination provides practitioners with a more precise tool for selecting photovoltaic panels in sustainable energy projects, contributing unique insights into decision-making frameworks for FPV applications.

This paper is organised as follows: section two presents the theoretical foundation of this study, section three outlines the research methodology used and section four presents the results.

## 2. Theoretical background

Jin et al. (2023) report that the growing global energy demand and the need for decarbonisation in electricity generation have driven the search for renewable energy sources, with solar photovoltaic energy emerging as a prominent alternative. Among the various configurations of solar photovoltaic generation, floating photovoltaic systems (FPV) installed in reservoirs offer advantages over conventional ground-mounted solar systems in several aspects, such as land conservation, increased efficiency, and reduced water loss.

Kumar, Niyaz, and Gupta (2021) highlight the various benefits of implementing floating photovoltaic projects. Among them is the fact that there is no need to use land surfaces, as the arrays utilise the surfaces of lakes and hydroelectric reservoirs (UHE). Additionally, they help reduce evaporation from these reservoirs and improve energy output, as the presence of water beneath the panels provides a cooling effect, enhancing efficiency. According to the same authors, other benefits of floating projects include synergy with existing systems, forming a hybrid system where hydroelectric plants are integrated with floating photovoltaic systems. This integration reduces investment costs and facilitates the connection of this system to integrated energy systems.

Regarding the topic of hybrid systems, Murphy, Schleifer, and Newman (2021) report that these systems are characterised by their economic viability due to the resulting coupling of multiple generation technologies, such as in this case hydroelectric and photovoltaic solar. They are classified into three hybridisation configurations, with selected criteria being: cost improvement, performance, and in some cases, both cost and performance. Padilha et al. (2022) estimate that Brazil has 200 artificial water bodies of the UHE type suitable for the installation of FPV projects, considering only 1% of the reservoir surface. This represents 33,140 $km^2$ of area, with an installation capacity of 31,520 MWp and 57,384 GWh/year, equivalent to 82.1% of the generation of the Itaipu Hydroelectric Plant.

The challenges of implementing floating photovoltaic systems can be exemplified in several points. Cazzaniga et al. (2020) mention the impact of humidity on panel structures, which can affect their longevity. They also highlight the effects of water quality in reservoirs, with possible changes in the chemical and biological parameters of water bodies. Essak and Ghosh (2022) discuss the need for specific mooring systems, which may use anchors on the ground or at the bottom of reservoirs, allowing the arrays to remain in their established positions and withstand changes in wind regimes and water movement.

Another important aspect for the success of floating installations is the selection of the appropriate photovoltaic (PV) solar panel which is crucial to ensure that the photovoltaic system operates efficiently and reliably. Particularly for the development of offshore projects, this panel selection process is essential, requiring consideration of various criteria and a thorough analysis of parameters. The literature offers several examples of the application of MCDM (multiple-criteria decision making) methods for selecting solar panels.

Alao et al. (2020) describe the TOPSIS method as a tool used to rank alternatives in decision-making problems with multiple criteria. Decision-makers categorise criteria into cost and benefit categories, with the best alternative being the one closest to the Positive Ideal Solution (PIS) and farthest from the Negative Ideal Solution (NIS), using the Euclidean distance principle.

Kaur, Gupta, and Dhingra (2023) used the Entropy and TOPSIS methodologies for rural electrification. Kozlov and Sałabun (2021) applied MCDM methods, using the COMET and TOPSIS methodologies, to evaluate solar panels. Ziemba (2023) conducted the selection of photovoltaic panels for use in the Polish market, based on balanced weight ranges and evaluation criteria, employing the PROSA methodology, supported by a stochastic approach based on the Monte Carlo method. Seker and Kahraman (2021) performed a socioeconomic evaluation for selecting photovoltaic panels in a case study in Turkey. Zhang (2015) evaluated energy company suppliers using the TOPSIS and Entropy methodologies.

Table 1. Application of entropy and TOPSIS in the energy sector.

| Authors | Method | Applications |
|---|---|---|
| Alao et al. (2020) | Entropy, TOPSIS | Waste-to-energy |
| Fahmi et al. (2024) | Entropy, Fuzzy, TOPSIS | Natural gas |
| S. Zhu et al. (2024) | AHP, Entropy, TOPSIS | Hydropower optimisation |
| J. Li et al. (2024) | Entropy, TOPSIS | Rural heating systems |
| W. Zhu et al. (2024) | Entropy, TOPSIS | Hydrogen storage |
| Banadkouki (2023) | Entropy, Fuzzy, TOPSIS | Industrial energy efficiency |
| Wang et al. (2024) | AHP, Entropy, TOPSIS | Energy storage |
| H. Li et al. (2021) | Entropy, TOPSIS | Climate data generation |
| F. Sun and Yu (2021) | Entropy, TOPSIS, K-means | Energy performance of commercial buildings |
| Seker and Aydin (2020) | Entropy, TOPSIS | Hydrogen production |
| Agar et al. (2023) | DIRECT, SMART, SWING, AHP, PAPRIKA, Entropy, and TOPSIS | Biomass pellet classification |
| Kaur, Gupta, and Dhingra (2023) | Entropy, TOPSIS | PV panel selection |
| Ma et al. (2023) | G1-EW-TOPSIS | Carbon neutrality optimisation |
| Alamri, Saeed, and Saeed (2024) | TOPSIS, VIKOR, and MultiMOORA | Hydrogen generation |
| Dhiman and Deb (2020) | Fuzzy, TOPSIS | Hybrid wind farms |
| Dwivedi and Sharma (2023) | Entropy, TOPSIS | Electric vehicle battery optimisation |

Source: Authors' own creation.

Table 1 presents additional examples of studies that have applied the TOPSIS method combined with methods for weighting criteria in several areas of application in energy use.

Several studies are representative of recent advances in floating PV systems. X. Sun (2024), for instance, utilised a novel multicriteria risk assessment model to evaluate floating PV projects in China. This study contributes a fuzzy decision-making environment tailored to the risk management needs of floating PV systems, particularly in complex and variable climates.

Sarkodie, Ofosu, and Ampimah (2022) applied TOPSIS and entropy to evaluate renewable energy resources for a 5 MWp floating solar PV installation in Ghana. Their findings underscore the effectiveness of these decision-making tools in optimising criteria tailored to such installations, such as energy yield, environmental impact, and cost-effectiveness. Di Grazia and Tina (2024) also propose an optimal site selection for floating photovoltaic systems based on Geographic Information Systems (GIS) and multicriteria decision making using AHP and TOPSIS.

Guo et al. (2021) propose a locations appraisal framework for floating photovoltaic power plants based on relative-entropy measure and improved hesitant fuzzy linguistic DEMATEL-PROMETHEE method. Melek et al. (2024) propose a fuzzy Einstein-based decision-making model for the evaluation of site selection criteria of floating photovoltaic system.

Deveci, Pamucar, and Oguz (2022) propose a floating photovoltaic site selection approach using fuzzy rough numbers based LAAW and RAFSI model. Gökmener et al. (2023) conduct site selection for floating photovoltaic system on dam reservoirs using sine trigonometric decision making model. Finally, Velaz-Acera et al. (2024) brings a semi-automatic selection of optimal locations for FPV installations using MCDM-GIS.

## 3. Methods

Based on the extensive applicability of the TOPSIS methodology as a decision-making method in energy projects, as well as the growth of photovoltaic systems as an energy source, this work utilised this method along with the Entropy and CRITIC methods for weighting, in addition to sensitivity analysis in different scenarios, to validate the reliability of the results for selecting photovoltaic panels for electricity generation in floating systems.

Data from 20 commercially available panels were used in this study, including major suppliers in the European market, such as AE Solar; the North American market, represented by Canadian Solar; and the Asian market, such as Login Solar. The criteria adopted are based on certain premises found in various studies, such as Ziemba (2023), who included in his analysis the cost per watt (€/watt), the panel's maximum power ($P_{max}$ - W), short-circuit current ($I_{sc}$ - A), panel efficiency (%), maximum power current ($I_{mp}$ - A), and panel area ($m^2$). Additionally, for the analysis of the floating case proposed in this work, weight (kg) and the number of cells per panel were included. The selection of all these criteria allows for an understanding of different aspects of panel performance and suitability for the adaptation needs of the floating systems analysed.

This study focuses on developing a multi-criteria decision-making framework to select photovoltaic panels suited for floating installations on lake surfaces, particularly in hydroelectric reservoirs. Our methodology is designed to be adaptable across various lake environments, without specifying a particular location or gathering site-specific radiation data. Unlike terrestrial-focused studies, which evaluate panel performance based on precise geographical conditions, our approach generalises the panel selection process for aquatic environments. This allows for broader applicability of the proposal, enabling stakeholders to tailor the selection process to individual reservoir conditions as needed.

Table 2 presents the information collected for the 20 panels, used as decision-making criteria. The criteria were categorised as follows: cost per watt (C1), panel maximum power (C2), maximum power current (C3), short-circuit current (C4), panel efficiency (C5), number of cells per panel (C6), panel area (C7), and weight (C8). Among these criteria, C1, C6, and C8 are considered non-beneficial, while C2, C3, C4, C5, and C7 are considered beneficial.

The criteria selected for this study were based on their relevance to both floating and land-based photovoltaic systems, as identified in various studies on solar energy generation projects. Below is a more detailed justification for the selection of each criterion:

Table 2. Criteria of the photovoltaic panels analysed.

| Panel | Cost (€/watt) [C1] | $P_{max}$ (W) [C2] | $I_{mp}$ (A) [C3] | $I_{sc}$ (A) [C4] | Efficiency (%) [C5] | Number of cells [C6] | Area per Wp ($m^2$/Wp) [C7] | Weight per Wp (kg/Wp) [C8] |
|---|---|---|---|---|---|---|---|---|
| PV1 | 0.101 | 535 | 13.05 | 13.81 | 20.70 | 144 | 0.004809 | 0.054206 |
| PV2 | 0.097 | 530 | 12.83 | 13.72 | 20.51 | 144 | 0.004855 | 0.053962 |
| PV3 | 0.095 | 530 | 12.71 | 13.47 | 20.53 | 144 | 0.004855 | 0.05 |
| PV4 | 0.141 | 530 | 13.00 | 13.76 | 20.40 | 144 | 0.004894 | 0.054717 |
| PV5 | 0.140 | 550 | 13.12 | 13.93 | 21.30 | 144 | 0.004613 | 0.050909 |
| PV6 | 0.100 | 530 | 12.96 | 13.80 | 20.50 | 144 | 0.004874 | 0.060943 |
| PV7 | 0.145 | 545 | 13.04 | 13.92 | 21.10 | 144 | 0.004739 | 0.050459 |
| PV8 | 0.122 | 640 | 17.07 | 18.31 | 20.60 | 132 | 0.004853 | 0.059063 |
| PV9 | 0.108 | 585 | 17.21 | 18.26 | 20.70 | 120 | 0.004838 | 0.059658 |
| PV10 | 0.101 | 640 | 17.20 | 18.06 | 20.60 | 132 | 0.004853 | 0.053125 |
| PV11 | 0.135 | 435 | 9.99 | 10.64 | 21.80 | 144 | 0.004593 | 0.048276 |
| PV12 | 0.150 | 455 | 13.17 | 13.95 | 21.10 | 132 | 0.004743 | 0.053187 |
| PV13 | 0.130 | 400 | 17.30 | 18.36 | 20.82 | 80 | 0.004805 | 0.0525 |
| PV14 | 0.150 | 400 | 12.83 | 13.73 | 20.50 | 108 | 0.004888 | 0.055 |
| PV15 | 0.160 | 400 | 12.83 | 13.73 | 20.48 | 108 | 0.004883 | 0.065 |
| PV16 | 0.135 | 560 | 13.16 | 13.93 | 21.70 | 144 | 0.005518 | 0.057679 |
| PV17 | 0.120 | 535 | 12.90 | 13.78 | 20.71 | 144 | 0.004742 | 0.053458 |
| PV18 | 0.108 | 525 | 12.76 | 13.65 | 20.30 | 144 | 0.00492 | 0.060571 |
| PV19 | 0.113 | 670 | 17.50 | 18.51 | 21.57 | 132 | 0.004636 | 0.051493 |
| PV20 | 0.103 | 530 | 13.07 | 13.71 | 20.55 | 144 | 0.004874 | 0.050943 |

Source: Authors' own creation.

- Cost per watt (C1): This criterion is crucial in any photovoltaic project, as cost directly impacts the feasibility of large-scale implementation. For floating systems, this is even more significant, given the additional infrastructure required for installation on water surfaces.
- Panel maximum power (C2): The maximum power output ($P_{max}$) determines the energy generation capacity of a panel under standard conditions. Floating systems, benefiting from the cooling effect of water, can further enhance panel performance, making this a key criterion.
- Maximum power current (C3) and short-circuit current (C4): These electrical performance indicators are essential to ensure that the panels can efficiently generate electricity in floating conditions, where temperature and humidity levels may vary from land-based systems.
- Panel efficiency (C5): Although panel efficiency is typically a significant factor in solar panel selection, the differences between the panels analysed in this study were relatively small. Nonetheless, efficiency remains important, as higher efficiency reduces the space needed for installation, which can be advantageous even in floating systems.
- Number of cells per panel (C6): The number of cells affects the overall panel efficiency and durability. While the number of cells does not vary significantly between land-based and floating systems, it can influence the structural integrity of the panel. Floating systems may require reinforced structures to account for environmental conditions, which justifies the inclusion of this criterion in the analysis.
- Panel area (C7): This criterion determines the amount of surface area required for panel installation. In floating systems, larger panel areas might be feasible due to the available water surface, but the added size must be balanced against the capacity of the floating platform.
- Panel weight (C8): The weight of the panel is particularly important for floating systems, as heavier panels require more robust floating structures and mooring solutions. This criterion was therefore included to ensure that the panels selected are structurally suitable for floating installations.

The criteria selected in Table 2 represent key performance indicators for photovoltaic panel suitability in floating systems. The values in the table include both beneficial criteria, which positively impact performance (such as panel efficiency and maximum power), and non-beneficial criteria, which may impose limitations (such as panel weight and cost per watt). For instance, lower values for cost per watt (C1) indicate better economic efficiency, while higher values for panel efficiency (C5) and maximum power (C2) suggest greater energy output potential.

The cost per watt determines the price of the panel relative to its maximum power. A lower cost per watt ratio means better value for the consumer. Another important criterion is the panel's maximum power ($P_{max}$), which determines the amount of energy a panel can generate under Standard Testing Conditions (STC), which include an irradiance of 1000 W/$m^2$ and a cell temperature of 25°C (Kaur, Gupta, and Dhingra 2023).

The maximum power current (Imp) and short-circuit current (Isc) help determine the electrical performance of the panel. Panel efficiency indicates the proportion of energy that the panel can convert into electricity; the higher the panel's efficiency, the more energy will be generated from the available sunlight.

The inclusion of the panel's area, as well as the number of cells, should be considered, as it determines the land allocation required for installation. Smaller panels have an advantage in these cases (Kaur, Gupta, and Dhingra 2023). However, in the case presented in this work, a larger occupied area is not an issue due to the utilisation of surfaces on the lakes of UHE.

Another criterion highlighted in this study is the panel's weight, which becomes relevant in determining the type of structure to be used, as well as the other materials required for the installation of the project on a UHE reservoir, among other offshore examples. Figure 1 shows a FPV located in the Southeast of Brazil. In this figure the floating system beneath the panels can be seen. These structures are responsible for supporting the panels'

Figure 1. Floating photovoltaic system example at a Brazilian solar plant. Source: Authors.

weight. As such, materials are selected to meet this requirement, allowing thus for electricity generation.

In this study, several variables and indices are used to define the mathematical model and equations. Here, $X_{mn}$ represents the value associated with criterion $m$ for photovoltaic panel $n$, where $m$ and $n$ are indices corresponding to specific criteria and panels, respectively. The indices $i$ and $j$ are used for summation or iterative operations, generalising calculations across criteria and alternatives. The term $r_{jk}$ represents the amount of information generated by each criterion, where $j$ and $j$ indicate specific relationships or interactions between criteria in the model.

### 3.1. Entropy method

The entropy weighting approach, presented by Shannon (1948), is a weighting mechanism used to evaluate the distribution of value in decision-making. This approach employs probability theory, providing the methodologies and equations necessary to calculate entropy weights and conduct the evaluation of criteria. The descriptions of the equations will be presented below.

Initially, the decision matrix (Equation 1) includes the criteria and alternatives previously described.

$$\begin{bmatrix} x_{11}x_{12}\cdots x_{1n} \\ x_{21}x_{22}\cdots x_{2n} \\ \cdots\cdots\cdots\cdots \\ x_{m1}x_{m2}\cdots x_{mn} \end{bmatrix} \tag{1}$$

Next, the matrix is normalised using Equation 2.

$$p_{ij} = \frac{x_{ij}}{\sum_{i=1}^{n} x_{ij}} \tag{2}$$

Subsequently, the entropy value, $e_j$, is calculated using Equation 3. This factor can be used to quantify the information about the choice contained in the normalised matrix, in this case, the established value of a criterion in the study.

$$e_j = \frac{1}{\ln m}\sum\nolimits_{i=1}^{n} r_{ij}\ln\left(r_{ij}\right), i \in [1\cdots n], j \in [1\cdots m] \tag{3}$$

The degree of diversification, $d_j$ (Equation 4), of the decision matrix with the panel options and $n$ criteria, are the weights based on the satisfying of the established requirements.

$$d_j = 1 - e_j,\ j \in [1\cdots n] \tag{4}$$

Finally, the value of the criteria weights $(W_j)$ is obtained using Equation 5.

$$W_j = \frac{d_j}{\sum_{j=1}^{d_j} dj},\ j \in [1\cdots n] \tag{5}$$

The weight values found will be used in TOPSIS to calculate the performance of the alternatives, using entropy or uncertain information calculated based on probability theory.

### 3.2. CRITIC method

The CRITIC method uses an objective weighting approach based on the criteria data. This methodology considers not only the amount of information contained in the criteria, but also the divergence between the different schemes and the conflict between the criteria, resulting in more objective calculations (Diakoulaki, Mavrotas, and Papayannakis 1995).

The steps the calculation by the CRITIC method will be presented using the data decision matrix (Equation 1) which is then normalised using the membership function (Equation 6). It indicates how much the alternative $a_i$ is located between the best performing values $(f_j^{best})$ and worst performing values $(f_j^{worst})$.

$$x_{ij} = \frac{f_i(a_i) - f_j^{worst}}{f_j^{best} - f_j^{worst}} \tag{6}$$

The relative score matrix $x_{ij}$, means the value of alternative $i$ and criterion $j$. Then, the standard deviation $(\sigma_j)$ and the correlation coefficient $(p_{ij})$, are calculated, presented by Equation 7 and Equation 8, respectively.

$$\sigma_j = \sqrt{\frac{1}{m}\sum\nolimits_{m}^{m}\left(x_{ij} - \overline{x_{ij}}\right)^2} j = 1, 2, \cdots, n \tag{7}$$

$$p_{ij} = cov\left(X_i, X_j\right) / \left(\sigma_i, \sigma_j\right)\ i, j = 1, 2, \cdots, n \tag{8}$$

Where $x_{ij}$ means that the mean value of alternative $i$, $cov\left(X_i, X_j\right)$ refers to the covariance between row $i$ and row $j$ of the decision matrix $X$.

With the data obtained, a symmetric matrix (N x N) is structured, in which the elements represent the correlation between the parameters studied.

Then, the amount of information generated by each criterion $(r_{jk})$, is determined, subtracting 1 from each element of the symmetric linear correlation matrix ($N$ x $N$) and the sum is calculated for each row, as shown in Equation 9.

$$\sum_{k=1}^{m}\left(1 - r_{jk}\right) \tag{9}$$

Then, the value obtained is multiplied by the standard deviation $(\sigma_j)$ of each practice, previously calculated, to provide the amount of information of the criterion (Equation 10).

$$C_j = \sigma_j \times \sum_{k=1}^{m} (1 - r_{jk}) \tag{10}$$

To calculate the weight of each criterion, (Equation 11) is used.

$$w_j = \frac{C_j}{\sum_{k=1}^{m} C_k} \tag{11}$$

It is possible to observe that CRITIC is an objective weighting method that determines the weights of criteria based on the conflict between criteria and the amount of information they provide. This method contrasts with several other popular weighting approaches, such as Entropy, the Analytic Hierarchy Process (AHP) and Equal Weights methods.

Both CRITIC and the Entropy method are objective weighting techniques that rely on the distribution of information within the dataset. However, while Entropy focuses solely on the variation of values within each criterion to assign weights, CRITIC also considers the conflict between criteria, making it more robust in scenarios where criteria may have interdependencies or correlations. This allows CRITIC to capture more nuances in the data, especially when evaluating criteria with varying degrees of importance.

Unlike CRITIC, AHP is a subjective weighting method that depends on the decision-maker's judgement to assign relative importance to criteria through pairwise comparisons. AHP is beneficial in scenarios that require the incorporation of subjective preferences, but it can introduce bias into the decision-making process. CRITIC, being fully data-driven, avoids such biases, which is why it was selected as one of the weighting methods in this study. AHP, also, has the ranking reversal issue, which can represent a methodological challenge (Junior, Osiro, and Carpinetti 2014).

Assigning equal weights to all criteria is a simple approach that assumes all criteria have the same importance. This method is often used in scenarios where there is insufficient information to differentiate the importance of criteria. However, the equal weights method lacks the sensitivity to data variations that CRITIC provides, which limits its effectiveness in more complex decision-making contexts where criteria have different levels of influence.

By comparing CRITIC with these methods, we see that CRITIC's ability to account for both the amount of information and the conflict between criteria makes it particularly suitable for applications where a deeper understanding of the relationships between criteria is required, as in the case of photovoltaic panel selection for floating systems. This is why CRITIC was used in conjunction with Entropy and TOPSIS to ensure a comprehensive and objective analysis.

### 3.3. TOPSIS method

X. Li et al. (2011) describe the steps for processing decision matrix data. Initially, the decision matrix is normalised using Equation 12, obtaining the matrix $M_{ij}$, described below. This procedure ensures that all attributes are equivalent and have the same format.

$$M_{ij} = \frac{d_j}{\sqrt{\sum_{i=1}^{n} x_{ij}^2}}, i \in [1 \cdots n], j \in [1 \cdots m] \tag{12}$$

Then the weighted decision matrix is obtained, in which the normalised decision matrix is multiplied by the respective weights obtained using the Entropy method, as seen in Equation 13.

$$\hat{W}\dot{Z}_{ij} = [W_j \times M_{ij}] \tag{13}$$

To obtain the ideal solution, which is composed of the positive ideal solution and the negative ideal solution, the former is obtained by the highest value of the weighted decision matrix, as seen in Equation 14, and the latter is obtained by the lowest value of each attribute in the weighted decision matrix, as illustrated in Equation 15.

$$\dot{Z}^+ = \left\{ \dot{Z}_1^+, \dot{Z}_2^+ \cdots \dot{Z}_j^+ \cdots \dot{Z}_m^+ \right\} \tag{14}$$

$$\dot{Z}^- = \left\{ \dot{Z}_1^-, \dot{Z}_2^- \cdots \dot{Z} \cdots \dot{Z}_m^+ \right\} \tag{15}$$

We know that the positive ideal value and the negative ideal value are determined by Equation 16 and Equation 17, respectively,

$$\dot{Z}_j^+ = \{best(\hat{W}\dot{Z}_{ij})_{i=1}^n \tag{16}$$

$$\dot{Z}_{j'}^- = \{worst(\hat{W}\dot{Z}_{ij'})_{i=1}^n \tag{17}$$

The Euclidean distance was used to calculate the separation measures of each alternative from the positive ideal solution ($Sep_i^+$), for beneficial qualities, and from the negative ideal solution ($Sep_i^-$), for non-beneficial qualities. Thus, the measures are obtained through Equation 18 and Equation 19, respectively.

$$Sep_i^+ = \left\{ \sum_{j=1}^{m} \left( Z_{ij} - \dot{Z}_j^+ \right)^2 \right\}^{0,5} \tag{18}$$

$$Sep_i^- = \left\{ \sum_{j'=1}^{m'} \left( Z_{ij} - \dot{Z}_j^- \right)^2 \right\}^{0,5} \tag{19}$$

Finally, the relative degree of approximation $Ci^*$ is determined by Equation 20.

$$Ci^* = \frac{Sep_i^-}{Sep_i^+ + Sep_i^-} \tag{20}$$

The ranking of the evaluation object is based on the value of the relative degree of approximation. The higher the value, the better the evaluation object.

In addition to TOPSIS, other MCDM methods such as AHP and VIKOR are commonly used in decision-making scenarios. Each of these methods has distinct advantages and limitations, which make them suitable for different types of decision problems.

TOPSIS was selected for our study because it evaluates alternatives based on their distance from an ideal solution, considering both beneficial and non-beneficial criteria. TOPSIS is well-suited for cases where precise criteria performance values are available, and the decision-making process needs to consider trade-offs between different criteria. A notable strength of TOPSIS is its ability to handle large datasets and provide a clear ranking of alternatives, making it particularly effective in engineering applications such as photovoltaic panel selection. However, one limitation of TOPSIS is that the results can be sensitive to the normalisation process, and it does not account for the subjective preferences of decision-makers unless combined with other methods like entropy or AHP.

AHP is a widely used MCDM method that involves structuring decision problems into a hierarchy and then performing pairwise comparisons to assign relative weights to each criterion. AHP's strength lies in its ability to incorporate the decision-makers' judgements and preferences, making it highly effective in scenarios where subjective opinions are essential. However, for a study like ours, which focuses on quantitative criteria and objective data, AHP may be less appropriate, as it can become complex and time-consuming when dealing with a large number of alternatives and criteria. AHP also has the ranking reversal issue, which can directly impact its results (Junior, Osiro, and Carpinetti 2014).

VIKOR is another popular MCDM technique, which focuses on ranking alternatives based on the concept of compromise solutions. It is particularly effective when the decision-makers aim to find a balance between conflicting criteria. VIKOR's strength lies in its capacity to handle decision-making problems with high levels of conflict among criteria, making it useful for problems involving trade-offs between multiple stakeholders. However, for our study, which prioritises a clear ranking based on objective data, VIKOR's focus on compromise solutions was less aligned with our goal of selecting the best photovoltaic panel for floating systems.

By choosing TOPSIS, we leveraged its strengths in ranking alternatives based on objective criteria and clear distance measures from ideal solutions. In contrast, methods like AHP and VIKOR would have added complexity without providing significant advantages for the type of quantitative data used in this study.

## 4. Results and discussions

### 4.1. Photovoltaic panel analysis and selection

The analysis revealed that panel P15 consistently ranked as the top-performing option across all weighting scenarios, regardless of the specific method used – Entropy, CRITIC, or equal weighting. This consistent dominance suggests that PV15 offers an optimal balance of cost-efficiency, energy output, and structural suitability, making it particularly robust for FPV applications. Its top ranking highlights its versatility and reliability across different project priorities and conditions, underscoring P15 as a preferred choice for FPV installations.

However, to reach this conclusion, it is essential to understand the underlying calculations that led to PV15's high ranking. The consistent performance of PV15 is a result of the weight calculations applied to each criterion, which we detail in the following sections. By examining how different criteria weights affect the panel rankings, we can confirm the robustness of PV15 in comparison with other panels, ensuring that the selection process aligns with diverse project requirements and methodological rigour. With this initial conclusion established, we proceed to examine the criteria weight distributions calculated using the Entropy and CRITIC methods

Figure 2 represents the weights found using the Entropy methodology for the 20 panels selected in the study, analysing the eight criteria. This figure illustrates the distribution of weights assigned to each criterion using the Entropy method. Higher weights, such as those for cost per watt (C1) and panel weight (C8), indicate criteria with more variation across the analysed alternatives, suggesting a stronger influence on the decision-making process. In contrast, lower weights, such as for panel efficiency (C5), reflect criteria with less variability, which the Entropy method interprets as less significant in distinguishing between alternatives.

An evaluation of the weight relationship among various criteria highlights those with the highest values, indicating good criteria to be used: cost per watt (C1) had a weight value of 17.4%, and panel weight (C8) had a value of 16.4%. On the other hand, panel efficiency (C5) had the lowest weight, 0.3%, as well as the number of cells (C6) with 11.2%. In this case, both are not good criteria for panel selection.

Specifically, the natural cooling effect of the water surface can enhance the performance of all panels uniformly, reducing the significance of efficiency differences (C5) that are often critical in land-based systems where temperature variations impact panel performance more directly. In FPV systems, this cooling effect minimises performance disparities, making other factors, such as cost per watt (C1) and structural characteristics (e.g. panel weight and area), more decisive for ensuring feasibility and stability.

Furthermore, the number of cells per panel (C6) also has a lower impact in FPV contexts. This criterion is typically relevant in land-based installations where structural limitations and space constraints require optimised panel layouts. In FPV projects, however, the available space on water bodies is generally more flexible, allowing for larger and varied configurations without strict cell count constraints. Therefore, while the number of cells can influence the electrical output, it is less crucial in FPV systems compared to other criteria that directly affect installation and operational stability on water. Additionally, the reflective properties of water may increase irradiance levels, further diminishing the marginal advantage of high-efficiency panels and cell counts in FPV contexts.

The Entropy methodology considers efficiency as a less relevant criterion because the method analyzes the variation of values to generate its weights. Therefore, since the efficiencies of the selected panels do not have significant variations among their values, the Entropy method deemed this criterion less relevant. However, in other analyses, if the efficiency of the panels shows significant differences, this criterion would have a higher degree of importance.

By normalising the decision matrix using Equation 12 and then weighting the data using Equations 16 and 17, the following values are obtained, as described in Table 3.

Using Equations 17 and 18, the worst and best ideal values are obtained. For this calculation, the maximum parameters

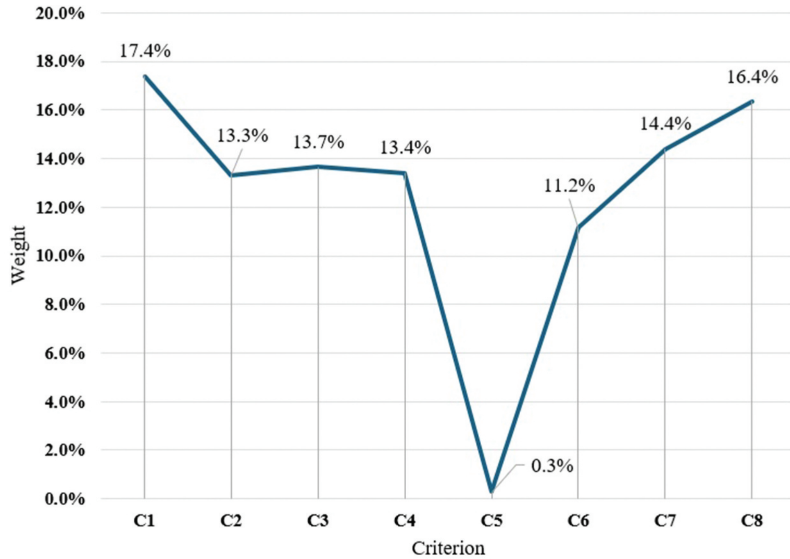


Figure 2. Criteria weight calculation using the Entropy method. Source: Authors' own creation.

Table 3. Values obtained for ideal solutions for each criterion.

| | C1 | C2 | C3 | C4 | C5 | C6 | C7 | C8 |
|---|---|---|---|---|---|---|---|---|
| $W_j$ | 0,174 | 0,133 | 0,137 | 0,134 | 0,003 | 0,112 | 0,144 | 0,164 |
| $Z^+$ | 5,34E−02 | 1,58E−05 | 6,07E−04 | 5,58E−04 | 7,08E−06 | 2,47E−05 | 3,37E−03 | 2,02E−04 |
| $Z^-$ | 9,00E−02 | 9,42E−06 | 3,46E−04 | 3,21E−04 | 6,59E−06 | 4,44E−05 | 6,59E−06 | 3,37E−03 |

Source: Authors' own creation.

for criteria C2, C3, C4, C5 and C7 are considered as ideal criteria; and the minimum ideal values for parameters C1, C6 and C8. The results are described in Table 4, which presents the positive ideal solution (*sepi*+), for beneficial qualities, and the negative ideal solution (*sepi*-). Finally, the relative degree of approximation *Ci* determined by Equation 20 is obtained.

The values presented in Table 4, located in the last column of the table, determine the best classification for choosing the panel. After analysing the results, panel 15 (PV15) presents the best classification, with a value of 0.921; then PV12, with an order of 0.828, represents the second option.

The selection of SP15 as the best panel is a result of its balanced performance across several important criteria, rather than excelling in any single attribute. Using the Entropy and CRITIC methods, we calculated weights that emphasise criteria most relevant to floating photovoltaic (FPV) applications, such as cost per watt (C1) and panel weight (C8). SP15's closeness to the Positive Ideal Solution (PIS) in the TOPSIS analysis resulted in the highest relative closeness coefficient among all panels.

Although SP15 is not the lightest, cheapest, or most efficient in isolation, its consistent ranking across multiple scenarios – including sensitivity analyses using different weighting methods – confirms its robustness. This is particularly important for FPV systems, where the structural demands and economic constraints necessitate a well-rounded panel choice that provides reliability, durability, and economic feasibility under varying environmental conditions. SP15's balanced attributes make it the most suitable choice within this context, aligning technical, structural, and economic requirements for FPV installations.

Although this study presents a generalisable approach, its application can be particularly beneficial for FPV installations in hydroelectric reservoirs, such as those in Brazil's Tucuruí (Pará) and Billings (São Paulo). By applying our multi-criteria decision-making framework, decision-makers can select PV panels that align with the specific structural and environmental demands of these reservoirs. This practical example underscores how our method can guide PV panel selection in diverse hydroelectric contexts, promoting sustainable energy solutions while adapting to unique site requirements.

Table 4. Selection using entropy-TOPSIS.

| Panel | Sep+ | Sep- | $C_i$* | Ranking |
|---|---|---|---|---|
| PV15 | 0.037 | 0.003 | 0.921 | 1st |
| PV12 | 0.031 | 0.006 | 0.828 | 2nd |
| PV14 | 0.031 | 0.006 | 0.827 | 3rd |
| PV7 | 0.028 | 0.009 | 0.758 | 4th |
| PV4 | 0.026 | 0.011 | 0.700 | 5th |
| PV5 | 0.025 | 0.012 | 0.685 | 6th |
| PV16 | 0.023 | 0.014 | 0.610 | 7th |
| PV11 | 0.023 | 0.014 | 0.610 | 8th |
| PV13 | 0.020 | 0.017 | 0.535 | 9th |
| PV8 | 0.015 | 0.022 | 0.414 | 10th |
| PV17 | 0.014 | 0.023 | 0.384 | 11th |
| PV19 | 0.010 | 0.027 | 0.277 | 12th |
| PV18 | 0.007 | 0.029 | 0.201 | 13th |
| PV9 | 0.007 | 0.029 | 0.201 | 14th |
| PV20 | 0.005 | 0.032 | 0.125 | 15th |
| PV1 | 0.003 | 0.033 | 0.095 | 16th |
| PV10 | 0.003 | 0.033 | 0.094 | 17th |
| PV6 | 0.003 | 0.034 | 0.080 | 18th |
| PV2 | 0.001 | 0.036 | 0.031 | 19th |
| PV3 | 0.001 | 0.037 | 0.016 | 20th |

Source: Authors' own creation.

### 4.2. Sensitivity analysis

A sensitivity analysis of the weights was conducted to examine the reliability of the Entropy-TOPSIS method in determining the best panel option to be adopted for the floating project. For this purpose, three additional evaluation scenarios were proposed, in which the criteria weights were modified, totalling four scenarios. The base scenario for the sensitivity analysis was Entropy.

In the second scenario, all criteria were assigned equal weights, with each representing 12.5%. In the third scenario, the CRITIC method was used, as described in section 3.2, resulting in a variation in the weights compared to the Entropy method. In this analysis, the criteria considered good for selection are as follows: Panel Efficiency (C5) has a weight of 20.14%, and Cost per Watt (C1) has a weight of 18.85%. On the other hand, the panel's Maximum Power (C2) and Panel Weight (C8) obtained the lowest weights, 4.25% and 6.14%, respectively, indicating that they are not as relevant criteria for panel selection by this methodology.

In the fourth scenario, the criteria were weighted according to the technical and economic aspects necessary for the success of floating projects, assigning higher weights to Cost, Efficiency, Area, and Weight, each with 15%, while the other criteria received 10%. Figure 3 represents the distribution of weights in the established scenarios.

In this study, the weighting of the criteria was conducted using the Entropy and CRITIC methods, both of which offer objective, data-driven insights into the importance of each criterion. The Entropy method assigns weights based on the distribution of values within each criterion, ensuring that criteria with significant variation across alternatives – such as cost per watt (C1) and panel weight (C8) – receive higher importance. This minimises subjective bias, providing weights based solely on data variability. However, this focus on variability can lead to the underweighting of criteria that show minimal differences among alternatives, such as panel efficiency (C5), even if they are important in practice.

In contrast, the CRITIC method incorporates both the variability of each criterion and the degree of conflict between criteria, giving greater weight to criteria that provide unique, non-redundant information. For example, while Entropy de-emphasised panel efficiency due to its low variability, CRITIC identified it as more relevant based on its distinct informational contribution. This approach helps capture criteria interdependencies and better reflects real-world complexity. The dual use of Entropy and CRITIC in this analysis thus provides a balanced evaluation, though some biases may still arise. For instance, methods emphasising cost (like Entropy) may overlook critical technical attributes, while methods focusing on information diversity (like CRITIC) might assign greater weight to less economically impactful criteria.

By clarifying the weighting processes and addressing potential biases, we aim to help practitioners align the weighting interpretation with project-specific priorities, facilitating informed decision-making in real-world floating photovoltaic applications.

Table 5 provides a detailed presentation of the results obtained for the 20 selected panels. There is a slight variation in the ranking of the panels, as evidenced by the variation in the values of the relative closeness coefficients ($C_i^*$), demonstrating that, despite the variations in the scenarios, PV15 remains the best option, followed by PV12 and PV14.

In Figure 4, it is possible to visualise the closeness coefficient values found for the four scenarios. This figure shows the closeness coefficient values for each photovoltaic panel under the different weighting scenarios tested in the sensitivity analysis. Panels with consistently high coefficients, such as PV15, demonstrate robustness across weighting methods, making them strong candidates for practical applications. Variability in closeness coefficients for lower-ranked panels, such as PV3 and PV2, suggests that their suitability is more dependent on specific project priorities and chosen weighting methods.

The dominance of the PV15 panel across all tested scenarios highlights its performance across a range of criteria. This result is particularly significant in light of the challenges posed by floating photovoltaic systems, where the balance between technical performance and structural feasibility is crucial. PV15's ability to consistently rank highest suggests that it meets the complex demands of floating installations, where weight, structural integrity, and economic considerations are as important as energy output.

The sensitivity analysis further supports the robustness of the methodology employed. Despite variations in weighting techniques, the top-performing panels remained largely consistent, indicating that the selection process is not overly

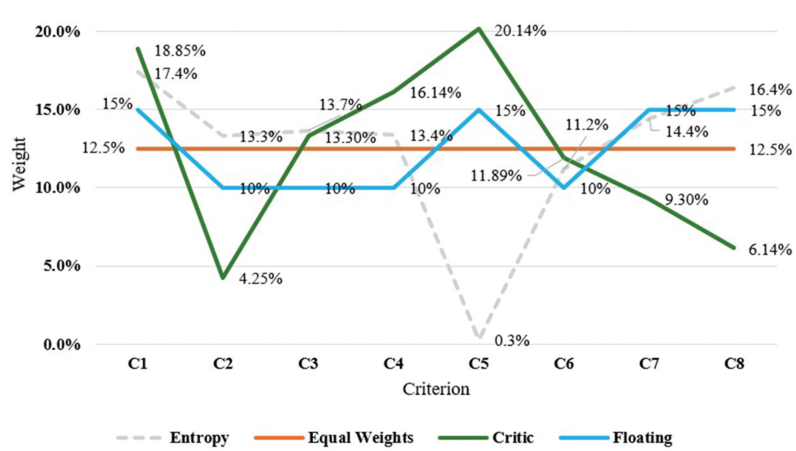


Figure 3. Weight values for sensitivity analysis. Source: Authors' own creation.

Table 5. Closeness coefficient and rankings of sensitivity analysis considering all scenarios.

| | Entropy | | Equal Weights | | CRITIC | | Floating | |
|---|---|---|---|---|---|---|---|---|
| Panel | $C_i$ | Ranking | $C_i$ | Ranking | $C_i$ | Ranking | $C_i$ | Ranking |
| PV1 | 0.095 | 16 | 0.094 | 16 | 0.095 | 16 | 0.096 | 17 |
| PV2 | 0.031 | 19 | 0.028 | 19 | 0.033 | 19 | 0.035 | 19 |
| PV3 | 0.017 | 20 | 0.011 | 20 | 0.020 | 20 | 0.023 | 20 |
| PV4 | 0.700 | 5 | 0.700 | 5 | 0.692 | 5 | 0.697 | 5 |
| PV5 | 0.685 | 6 | 0.685 | 6 | 0.677 | 6 | 0.682 | 6 |
| PV6 | 0.080 | 18 | 0.079 | 18 | 0.080 | 18 | 0.081 | 18 |
| PV7 | 0.758 | 4 | 0.759 | 4 | 0.747 | 4 | 0.754 | 4 |
| PV8 | 0.414 | 10 | 0.414 | 10 | 0.411 | 10 | 0.414 | 10 |
| PV9 | 0.200 | 14 | 0.200 | 14 | 0.200 | 14 | 0.202 | 13 |
| PV10 | 0.093 | 17 | 0.093 | 17 | 0.093 | 17 | 0.101 | 16 |
| PV11 | 0.610 | 7 | 0.611 | 7 | 0.605 | 8 | 0.608 | 8 |
| PV12 | 0.828 | 2 | 0.829 | 2 | 0.812 | 2 | 0.822 | 2 |
| PV13 | 0.535 | 9 | 0.535 | 9 | 0.531 | 9 | 0.533 | 9 |
| PV14 | 0.827 | 3 | 0.829 | 3 | 0.812 | 3 | 0.822 | 3 |
| **PV15** | **0.921** | **1** | **0.924** | **1** | **0.892** | **1** | **0.909** | **1** |
| PV16 | 0.610 | 8 | 0.611 | 8 | 0.605 | 7 | 0.609 | 7 |
| PV17 | 0.384 | 11 | 0.384 | 11 | 0.381 | 11 | 0.383 | 11 |
| PV18 | 0.201 | 13 | 0.201 | 13 | 0.200 | 13 | 0.201 | 14 |
| PV19 | 0.277 | 12 | 0.277 | 12 | 0.275 | 12 | 0.279 | 12 |
| PV20 | 0.125 | 15 | 0.124 | 15 | 0.125 | 15 | 0.126 | 15 |

Source: Authors' own creation.

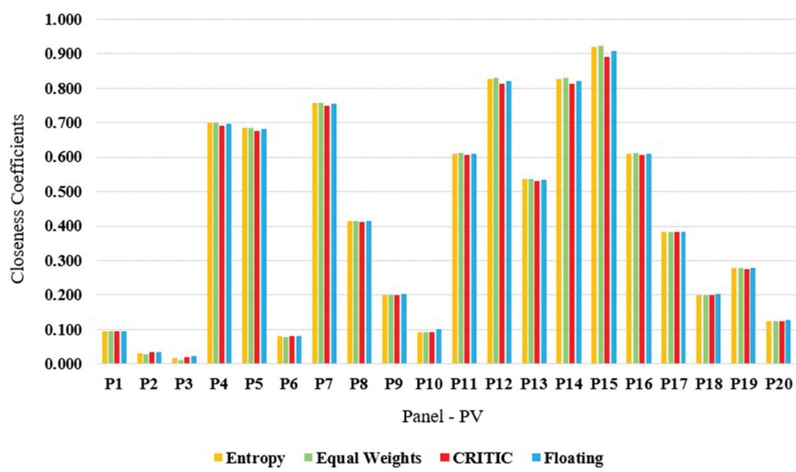


Figure 4. Closeness coefficients in sensitivity analysis. Source: Authors' own creation.

sensitive to shifts in criteria prioritisation. This robustness is crucial for floating systems, which must operate under diverse environmental conditions, including variable water levels, weather patterns, and structural constraints. The fact that PV15 remained the top choice under different weighting schemes suggests that it offers a level of adaptability that is particularly valuable in floating photovoltaic projects.

The lower emphasis on panel efficiency (C5) as a key factor also merits discussion. While efficiency is traditionally a critical criterion in solar panel selection, the relatively small range of efficiency values among the panels studied explains why it had less impact in this analysis. Cooling effects from water surfaces can mitigate efficiency losses, making other factors like cost and weight more critical. In this context, the cooling effect of water bodies on floating panels may allow for less emphasis on small efficiency gains, shifting the focus to other criteria that affect the long-term viability and cost-effectiveness of the project.

Furthermore, the prominence of panel weight (C8) in the analysis reflects the structural demands unique to floating systems. Unlike land-based installations, where weight is generally less of a concern, floating systems require buoyant structures that can support the panels. Heavier panels may necessitate more robust and expensive support systems, impacting the overall project cost. This is particularly relevant in large-scale installations, where the cumulative weight of hundreds or thousands of panels could significantly influence the design and cost of the floating platform. The high weight given to cost per watt (C1) in this analysis is consistent with the growing focus on making renewable energy more competitive with traditional energy sources.

For researchers, the use of approaches like TOPSIS, alongside sensitivity analysis, provides a replicable framework for future studies in renewable energy project selection. Practitioners in the field can benefit from this approach by optimising project implementation, ensuring that selected photovoltaic panels meet the specific technical and economic requirements of floating systems. The identified best-performing panels, such as PV15 and PV12, are well-suited for environments where factors like structural support and cost-effectiveness are critical, contributing to more efficient energy production.

The sensitivity analysis conducted in this study aimed to assess the robustness of the panel selection process under different weighting schemes. By comparing the Entropy method, CRITIC, and equal weights, we were able to evaluate how each method influenced the ranking of the panels and identify the criteria that had the greatest impact on the final decision.

When using the CRITIC method, the criteria with the highest weights were panel efficiency (C5) and cost per watt (C1), indicating that these two factors were deemed the most influential in the decision-making process. The CRITIC method, by considering both the variability of the data and the conflict between criteria, gives more importance to criteria that show significant differences between alternatives. This suggests that, in real-world applications, the CRITIC method would be particularly useful in contexts where certain criteria, such as efficiency or cost, show marked variation and need to be prioritised to optimise performance. For example, in a scenario where energy output is critical, the emphasis on efficiency would guide the selection towards panels that offer higher performance, despite possible higher costs.

On the other hand, the equal weights method assigned the same level of importance to all criteria, leading to a more balanced influence of each factor on the ranking of the panels. While this approach simplifies the decision-making process by avoiding subjective bias or complex calculations, it may overlook the nuances between criteria that have different levels of significance in real-world applications. For instance, treating panel efficiency and weight as equally important could lead to suboptimal choices in floating systems, where weight plays a crucial role in determining the structural feasibility of the installation. In practical terms, the equal weights method might be more suitable in early-stage evaluations, where decision-makers are exploring a wide range of alternatives without specific priorities, or when data on the relative importance of criteria is limited.

The results of the sensitivity analysis highlight that the choice of weighting method can significantly influence the final ranking of photovoltaic panels. In all scenarios tested, panel PV15 consistently ranked highest, demonstrating its robustness as the best option across different weighting schemes. However, panels that ranked lower, such as PV3 and PV2, showed more variability in their performance, indicating that their selection would depend heavily on the specific priorities of the project.

This has important implications for real-world applications: if cost minimisation is the primary goal, methods like CRITIC, which place higher weight on economic factors, would be more effective. Conversely, if operational reliability is a priority, methods that give equal importance to all criteria may lead to a more balanced, if less optimised, decision.

### 4.3. *Environmental impacts and sustainability considerations*

FPVs present a promising solution for sustainable energy generation, offering several advantages, particularly in terms of land conservation and improved energy efficiency. One of the most notable benefits of FPVs is their ability to reduce water evaporation by covering portions of water bodies. This is especially valuable in regions with high evaporation rates, where preserving water levels is crucial for both water conservation and the operational efficiency of hydroelectric plants. By reducing evaporation, FPVs contribute to the overall sustainability of water resources, creating a synergy between solar and hydroelectric energy production.

However, it is important to consider potential environmental impacts, particularly related to water quality and aquatic ecosystems. The installation of FPVs can influence the physical and chemical characteristics of water, such as temperature and oxygen levels. While the shading effect from panels can reduce water temperature, which may benefit certain species in warmer climates, it can also affect light penetration, potentially impacting the photosynthesis of aquatic plants and microorganisms. These effects tend to be localised and manageable, especially with careful monitoring and site selection to minimise ecological disruption.

Aquatic ecosystems may also experience some changes due to the presence of FPVs, as the shading and structure of the panels can modify habitat conditions. In certain cases, this could create cooler areas that benefit specific species, while in others, reduced sunlight might disturb the behaviour of aquatic organisms. Additionally, the anchoring systems used to stabilise floating platforms need to be carefully designed to avoid disturbing sediments and underwater vegetation.

Therefore, it is essential to implement these systems responsibly, with ongoing environmental assessments to ensure that any impacts on water quality or ecosystems are managed effectively. With appropriate planning and monitoring, FPVs can contribute positively to the renewable energy landscape while minimising environmental concerns.

## 5. Conclusions

MCDM techniques were used to rank the ideal panel options, assisting decision-makers in choosing the best option according to their specific demands for the construction of the floating project. Through the use of the TOPSIS methodology weighted by Entropy and subsequently CRITIC, it was possible to select the best option among the 20 panels considered for the floating project.

Among the eight criteria considered, the non-beneficial ones were cost per watt (C1), the number of photovoltaic cells (C6), and weight (C8), since these criteria would be detrimental to a floating project. On the other hand, the beneficial criteria included the panel's maximum power (C2), maximum power current (C3), short-circuit current (C4), panel efficiency (C5), and panel area (C7).

The results indicated that the best panel option for the floating system is P15, followed by option P12. Using the weights obtained through the Entropy methodology, the relative closeness coefficients obtained in the TOPSIS technique were 0.921 for P15 and 0.828 for P12.

A sensitivity analysis was conducted, using three additional scenarios: the second scenario with equal weights, the third with weights obtained through the CRITIC methodology, and a fourth scenario called the 'floating scenario', where higher weights are assigned according to the technical and economic aspects necessary for the project's success.

The sensitivity analysis results pointed to the same options proposed by the Entropy-TOPSIS approach. However, there was a noticeable change in the closeness coefficients ($C_i^*$) for scenario 2 (Equal Weights), where the $C_i$ for PV15 was 0.924; for scenario 3

(CRITIC), this value was 0.892; and for the fourth scenario (Floating), the closeness coefficient was 0.909. Therefore, we infer that using other panels could potentially change the ranking of the top panels selected by the method used.

It is important to highlight that the weights obtained in the analyses, especially for the cost and panel weight criteria, showed more significant values for the Entropy methodology. However, for the CRITIC method, the most relevant criteria were not only cost but also efficiency, with panel weight being one of the least relevant criteria. Thus, it is possible to observe that depending on the choice of the decision-making method, the weights of the criteria can vary, and therefore, specific characteristics of each system must be taken into account.

The results obtained, as well as the sensitivity analysis, demonstrate the importance of using MCDM to identify the best panel for installation in floating systems, and that the Entropy methodology proved to be suitable for the selection of these panels. Therefore, the weight of the panel is particularly relevant, as it influences the choice of the type of structure and materials needed for the installation of the offshore photovoltaic plant. Thus, the fourth scenario analysed emphasises panel weight, along with efficiency, area, and cost, as the most relevant criteria for this study, in line with the base scenario (Entropy) presented in the first analysis.

Thus, this research contributed significantly to decision-making regarding photovoltaic panels in floating installations, allowing decision-makers to choose the best sustainable energy projects considering the specific characteristics of each system. Future research could explore other alternatives such as bifacial panels and solar tracking systems to increase the efficiency of these floating projects. In addition, it is important that future research considers new evaluation criteria for photovoltaic panels, expanding the dimensions of sustainability analysed, including economic, environmental and social aspects.

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## Data availability statement

Data will be made available on request from the corresponding author.

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