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Optimizing Solar PV Deployment in Manufacturing: A Morphological Matrix and Fuzzy TOPSIS Approach

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Abstract: The growing energy demand of the industrial sector and the need for sustainable solutions highlight the importance of efficient decision making in solar photovoltaic (PV) implementation. Selecting optimal PV configuration is complex due to the interdependent technical, economic, environmental, and social factors involved. This study introduces an integrated decision-making method combining a morphological matrix and fuzzy TOPSIS to systematically select and rank optimal PV system configurations for manufacturing firms. While the morphological matrix exhaustively examines possible design solutions based on sensing, smart, sustainable, and social (S4) attributes, the fuzzy TOPSIS method ranks the alternatives by handling uncertainty in decision making. A case study conducted in a Mexican manufacturing company validates the methodology's effectiveness. The optimal PV configuration identified comprehensively addresses operational and sustainability criteria, covering all lifecycle stages. This approach demonstrates quantitative superiority and greater robustness compared to existing fuzzy TOPSIS-based methods for solar PV applications. The findings highlight the practical value of data-driven, multi-criteria decision making for industrial solar energy adoption, enhancing project feasibility, cost efficiency, and environmental compliance. Future research will incorporate discrete event simulation (DES) to further refine energy consumption strategies in manufacturing.

Keywords: solar energy; decision making; manufacturing; morphological matrix; fuzzy TOPSIS; sustainability

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1. Introduction

In recent decades, the rapid rise in energy demand has positioned energy consumption as a critical issue, primarily because most of the energy is produced by fossil fuels [1]. These fuels are significant contributors to environmental problems such as climate change and global warming, leading to health problems for humans [2]. These challenges have been instrumental in accelerating the adoption of alternative energies, including solar radiation, wind power, biomass, water, and geothermal resources. These resources are characterized by their unlimited availability, minimal to zero greenhouse gas (GHG) emissions, and lower costs than traditional energy sources [3]. Solar energy, with the potential to generate 6500 TW (sufficient to surpass global energy demands), is regarded as one of the cleanest forms of energy available [4]. Solar energy offers numerous environmental benefits over conventional energy sources, including the reduction in CO_2 emissions and other harmful greenhouse gases, and contributes to energy independence and security [5]. Solar energy is vitally important in the global transition toward sustainable energy solutions. Solar energy is one of the critical strategic choices to meet future local and international energy needs. Solar energy is pivotal in integrating renewable energy sources to mitigate adverse climate change effects [6]. However, integrating solar energy and other alternative sources requires comprehensive evaluation methods to maximize energy generation benefits while minimizing environmental impacts. Additionally, assessing their technical, environmental, economic, and social impacts is crucial for the effective utilization of solar energy and other renewables.

Despite its many advantages, in 2020, solar energy accounted just for 3.8% of the electricity produced worldwide, just behind hydropower (16.7%) and nuclear energy (9.8%). Meanwhile, fossil fuels produce more than 61% of the electricity [7]. Moreover, China remains by far the main producer of electricity by solar energy [8].

Although industrial production is crucial for economic growth, it also leads to an increase in energy consumption [4]. The significance of energy in the advancement of industries is highly critical, as a large portion of energy is consumed during industrial processes. The energy supplied to the industrial sector is employed in four main areas, which are construction, agriculture, mining, and manufacturing [9]. Furthermore, in 2019, the industrial sector consumed more than 40% of the electricity produced worldwide [10], thus, the use of alternative and renewable energy sources in industries lead to sustainable economic development and low-carbon production [11].

Solar energy is attracting attention as an excellent promising option to be used in industry sector, mainly for two applications: the solar thermal and the photovoltaic (PV). The most common applications of solar energy in industry are: hot water, steam, drying and dehydration processes, preheating, concentration, pasteurization, sterilization, washing, cleaning, chemical reaction, industrial space heating, food, plastic, building, textile and even business concerns [9].

The selection and configuration of PV systems have become complex as industries aim to transition towards more sustainable practices [12]. Traditional decision-making methods may not sufficiently encompass the diverse technical, social, economic, and environmental considerations pertinent to PV systems throughout their lifecycle. Consequently, this research is driven by the necessity to equip industries with a systematic and data-driven approach for assessing and selecting optimal PV system configurations connected with their specific technical demands and social and environmental obligations. By integrating decision-making techniques, such as the morphological matrix and fuzzy TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution), this research enhances the efficiency and effectiveness of PV system selection within industrial contexts, thereby contributing to the advancement of sustainable energy solutions.

Existing MCDM approaches, such as AHP (Analytic Hierarchy Process), ANP (Analytic Network Process), and traditional TOPSIS, have been applied to solar PV selection. However, these methods have limitations:

- Rigid decision structures: AHP and ANP rely on strict hierarchical structures, making them less adaptable to dynamic industrial needs.
- Lack of comprehensive lifecycle assessment: Most studies focus on site selection or economic feasibility, neglecting the complete PV system lifecycle (analysis, installation, operation, and disposal).

- Limited handling of uncertainty: Traditional TOPSIS does not effectively incorporate fuzzy logic, which is essential for dealing with uncertain or subjective decision-making criteria.

This research aims to formulate a comprehensive decision-making framework for selecting and configuring PV solar energy systems in industrial environments. This framework will incorporate technical, economic, environmental, and social aspects throughout the entire lifecycle of the systems, including phases of analysis, installation, operation, and disposal. This work proposes the utilization of a morphological matrix to identify potential solution trajectories for solar energy projects by considering various attributes, including sensing, smart, sustainability, and social factors. Subsequently, a fuzzy TOPSIS approach is employed to evaluate and determine the most appropriate configuration for a specific solar energy project. Compared to traditional methods, such as AHP, ANP, and traditional TOPSIS, the proposed hybrid approach of this work demonstrates enhanced capability to manage decision uncertainty, greater flexibility in incorporating lifecycle-based criteria, and improved adaptability to dynamic industrial scenarios. This methodology ensures that decisions are holistic, balancing all relevant factors and leading to the most advantageous outcomes for industrial solar energy utilization.

The structure of this work is as follows: Section 2 shows a literature review of multi-criteria decision making methods and the definition of the morphological matrix; Section 3 presents basic definitions of the fuzzy TOPSIS method, and the methodology proposed; a case study is presented in Section 4; results and discussion are in Section 5; and finally, Section 6 exposes the conclusions and policy implications.

2. Literature Review

2.1. Multi-Criteria Decision Making

According to the University of Massachusetts Dartmouth [13], decision making is the process of making choices by identifying a decision, gathering information, and assessing alternatives resolution. An adequate decision-making process, together with the use of an effective method, can help to analyze all the relevant information, define alternatives, and increase the chances of choosing the most suitable option possible that meets the needs and objectives of the problem.

Multi-criteria decision making (MCDM) is a research area that involves different decision-making methods that compare and analyze various available choices for one particular problem considering multiple and often conflicting qualitative or quantitative criteria with the objective of selecting the most satisfying alternative in certain, uncertain, fuzzy or risky environments [14,15]. MCDM improves the quality of decision making to become more rational and efficient and it can be applied in different disciplines and areas including economics and finance, engineering, health, energy, construction, among others [16].

According to [17,18], key steps in MCDM problems are: (1) problem identification, (2) goal definition, (3) criteria selection, (4) alternative identification, (5) criteria weighting, (6) alternative ranking using a suitable method, and (7) evaluation of outcomes.

There are many methods for solving MCDM problems and the choice is made based on the nature of the problem and the level of complexity of the decision-making process [19]. In [20], the authors divided MCDM problems into two general sub-categories:

- Multi-attribute decision making (MADM): problems with a finite (or discrete) number of alternatives. Goals, attributes (criteria), and options are clear; limitations are not.
- Multi-objective decision making (MODM): problems with a infinite (or continuous) number of alternatives. Goals are not clear, but limitations are.

In [21], Ilbahar et al. conducted a state-of-the-art review about MADM methods used throughout the renewable energy literature for the following purposes: evaluation of renewable energy sources, evaluation of renewable energy technologies, evaluation of renewable energy facility location, evaluation of renewable energy projects or investments, and design of renewable energy systems. The review concluded that the MADM methods most commonly used, including their various combinations, for solving the renewable energy problems mentioned before are Analytic Hierarchy Process (AHP) [22,23], Analytic Network Process (ANP) [22,23], Elimination Et Choix Traduisant la Realité (ELECTRE) [22,24] and Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) [22,25].

While MCDM techniques have been widely applied to solar energy projects, they often fail to comprehensively address the complexity of industrial solar PV deployment, particularly in manufacturing settings. One of the identified limitations is that most studies focus on the site selection or financial evaluation phase, without considering the installation, operation, and disposal phases critical to industrial settings. In addition, methods such as AHP and ANP assume statistic hierarchical structures, which do not adapt well to complex and dynamic industrial needs. Traditional TOPSIS assigns fixed numerical values, failing to incorporate expert judgement, uncertainty, and qualitative assessments, which are critical in solar PV investment decisions.

TOPSIS is one of the fundamental MCDM methods and is a highly regarded, applied, and adopted method because of its simplicity and ease of applicability. For these reasons, this method was chosen for the proposal presented in this work.

TOPSIS is based on the premise that the best solution has the shortest Euclidean distance from the positive ideal solution and the longest distance from the negative ideal one [26]. In a general view, TOPSIS assigns and measures weights for each parameter, normalizes scores, and determines the numerical difference for each alternative with respect to the optimal alternative and ranks them to determine the optimal one [27].

Traditional MCDM methods struggle with handling subjectivity and uncertainty in decision making, which is where fuzzy TOPSIS provides an advantage.

2.2. Fuzzy Sets

Humans predominantly use natural language to describe their everyday experiences. Nevertheless, using crips numerical values like 0 and 1 to represent truth and falsity is not always entirely accurate. For instance, when evaluating energy efficiency, traditional approaches often categorize appliances or systems as either ‘energy efficient’ or ‘not energy efficient’, which, in mathematical terms, equate to the discrete numbers 1 and 0, respectively. By employing fuzzy sets, individuals can provide more nuanced descriptions. Individuals can characterize the system as ‘highly energy efficient’, ‘moderately energy efficient’, ‘marginally energy efficient’, ‘energy neutral’, ‘slightly energy inefficient’, ‘highly energy inefficient’, etc. Fuzzy sets enable to convey the subtleties in a more natural and descriptive way, reducing the need for binary, all-or-nothing categorizations [28].

According to [29], the presence of imperfect information in the decision-making process poses challenges in establishing precise preferences among decision makers. This imperfection in decision-related information arises from various factors, including the limitations of decision makers, the complexity of available options, and the influence of psychological biases. Fuzzy numbers allow for a more flexible and realistic way to model this uncertainty in decision-making problems.

Decision making often involves imprecision and vagueness which can be effectively managed by fuzzy sets and fuzzy decision-making techniques [30]. Fuzzy numbers help to express linguistic variables and describe the subjective judgement of a decision maker (DM) in a quantitative manner, thus, fuzzy sets can deal with incomplete and uncertain knowledge and information [31]. Triangular, trapezoidal, and Gaussian are the fuzzy numbers most often used.

In TOPSIS, fuzzy numbers make it simple for evaluation and a realistic form of a modelling and countervailing method which include or exclude alternative solutions based on ruling-out process [32].

2.3. Applications of Fuzzy TOPSIS in Solar PV Energy

Table 1 shows a literature review about the fuzzy TOPSIS method applied in PV solar energy. As can be observed, this approach has primarily been used in the Asian context. This review also reveals that most studies (five) employed this technique to determine suitable locations for solar PV system installations [33–37]. Two studies focused on identifying risk and barriers associated with solar PV energy deployment [38,39], two explored the best alternative energy sources for investment [40,41], and one study centered on the selection of solar panels [42].

Table 1. Literature review fuzzy TOPSIS applied in solar photovoltaic energy.

Authors, (Year)	Title	Location/Country	Main Problem Addressed
Hooshangi et al. (2023) [33]	Evaluation of potential sites in Iran to localize solar farms using a GIS based Fermatean Fuzzy TOPSIS	Iran	PV plant location
Ranganath et al. (2022) [38]	Application of fuzzy TOPSIS method for risk evaluation in development and implementation of solar park in India	India	Risks identification and analysis
Qian et al. (2021) [34]	Fuzzy Technique Application in Selecting Photovoltaic Energy and Solar Thermal Energy Production in Belt and Road Countries	Case study in China	PV plant location
Ali Sadat et al. (2021) [39]	Barrier analysis of solar PV energy development in the context of Iran using fuzzy AHP-TOPSIS method	Iran	PV energy production barriers
Anser et al. (2020) [35]	Assessing the integration of solar power projects: SWOT-based AHP–F-TOPSIS case study of Turkey	Turkey	PV plant location
Taylan et al. (2020) [40]	Assessment of Energy Systems Using Extended Fuzzy AHP, Fuzzy VIKOR, and TOPSIS Approaches to Manage Non-Cooperative Opinions	Saudi Arabia	Energy source evaluation and selection
Sasikumar and Ayyappan (2019) [42]	Multi-criteria Decision Making for Solar Panel Selection Using Fuzzy Analytical Hierarchy Process and Technique for Order Preference by Similarity to ideal Solution (TOPSIS): An Empirical Study	Not specified	Solar panel selection
Ligus and Peternek (2018) [41]	Determination of most suitable low-emission energy technologies development in Poland using integrated fuzzy AHP-TOPSIS method	Poland	Energy source evaluation and selection
Sindhu et al. (2017) [36]	Investigation of feasibility study of solar farms deployment using hybrid AHP-TOPSIS analysis: Case study of India	India	PV plant location
Kengpol et al. (2013) [37]	A Decision Support System for Selection of Solar Power Plant Locations by Applying Fuzzy AHP and TOPSIS: An Empirical Study	Thailand	PV plant location

The limited number of research works involving fuzzy TOPSIS applied to PV solar energy within the industrial sector, especially within the context of Latin America countries, underscores the importance of this proposal. Furthermore, the assessment of solar technologies presents an opportunity for the application of MCDM methods due to the numerous criteria that come into play during the decision-making process.

This proposal takes advantage of the S4 Framework introduced by Molina et al. [43] and Ponce et al. [44], which has arisen as a response to the rethinking and reshaping of business processes initiated by the adoption of innovative practices and operational strategies, facilitated by the integration of new technologies. This approach has enhanced the development of products and services. The incorporation of distinct features and functionalities into S4 products, processes, manufacturing systems, and enterprises provide additional value, thereby serving as a strategy to maintain competitiveness in the market by providing solutions to current societal challenges and addressing evolving consumer needs [43].

While previous studies have successfully applied fuzzy TOPSIS for site selection, risk assessment, and technology comparison, none have combined it with a morphological matrix for industrial PV system design. This research fills that gap by integrating both methodologies to optimize PV configurations based on sensing, smart, sustainable, and social (S4) factors.

2.4. The Morphological Matrix

General Morphological Analysis (GMA) is a method for identifying and analyzing the total set of possible relationships or configurations that compose a given multidimensional, non-quantifiable, and complex problem. Its principle is decomposing a complex (multivariate) concept into a number of ("simple") one dimensional concepts and thus, to establish which of the configurations are possible, viable, and practical, and which are not [45,46].

Morphological matrices are a very powerful, simple, and systematic combinatorial tool which use the principle of morphological analysis to explore the complete set of possible relationships within a system, it helps to reduce the total problem space to a relevant solution space [47].

In the morphological matrix, the functions are listed along the column and the possible solutions for each function are listed along the corresponding rows. Figure 1 shows the morphological matrix proposed in this work, considering the S4 Framework proposed by Pérez et al. [48], thus, the sensing, smart, sustainable, and social needs are considering as functions, while the solutions will be the sensing, smart, sustainable, and social features.

The morphological matrix helps to visualize all the possible combinations existing for each function. As observed in Figure 1, the output for the matrix will be the "solution paths" created from each combination.

Since in a solar energy project it may exist a huge number of solution paths, it is important to first identify the technical and social needs of the project, in this case, the needs are divided in sensing, smart, sustainable, and social, and thus, reduce the number of solutions contained in the matrix, so the solution paths resulted will be those that best meet the needs. In this case, the fuzzy TOPSIS method will help to choose the best solution path created from a morphological matrix.

Based on the literature review, several key gaps in existing research have been identified. First, most studies focus on PV site selection or economic analysis, but few address installation, operation, and disposal. Furthermore, while morphological matrices have been used in engineering design, their application in MCDM for solar PV selection remains underexplored. Finally, previous applications of fuzzy TOPSIS focus on site selection and risk assessment, not industrial PV system configuration.

This research addresses these gaps by proposing a hybrid framework that integrates a morphological matrix with fuzzy TOPSIS to systematically generate PV system configurations tailored to industrial manufacturing firms and accounts for uncertainty in decision making using fuzzy logic.

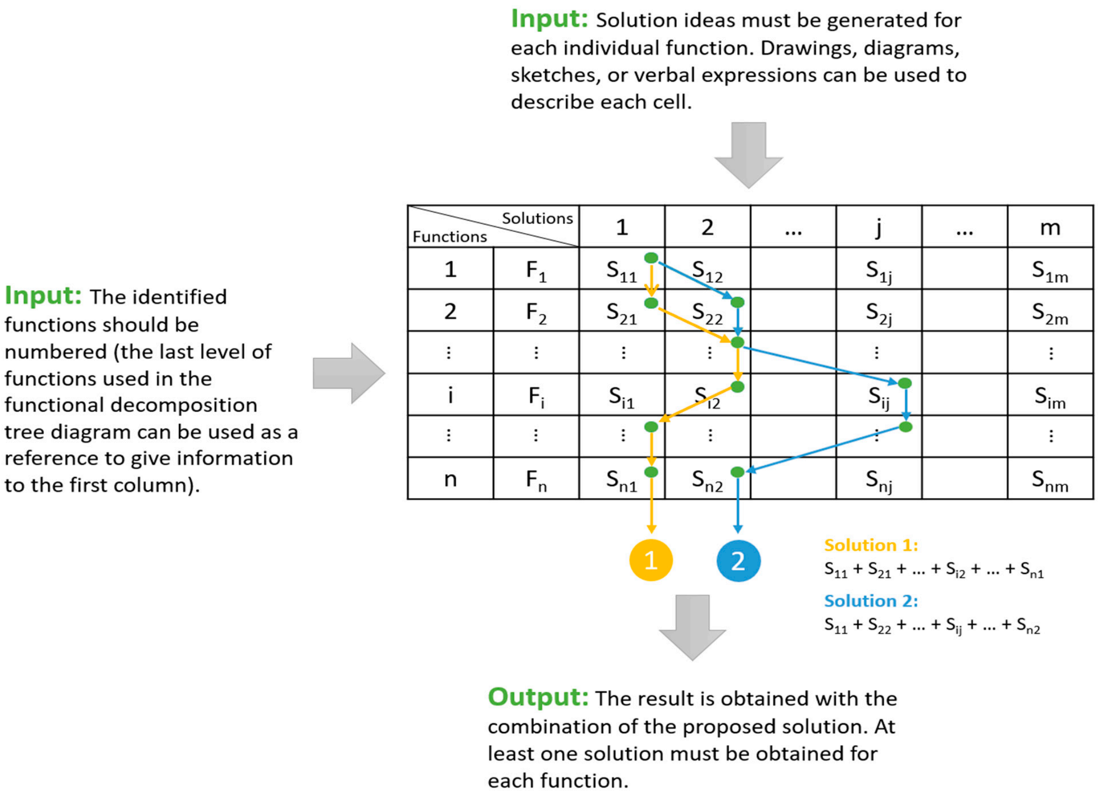

Figure 1. Example of a morphological matrix.

3. Methodology

Below, some basic definitions of fuzzy sets, fuzzy numbers, and linguistic variables are presented [49]. Then, the morphological matrix and the fuzzy TOPSIS approach proposed are presented.

3.1. Fuzzy TOPSIS Definitions

Definition 1. *A fuzzy set, denoted as $\tilde{a}$, ascertained within a designated universe of discourse, X, is characterized by a membership function symbolized as $\mu\tilde{a}(x)$. This function allocates a real number within the range of 0 to 1, inclusive, to each constituent element, x, within X. The computed numerical value, $\mu\tilde{a}(x)$, elucidates the degree to which element x is associated with the fuzzy set $\tilde{a}$.*

Definition 2. *A fuzzy number is defined as a specific subset within the universe of discourse, X, that possesses the dual characteristics of normality and convexity. As depicted in Figure 2, a representative fuzzy number, denoted as $\tilde{a}$, duly satisfies these prerequisites within the predefined universe of discourse, X.*

A triangular fuzzy number, denoted as $\tilde{a}$, can be encapsulated through a triadic representation composed of elements (a_1, a_2, a_3). Its intellectual framework and the corresponding mathematical elucidation are demonstratively represented in Equation (1).

$$\mu_{\tilde{a}}(x) = \begin{cases} 0, & x \leq a_1, \\ (x - a_1)/(a_2 - a_1), & a_1 < x \leq a_2 \\ (a_3 - x)/(a_3 - a_2), & a_2 < x \leq a_3 \\ 0, & x > a_3 \end{cases} \quad (1)$$

Definition 3. *The foundational operations pertinent to fuzzy triangular numbers are hereby established, presuming that $\tilde{a} = (a_1, a_2, a_3)$ and $\tilde{b} = (b_1, b_2, b_3)$ are both real number configurations:*

$\widetilde{a}$ multiplied by $\widetilde{b}$ results in ($a_1 \times b_1$, $a_2 \times b_2$, $a_3 \times b_3$) representing multiplication, whereas the sum of $\widetilde{a}$ and $\widetilde{b}$ produces ($a_1 + b_1$, $a_2 + b_2$, $a_3 + b_3$) representing addition.

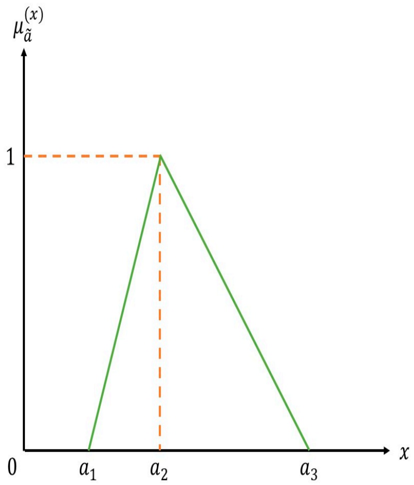

Figure 2. A triangular fuzzy number $\widetilde{\mathrm{a}}$.

Definition 4. *A matrix, symbolized as $\widetilde{D}$, is acknowledged as a fuzzy matrix on the condition that it incorporates at least one constituent element identifiable as a fuzzy number.*

Definition 5. *A linguistic variable constitutes a variable expressed in linguistic terminologies. This concept is advantageous in describing complex situations that elude traditional quantitative definitions. For instance, "weight" serves as a linguistic variable capable of accommodating values such as very low, low, medium, high, and very high.*

Definition 6. *The fuzzy MADM construct can be transcribed using matrices as observed in Equations (2) and (3):*

$$C_1 \quad C_2 \quad C_3 \quad \cdots \quad C_n \widetilde{D} = \begin{array}{c} A_1 \\ A_2 \\ A_3 \\ \vdots \\ A_m \end{array} \begin{bmatrix} \widetilde{x}_{11} & \widetilde{x}_{12} & \widetilde{x}_{13} & \cdots & \widetilde{x}_{1n} \\ \widetilde{x}_{21} & \widetilde{x}_{22} & \widetilde{x}_{23} & \cdots & \widetilde{x}_{2n} \\ \widetilde{x}_{31} & \widetilde{x}_{32} & \widetilde{x}_{33} & \cdots & \widetilde{x}_{3n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \widetilde{x}_{m1} & \widetilde{x}_{m1} & \widetilde{x}_{m3} & \cdots & \widetilde{x}_{mn} \end{bmatrix}, \tag{2}$$

$$\widetilde{W} = \left[\widetilde{w}_1, \widetilde{w}_2, \cdots, \widetilde{w}_n\right], \tag{3}$$

where $\widetilde{x}_{ij}$ (i = 1, 2, ..., m; j = 1, 2, ..., n) and $\widetilde{w}_j$ (j = 1, 2, ..., n) denote the linguistic triangular fuzzy numbers such that $\widetilde{x}_{ij}$ = (a_{ij}, b_{ij}, c_{ij}) and $\widetilde{w}_j$ = (w_{j1}, w_{j2}, w_{j3}). Here, $\widetilde{w}_j$ characterizes the weight of the jth criteria, C_j, and $\widetilde{x}_{ij}$ denotes the performance rating of the ith alternative, Ai, concerning the jth criteria, C_j, evaluated by k evaluators. In their study, Mahdavi et al. (2008) [49] *deployed the method of average value to amalgamate the fuzzy performance score $\widetilde{x}_{ij}$ for k evaluators concerning the same evaluation criteria of Equation (4):*

$$\widetilde{x}_{ij} = (1/k)\left(\widetilde{x}_{ij}^{1} + \widetilde{x}_{ij}^{2} + \cdots + \widetilde{x}_{ij}^{k}\right), \tag{4}$$

where $\widetilde{x}_{ij}^{k}$ is the rating of alternative A_i concerning criterion C_j evaluated by kth evaluators, and $\widetilde{x}_{ij}^{k} = \left(\widetilde{a}_{ij}^{k}, \widetilde{b}_{ij}^{k}, \widetilde{c}_{ij}^{k}\right)$.

Definition 7. *The normalized fuzzy decision matrix denoted by $\widetilde{R}$ is shown as Equation (5):*

$$\widetilde{R} = \left[\widetilde{r}_{ij}\right]_{m\times n}, \tag{5}$$

In the case of possessing triangular fuzzy numbers denoted by $\widetilde{x}_{ij}$, with i spanning from 1 to m and j from 1 to n, the procedure for conducting normalization can be articulated as follows in Equations (6) and (7):

$$\widetilde{r}_{ij} = \left(a_{ij}/c_j^*,\ b_{ij}/c_j^*,\ c_{ij}/c_j^*\right) \qquad i = 1,2,\ldots m,\ j \in B \tag{6}$$

$$\widetilde{r}_{ij} = \left(a_j^-/c_{ij},\ a_j^-/b_{ij},\ a_j^-/a_{ij}\right) \qquad i = 1,2,\ldots m,\ j \in C \tag{7}$$

where B and C are the set of benefit criteria and cost criteria, respectively, and

$$c_j^* = \max c_{ij}\ j \in B$$

$$a_j^- = \min a_{ij}\ j \in C$$

The normalized entities, denoted as $\widetilde{r}_{ij}$, remain as triangular fuzzy numbers. The process of normalization can be implemented in a similar manner for trapezoidal fuzzy numbers. Equation (8) illustrates the weighted fuzzy normalized decision matrix:

$$\widetilde{V} = \begin{bmatrix} \widetilde{v}_{11} & \widetilde{v}_{12} & \widetilde{v}_{13} & \cdots & \widetilde{v}_{1n} \\ \widetilde{v}_{21} & \widetilde{v}_{22} & \widetilde{v}_{23} & \cdots & \widetilde{v}_{2n} \\ \widetilde{v}_{31} & \widetilde{v}_{32} & \widetilde{v}_{33} & \cdots & \widetilde{v}_{3n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \widetilde{v}_{m1} & \widetilde{v}_{m1} & \widetilde{v}_{m3} & \cdots & \widetilde{v}_{mn} \end{bmatrix} = \begin{bmatrix} \widetilde{w}_1\widetilde{r}_{11} & \widetilde{w}_2\widetilde{r}_{12} & \cdots & \widetilde{w}_j\widetilde{r}_{1j} & \cdots & \widetilde{w}_n\widetilde{r}_{1n} \\ \widetilde{w}_1\widetilde{r}_{21} & \widetilde{w}_2\widetilde{r}_{22} & \cdots & \widetilde{w}_j\widetilde{r}_{2j} & \cdots & \widetilde{w}_n\widetilde{r}_{2j} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ \widetilde{w}_1\widetilde{r}_{i1} & \widetilde{w}_2\widetilde{r}_{i2} & \cdots & \widetilde{w}_j\widetilde{r}_{ij} & \cdots & \widetilde{w}_n\widetilde{r}_{in} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ \widetilde{w}_1\widetilde{r}_{m1} & \widetilde{w}_2\widetilde{r}_{m2} & \cdots & \widetilde{w}_j\widetilde{r}_{mj} & \cdots & \widetilde{w}_n\widetilde{r}_{mn} \end{bmatrix} \tag{8}$$

3.2. Proposed Methodology

Bulleted lists look like this: This section delineates the methodology proposed, providing an initial overview of the utilization of the morphological matrix and the fuzzy TOPSIS method, followed by a more comprehensive exploration of each method separately.

The methodology employed herein draws upon the S4 Framework proposed by Pérez et al. [48]. The framework is bifurcated in its application, firstly in the derivation of solutions via the morphological matrix, and secondly in the selection of criteria used for the assessment of alternatives within the fuzzy TOPSIS method. The S4 Framework is subdivided into four principal categories:

- Sensing (s1): Sensors presented in the analysis, installation, operation, and disposal of the PV system for measuring meteorological and power variables, as well as for maintenance and monitoring purposes.
- Smart (s2): Features that collect data/information through automated reasoning for decision-making purposes.
- Sustainable (s3): Environmental impact analysis of the PV system component through their lifespan.
- Social (s4): Legal and regulatory framework for installing, operating, and disposing a PV system; economic viability, and analysis of population acceptance.

Figure 3 provides an overview of the methodological steps, highlighting the integration of the morphological matrix and fuzzy TOPSIS for industrial solar PV decision making. Initially, the needs identified under the sensing, smart, sustainable, and social categories, along with their potential solutions for the PV project, are allocated within the morphological matrix. Consequently, the matrix generates solution paths tailored to each functional requirement. This matrix output subsequently functions as the input for the fuzzy TOPSIS method. The fuzzy TOPSIS method is then executed, taking into consideration the S4 Framework's criteria. The ultimate output from this methodology will be the optimal solution path that adeptly satisfies all the technical and social requirements intrinsic to the PV solar project.

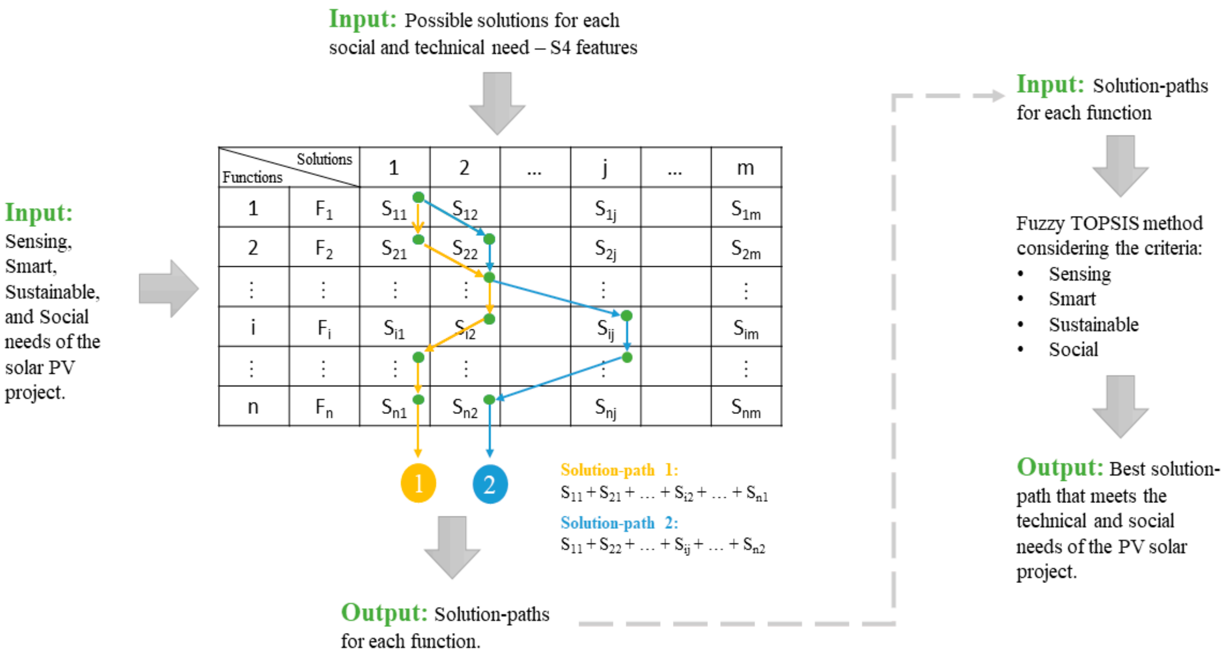

Figure 3. Proposed method: morphological matrix + fuzzy TOPSIS for solar PV projects.

Figure 4 summarizes the proposed methodology and Figure 5 shows the flow diagram for the use of (a) the morphological matrix and (b) the fuzzy TOPSIS method in PV solar energy projects.

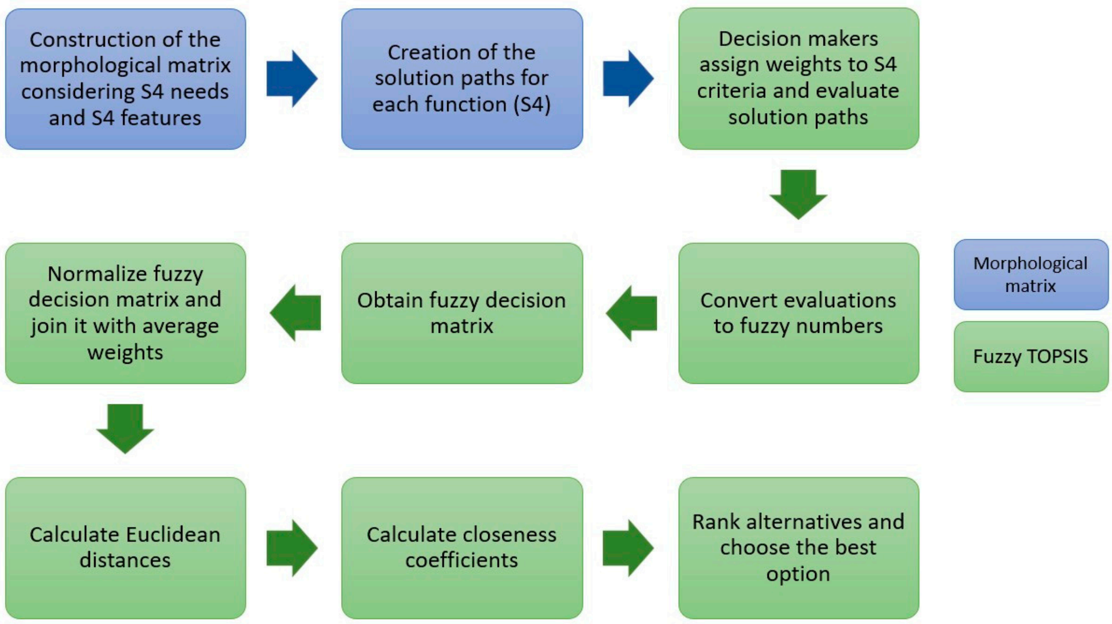

Figure 4. Summarized proposed methodology.

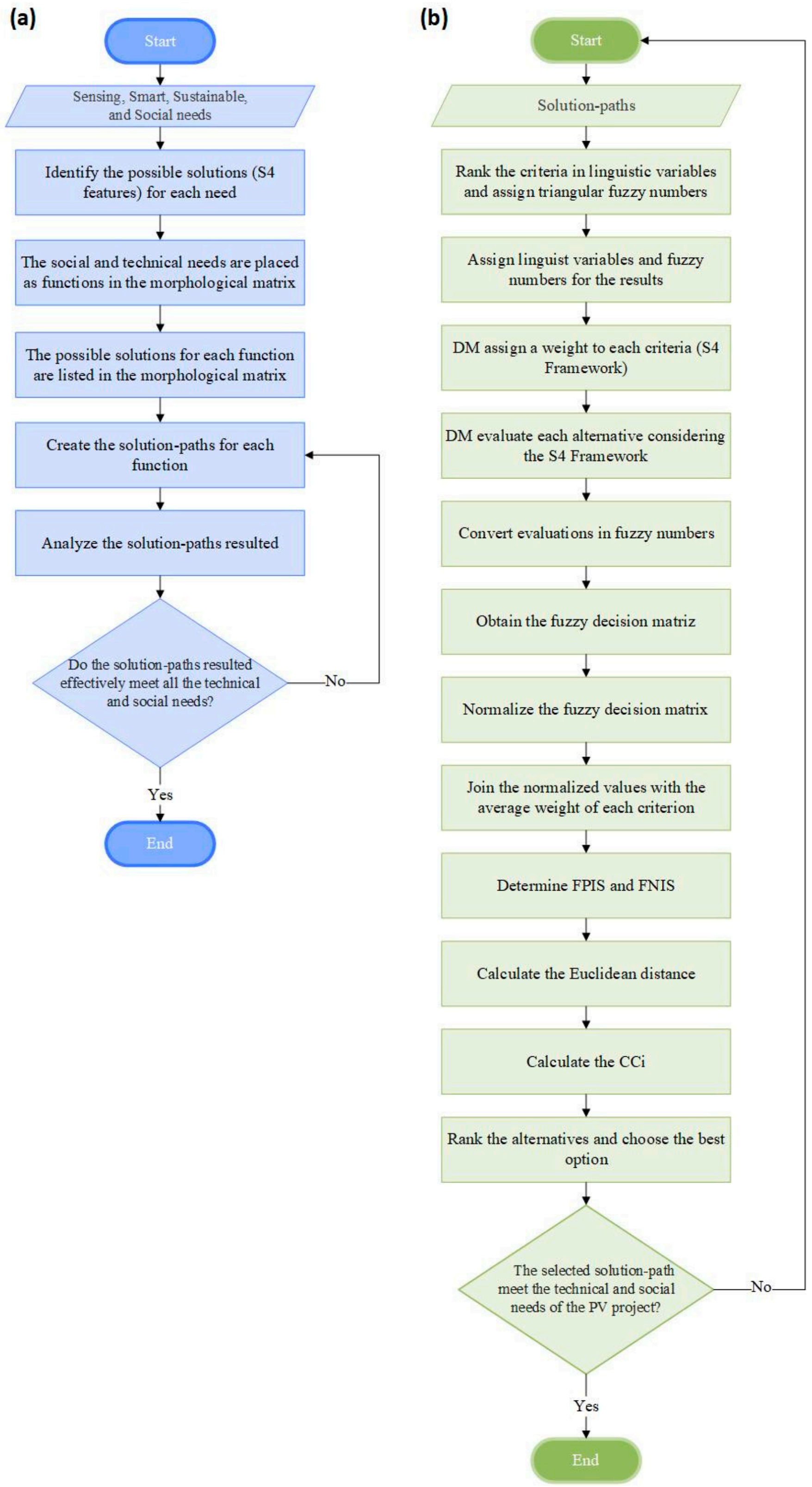

Figure 5. Flowchart for the use of the morphological matrix and fuzzy TOPSIS method in PV solar energy projects. (**a**) Flowchart for the use of the morphological matrix; (**b**) flowchart for the use of the fuzzy TOPSIS method.

3.2.1. The Morphological Matrix Method

The proposed method for the use of morphological matrices in solar PV projects is as follows:

Step 1. Determine the sensing, smart, sustainable, and social needs of the project. According to [48], the needs of a PV project can be divided in technical and social needs:

- Technical needs: electricity consumption, available area to install the PV system, and solar radiation received.
- Social needs: investment considering governmental incentives, and governmental restriction (current regulations).

In addition, depending on the PV project, there may be more needs that must be considered for each stage of the system's lifecycle (analysis, installation, operation, and disposal), such as

- Measurement of meteorological variables (radiation, air, temperature, etc.).
- Measurement of power variables (voltage and current).
- Data storage and analysis (store main variables and adjust sample time autonomously).
- Monitoring system.
- Battery management system (if the system is stand-alone).
- Environmental impact analysis.
- Legal and regulatory framework applicable.
- Population acceptance.

The needs mentioned above are just some of the many that may exist depending on the PV solar project, so the user can add or remove needs depending on their context. Moreover, according to the definition of sensing, smart, sustainable, and social mentioned above, technical and social needs can be further divided into S4 needs.

Step 2. Identify the possible solutions for each S4 need detected in the previous step. Depending on the need, the solutions will be sensing, smart, sustainable, or social features. Figure 6 presents the features of each "S" category and a more detailed description of each feature can be consulted at [48].

Step 3. Place the S4 needs as functions along the morphological matrix columns.

Step 4. Listed the possible solutions (S4 features) identified in Step 2 along the rows of the morphological matrix.

Step 5. Create the solution paths for each function. In this step, one solution for each function (need) must be selected.

Step 6. Analyze the solution paths resulted and verify which of them effectively meet all the technical and social needs. If there is not any solution path that satisfy all the needs, the user must return to Step 5.

3.2.2. The Fuzzy TOPSIS Method

In this work, the fuzzy TOPSIS approach proposed by Ponce et al. [50] is expanded to create a methodology for addressing a multi-attribute decision-making challenge within the solar energy environment. Considering the uncertainty present in the decision data, linguistic variables are utilized to evaluate the significance of each criterion and the performance rating of each alternative concerning these criteria. After pooling the fuzzy ratings provided by decision makers, the decision matrix is transformed into a fuzzy decision matrix and subsequently establishes a weighted normalized fuzzy decision matrix. Then, the degree of fuzzy similarity of each alternative concerning the fuzzy positive ideal solution (FPIS) and the fuzzy negative ideal solution (FNIS) is calculated. Ultimately, a closeness coefficient is defined for each alternative to ascertain their rankings. A higher closeness coefficient signifies that an alternative is closer to FPIS and, simultaneously, farther from FNIS.

Once the solution paths were created (it is necessary to have more than one to run this process), the fuzzy TOPSIS method is as follows.

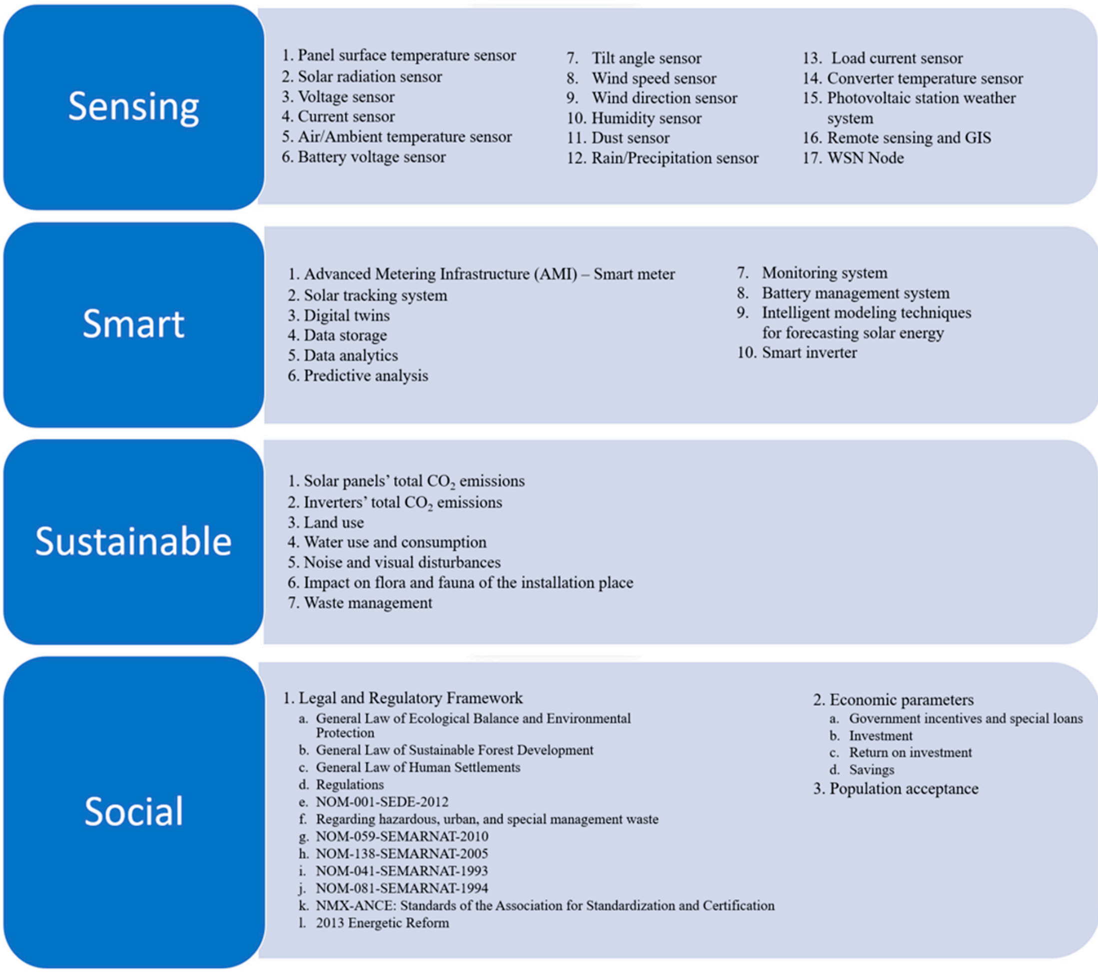

Figure 6. S4 Framework features.

Step 1. Rank each criterion in linguistic variables and assign a triangular fuzzy number from 0–1 ($\widetilde{x}_{ij}$, $i = 1, 2, \ldots, m$, $j = 1, 2, \ldots, n$) (Table 2). For this instance, the $\widetilde{D}$ defined by Equation (2) es equivalent to the $\widetilde{R}$ defined by Equation (5).

Table 2. Linguistic variables for the importance weight of each criterion.

Linguistic Variables	Fuzzy Numbers
Very low (VL)	(0; 0; 0.1)
Low (L)	(0; 0.1; 0.3)
Medium–low (ML)	(0.1; 0.3; 0.5)
Medium (M)	(0.3; 0.5; 0.7)
Medium–high (MH)	(0.5; 0.7; 0.9)
High (H)	(0.7; 0.9; 1.0)
Very high (VH)	(0.9; 1.0; 1.0)

Step 2. Assign linguistic variables ($\widetilde{w}_j$, $j = 1, 2, \ldots, n$) to rank the results of each alternative, in this case, the alternatives are the solution paths created from the morphological matrix (Table 3).

Step 3. DM assign a weight to each criterion (sensing, smart, sustainable, and social) using the linguistic variables from Table 2.

Step 4. DM evaluate each solution path according to the criteria and the linguistic variables from Table 3.

Step 5. The evaluations are converted to fuzzy triangular numbers defined in step 1.

Table 3. Linguistic variables for the ratings.

Category/Benefit Criteria	Linguistic Variable	Fuzzy Numbers
s1, s2, s3, s4	Very poor (VP)	(0; 0; 1)
	Poor (P)	(0; 1; 3)
	Medium poor (MP)	(1; 3; 5)
	Fair (F)	(3; 5; 7)
	Medium good (MG)	(5; 7; 9)
	Good (G)	(7; 9; 10)
	Very good (VG)	(9; 10; 10)

Step 6. Obtain the fuzzy decision matrix by determining the average score of each criterion for each solution path and calculating each criterion's average weight.

Step 7. Normalize the fuzzy decision matrix by finding the fuzzy number with which each criterion is maximized (the maximum number) and dividing all the fuzzy numbers of that criterion by that maximum value. This ensures that all the criteria are given appropriate importance in the decision-making process.

Step 8. The normalized values are joined with the average of the weight of each criterion by multiplying the normalized values with the weight averages obtained in step 6.

Step 9. Determine the FPIS and the FNIS. In this method, the FPIS and the FNIS for all the criteria is as follows, considering that 1 is the best possible score (very high) and 0 is the worst possible (very low):

$$A^* = (1.00; 1.00; 1.00)$$

$$A^- = (0.00; 0.00; 0.00)$$

Step 10. Calculate the Euclidean distance for each solution path concerning the FPIS and FNIS using Equation (9) and Equation (10).

$$D = \sqrt{\frac{1}{3}\left[\sum_{i=1}^{3}(b_i - a_i)^2\right]} \tag{9}$$

$$D_{A_m} = \sum_{i=1}^{4} D_i \tag{10}$$

where for triangular fuzzy numbers $\widetilde{a} = (a_1, a_2, a_3)$ and $\widetilde{b} = (b_1, b_2, b_3)$, in this case, $\widetilde{b}$ represents values for FPIS and FNIS.

Step 11. Calculate each solution paths' closeness coefficient (CC_i) using Equation (11).

$$CC_i = \frac{D^-_{A_m}}{D^*_{A_m} + D^-_{A_m}} \tag{11}$$

Step 12. Rank the solution paths according to CC_i and choose the best option, which will be the one closer to 1.

Step 13. Analyze if the selected solution path meets the company's preferences and objectives, including the S4 needs; if it does not, start the process again; if it does, end the process.

4. Case Study with a Medium-Sized Mexican Manufacturing Company

To validate the proposed methodology, a case study was conducted in a medium-sized Mexican manufacturing company. This section presents the main characteristics of the company and the evaluations made by the decision makers.

A medium-sized Mexican manufacturing company is interested in installing a grid-connected PV system in its production plant. The plant is located in Monterrey, Mexico, the sun's radiance is an abundant and reliable source of energy that makes the installation of solar panels a viable and attractive option for companies looking to reduce their carbon footprint and energy costs. With an average of over 300 days of sunshine per year, Monterrey is ideally situated for solar energy production. By harnessing the sun's energy, the company can generate electricity that is both cost-effective and environmentally friendly. The installation of solar panels will not only reduce the company's reliance on traditional energy sources but also contribute to a more sustainable future. The sun's radiance in Monterrey provides an excellent opportunity for companies to invest in clean energy and demonstrate their commitment to sustainability. As can be observed in Figure 7, although Monterrey does not receive as much solar radiation as other states, it is still a state with a lot of potential to install PV solar energy.

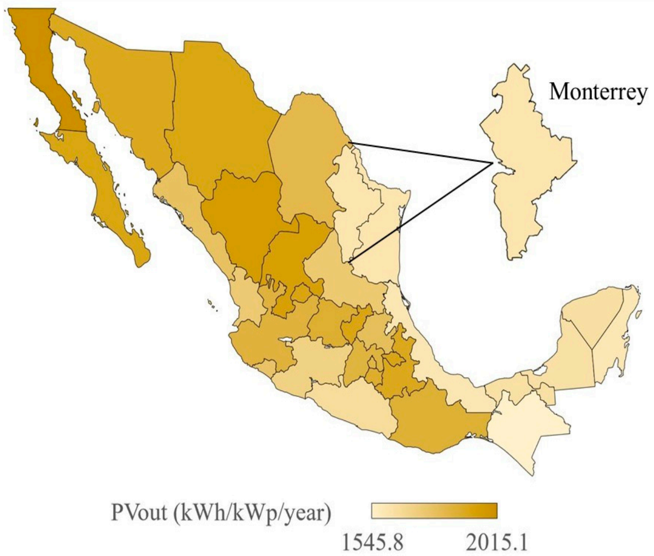

Figure 7. Photovoltaic power potential for Monterrey, Mexico (own elaboration with data from [51]).

The manufacturing company is specialized in developing car parts, so it has a variety of production processes and energy consumption patterns. In terms of energy consumption, the company's main energy usage comes from its production processes. Depending on the specific car parts being manufactured, the company uses a variety of manufacturing methods such as casting, stamping, or injection molding. These processes typically require significant amounts of electricity and may involve the use of large machinery or equipment. Additionally, the company uses other forms of energy such as natural gas, propane, or diesel fuel to power its equipment and heating systems. The amount of energy consumed depends on the production required. Given the increasing focus on sustainability and environmental responsibility, the company must explore novel ways to reduce its energy consumption and carbon footprint. They are looking into renewable energy sources such as solar or wind power, or implementing energy-efficient practices such as LED lighting and energy-efficient equipment.

Overall, a manufacturing company that develops car parts will likely have a significant focus on research and development and will consume energy primarily through its production processes. As the industry continues to evolve, there may be an increasing emphasis on sustainability and the use of renewable energy sources. In the case of PV panels, the company's needs have been divided in sensing, smart, sustainable, and social, and are shown in Table 4.

Five DM from the manufacturing company have analyzed these S4 needs, and they have chosen the S4 features that best meet them according to their judgement. Then, each DM has analyzed all the possible solutions and created solutions-paths by choosing the combinations of features that best meet the company's needs. Figure 8 shows the morphological matrix created with the S4 features chosen for the S4 needs by each DM, as well as the solutions-paths created by them; the number of the features corresponds to the number assigned in Figure 6.

Table 4. Sensing, smart, sustainable, and social needs from the manufacturing company.

Sensing	Smart	Sustainable	Social
Measurement of meteorological and power variables.	Data management and analysis for decision making and monitoring.	Environmental impact analysis applicable for a photovoltaic system installed on the ground	Legal framework applicable.
Battery system for backup.			Analysis of investment, return of investment, and savings considering governmental incentives.
			Adaptability for the user.

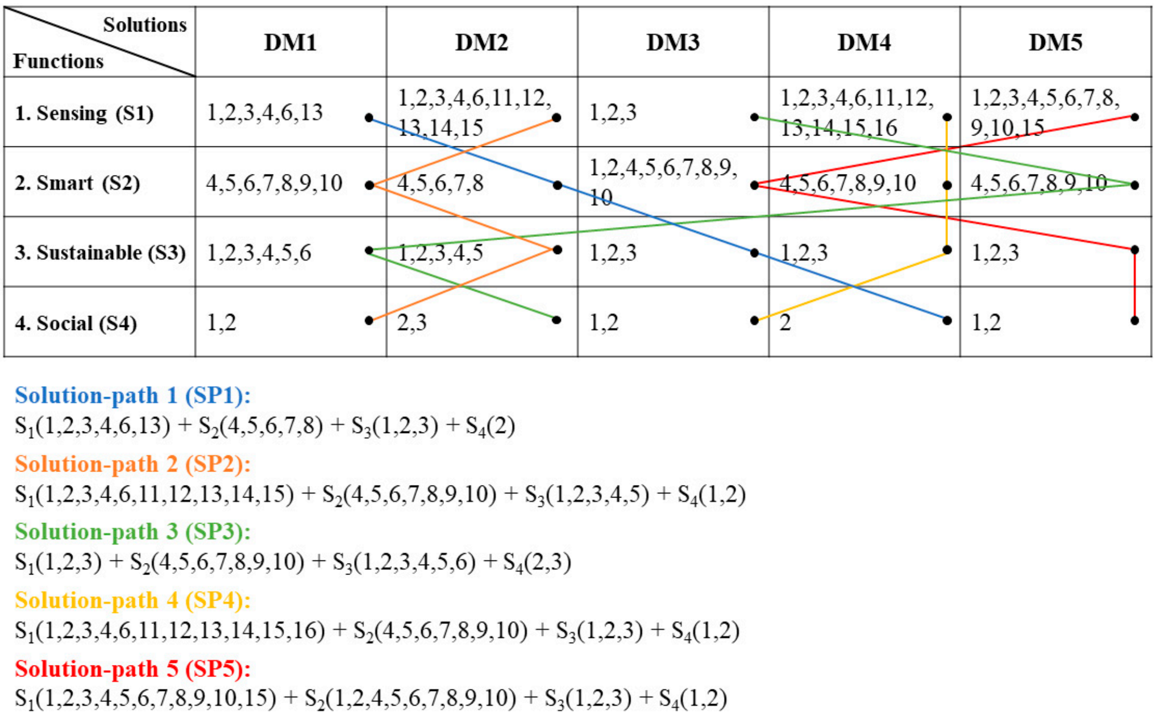

Figure 8. The morphological matrix with the solution paths created by the decision makers.

Table 5 presents the weight assignation for each criterion given by the DM using the linguistic variables from Table 2. Then, DM analyzed the solution paths created in Figure 8 and evaluated them considering the linguistic variables from Table 3 and the S4 criteria; the results are in Table 6.

Table 5. Weight of each criterion by the decision makers of the manufacturing company.

Criteria	DM1	DM2	DM3	DM4	DM5
s1	H	VH	L	VH	H
s2	MH	VH	VH	VH	H
s3	L	H	VH	M	L
s4	VH	VH	H	VH	VH

Table 6. Evaluation of each alternative by the decision makers from the manufacturing company.

Criteria	Alternative	DM1	DM2	DM3	DM4	DM5
s1	SP1	G	F	MG	F	MP
	SP2	VG	VG	VG	MG	G
	SP3	MP	P	P	MP	P
	SP4	VG	VG	VG	VG	VG
	SP5	VG	VG	VG	VG	VG
s2	SP1	MG	VG	MG	F	MP
	SP2	F	VG	G	MG	MG
	SP3	G	VG	VG	MG	MG
	SP4	G	VG	VG	G	G
	SP5	VG	VG	VG	VG	G
s3	SP1	P	MP	F	MP	MP
	SP2	G	F	G	MG	MG
	SP3	G	VG	G	G	VG
	SP4	F	MP	F	F	MP
	SP5	F	MP	F	F	MP
s4	SP1	VG	P	MP	MG	MP
	SP2	VG	VG	G	G	VG
	SP3	G	MG	VG	MG	F
	SP4	VG	VG	G	G	VG
	SP5	VG	VG	G	G	VG

5. Results and Discussion

In this section, the results of the fuzzy TOPSIS approach proposed for selecting the solution path that best meet the needs of the manufacturing company are presented.

Table 7 shows the transformation of the evaluations made by the DM (Table 6) to triangular fuzzy numbers considering the values of Table 3.

Table 7. Triangular fuzzy numbers of the evaluations of each alternative.

Criteria	Alternative	DM1	DM2	DM3	DM4	DM5
s1	SP1	(7; 9; 10)	(3; 5; 7)	(5; 7; 9)	(3; 5; 7)	(1; 3; 5)
	SP2	(9; 10; 10)	(9; 10; 10)	(9; 10; 10)	(5; 7; 9)	(7; 9; 10)
	SP3	(1; 3; 5)	(0; 1; 3)	(0; 1; 3)	(1; 3; 5)	(0; 1; 3)
	SP4	(9; 10; 10)	(9; 10; 10)	(9; 10; 10)	(9; 10; 10)	(9; 10; 10)
	SP5	(9; 10; 10)	(9; 10; 10)	(9; 10; 10)	(9; 10; 10)	(9; 10; 10)
s2	SP1	(5; 7; 9)	(9; 10; 10)	(5; 7; 9)	(3; 5; 7)	(1; 3; 5)
	SP2	(3; 5; 7)	(9; 10; 10)	(7; 9; 10)	(5; 7; 9)	(5; 7; 9)
	SP3	(7; 9; 10)	(9; 10; 10)	(9; 10; 10)	(5; 7; 9)	(5; 7; 9)
	SP4	(7; 9; 10)	(9; 10; 10)	(9; 10; 10)	(7; 9; 10)	(7; 9; 10)
	SP5	(9; 10; 10)	(9; 10; 10)	(9; 10; 10)	(9; 10; 10)	(7; 9; 10)
s3	SP1	(0; 1; 3)	(1; 3; 5)	(3; 5; 7)	(1; 3; 5)	(1; 3; 5)
	SP2	(7; 9; 10)	(3; 5; 7)	(7; 9; 10)	(5; 7; 9)	(5; 7; 9)
	SP3	(7; 9; 10)	(9; 10; 10)	(7; 9; 10)	(7; 9; 10)	(9; 10; 10)
	SP4	(3; 5; 7)	(1; 3; 5)	(3; 5; 7)	(3; 5; 7)	(1; 3; 5)
	SP5	(3; 5; 7)	(1; 3; 5)	(3; 5; 7)	(3; 5; 7)	(1; 3; 5)
s4	SP1	(9; 10; 10)	(0; 1; 3)	(1; 3; 5)	(5; 7; 9)	(1; 3; 5)
	SP2	(9; 10; 10)	(9; 10; 10)	(7; 9; 10)	(7; 9; 10)	(9; 10; 10)
	SP3	(7; 9; 10)	(5; 7; 9)	(9; 10; 10)	(5; 7; 9)	(3; 5; 7)
	SP4	(9; 10; 10)	(9; 10; 10)	(7; 9; 10)	(7; 9; 10)	(9; 10; 10)
	SP5	(9; 10; 10)	(9; 10; 10)	(7; 9; 10)	(7; 9; 10)	(9; 10; 10)

Table 8 presents the fuzzy decision matrix and the average weight of each criterion calculated from Table 5.

Table 8. The fuzzy decision matrix.

Alternative	s1	s2	s3	s4
SP1	(3.80; 5.80; 7.60)	(4.60; 6.40; 8.00)	(1.20; 3.00; 5.00)	(3.20; 4.80; 6.40)
SP2	(7.80; 9.20; 9.80)	(5.80; 7.60; 9.00)	(5.40; 7.40; 9.00)	(8.20; 9.60; 10.0)
SP3	(0.40; 1.80; 3.80)	(7.00; 8.60; 9.60)	(7.80; 9.40; 10.0)	(5.80; 7.60; 9.00)
SP4	(9.00; 10.0; 10.0)	(7.80; 9.40; 10.0)	(2.20; 4.20; 6.20)	(8.20; 9.60; 10.0)
SP5	(9.00; 10.0; 10.0)	(8.60; 9.80; 10.0)	(2.20; 4.20; 6.20)	(8.20; 9.60; 10.0)
Weight	(0.64; 0.78; 0.86)	(0.78; 0.92; 0.98)	(0.38; 0.52; 0.66)	(0.86; 0.98; 1.00)

Table 9 shows the fuzzy normalized decision matrix.

Table 9. The fuzzy normalized decision matrix.

Alternative	s1	s2	s3	s4
SP1	(0.38; 0.58; 0.76)	(0.46; 0.64; 0.80)	(0.12; 0.30; 0.50)	(0.32; 0.48; 0.64)
SP2	(0.78; 0.92; 0.98)	(0.58; 0.76; 0.90)	(0.54; 0.74; 0.90)	(0.82; 0.96; 1.00)
SP3	(0.04; 0.18; 0.38)	(0.70; 0.86; 0.96)	(0.78; 0.94; 1.00)	(0.58; 0.76; 0.90)
SP4	(0.90; 1.00; 1.00)	(0.78; 0.94; 1.00)	(0.22; 0.42; 0.62)	(0.82; 0.96; 1.00)
SP5	(0.90; 1.00; 1.00)	(0.86; 0.98; 1.00)	(0.22; 0.42; 0.62)	(0.82; 0.96; 1.00)

Table 10 presents the fuzzy weighted normalized decision matrix.

Table 10. The fuzzy weighted normalized decision matrix.

Alternative	s1	s2	s3	s4
SP1	(0.24; 0.45; 0.65)	(0.36; 0.59; 0.78)	(0.05; 0.16; 0.33)	(0.28; 0.47; 0.64)
SP2	(0.50; 0.72; 0.84)	(0.45; 0.70; 0.88)	(0.21; 0.38; 0.59)	(0.71; 0.94; 1.00)
SP3	(0.03; 0.14; 0.33)	(0.55; 0.79; 0.94)	(0.30; 0.49; 0.66)	(0.50; 0.74; 0.90)
SP4	(0.58; 0.78; 0.86)	(0.61; 0.86; 0.98)	(0.08; 0.22; 0.41)	(0.71; 0.94; 1.00)
SP5	(0.58; 0.78; 0.86)	(0.67; 0.90; 0.98)	(0.08; 0.22; 0.41)	(0.71; 0.94; 1.00)

In Table 11, the Euclidean distance of each solution path with respect to the FPIS and FNIS, calculated with Equations (9) and (10), is found.

Table 11. The Euclidean distance of each solution path.

Alternative	A^*	A^-
SP1	2.42	1.78
SP2	1.51	2.72
SP3	2.00	2.22
SP4	1.47	2.74
SP5	1.43	2.77

With Equation (11), CC_i was calculated for each solution path and then, the ranking was made. The results can be observed in Table 12.

Table 12. CC_i of each solution path.

Rank	Alternative	CC_i	Recommendation
1	SP5	0.66	Best choice
2	SP4	0.65	Feasible alternative
3	SP2	0.64	Acceptable option
4	SP3	0.53	Less optimal
5	SP1	0.42	Not recommended

As observed in Table 12, the best solution path for the manufacturing company is SP5 since it obtained the CC_i closest to the FPIS, which is (1.00, 1.00, 1.00). Thus, according to Figure 6, the S4 features that best meet the company's needs can be found in Table 13.

Table 13. S4 features for each solution path.

Sensing	Smart	Sustainable	Social
1. Panel surface temperature sensor 2. Solar radiation sensor 3. Voltage sensor 4. Current sensor 5. Air/Ambient temperature sensor 6. Battery voltage sensor 7. Tilt angle sensor 8. Wind speed sensor 9. Wind direction sensor 10. Humidity sensor 11. PV station weather sensor	1. Smart meter 2. Solar tracking system 3. Data storage 4. Data analytics 5. Predictive analysis 6. Monitoring system 7. Battery management system 8. Intelligent modelling techniques for forecasting solar energy 9. Smart inverter	1. Solar panels' total CO2 emissions 2. Inverters' total CO2 emissions 3. Land use	1. Legal and regulatory framework 2. Economic parameters

In alignment with the firm's sensing and smart requirements, it is unequivocally evident that the Sensing and Smart characteristics of SP5 optimally fulfil its requirements, principally pertaining to the measurement of meteorological and power variables, in addition to data analysis for informed decision making. Despite the PV system's grid-connection, the consideration of backup batteries has necessitated the inclusion of additional features for a battery system by the DM.

However, in terms of sustainability and social factors, SP5 lacks crucial features necessary to address the company's needs. For instance, considering the ground installation of the system, it is essential to account for the potential impacts of noise and visual disturbances, as well as effects on local flora and fauna. Furthermore, water usage and consumption are paramount factors, particularly during the operational phase, chiefly for maintenance and cleaning purposes. Finally, waste management, an aspect with substantial environmental impact, should have been considered given the significance of correct waste disposal in PV systems. It is noteworthy that none of the decision makers opted for waste management analysis (as shown in Figure 8), thus, hypothetically, none of the solution paths would adequately address the company's sustainability needs.

In relation to the Social category, SP5 does not account for population acceptance, a factor integral to ensuring a harmonious relationship between the user and the PV system. While some regulations may be applicable depending on the system, all three Social features are indispensable for PV systems. In this case, as illustrated in Figure 8, no decision maker selected all three Social features. Therefore, similar to the Sustainable category, no solution path adequately covers the social needs of the company.

5.1. Sensitivity Analysis

Sensitivity analysis is essential to evaluate the robustness of the methodology proposed and to determine how changes in decision criteria weights and fuzzy number assignments affect the final ranking of solar PV configurations.

The sensitivity analysis consists of two tests:

1. Weight variation analysis: Decision criteria weights are systematically adjusted to examine their impact on rankings and weights are increased/decreased for one criterion at a time while keeping the others constant.

2. Alternative fuzzy number assignments: Slight modifications to linguistic variable values are made (e.g., changing "Good" from (0.7, 0.9, 1.0) to (0.6, 0.8, 1.0)). The ranking stability is then evaluated under these variations.

5.1.1. Test 1: Weight Variation Analysis

Weights assigned to S4 criteria—sensing, smart, sustainable, and social—were varied in increments of ±10% while keeping the total sum equal to 1. A total of five weight variations were tested (Table 14).

Table 14. Weight scenarios.

Scenario	s1	s2	s3	s4
Base case	0.30	0.30	0.20	0.20
Scenario 1	0.40	0.25	0.20	0.15
Scenario 2	0.25	0.40	0.20	0.15
Scenario 3	0.25	0.25	0.30	0.20
Scenario 4	0.30	0.25	0.15	0.30

After applying fuzzy TOPSIS for each scenario, the CC_i of each solution path was recalculated (Table 15).

Table 15. Ranking results under different weight scenarios.

Scenario	SP1	SP2	SP3	SP4	SP5	Best Alternative
Base case	0.42	0.64	0.53	0.65	0.66	SP5
Scenario 1 (higher technical weight)	0.42	0.62	0.55	0.67	0.68	SP5
Scenario 2 (higher economic weight)	0.41	0.68	0.52	0.63	0.64	SP2
Scenario 3 (higher environmental weight)	0.40	0.60	0.55	0.66	0.67	SP5
Scenario 4 (higher social weight)	0.43	0.61	0.54	0.67	0.66	SP4

As observed in Table 14, SP5 remained the top-ranked solution in most scenarios, providing the robustness of the proposed methodology. SP2 moved up in Scenario 2, showing that when economic criteria were prioritized, SP2 was slightly more attractive. SP4 became the best choice in Scenario 4, indicating that if social aspects were weighted more heavily, SP4 would be the preferred alternative.

5.1.2. Test 2: Alternative Fuzzy Number Assignments

In this test, the linguistic variables assignments for fuzzy numbers were slightly modified to test their impact on rankings:

- "Good" changed from (0.7, 0.9, 1.0) to (0.6, 0.8, 1.0),
- "Fair" changed from (0.3, 0.5, 0.7) to (0.4, 0.6, 0.8), and
- "Poor" changed from (0.0, 0.1, 0.3) to (0.0, 0.2, 0.4).

Fuzzy TOPSIS was recalculated with the modified fuzzy number assignments (Table 16).

Table 16. Ranking results under different fuzzy number assignments.

Scenario	SP1	SP2	SP3	SP4	SP5	Best Alternative
Original fuzzy numbers	0.42	0.64	0.53	0.65	0.66	SP5
Modified fuzzy numbers	0.44	0.63	0.55	0.66	0.67	SP5

Table 16 shows that minor changes in fuzzy number assignments did not significantly impact rankings, confirming the stability of the decision-making process. SP5 remained the top choice of the decision-making process.

From the sensitivity analysis, it can be concluded that the proposed methodology is highly stable, as demonstrated by minimal ranking fluctuations under different conditions. SP5 remained the top-ranked alternative in almost all scenarios, showing that the decision is robust to minor variations in inputs. The methodology adapts to changes in decision criteria weights, allowing customization based on industry priorities. Future studies could extend sensitivity analysis by incorporating Monte Carlo simulations to further validate the robustness of the framework.

5.2. Comparison with Other Proposals

In Table 17, a comparison between this proposal and the proposals mentioned in the literature review (Table 1) that employ fuzzy TOPSIS to address various solar PV energy problems is presented. This comparison is intended to illustrate how the fuzzy TOPSIS method is applied, at which stage of the PV system's lifecycle the proposals are centered, and the type of criteria they focus on.

Table 17. Comparison between this proposal and others using the fuzzy TOPSIS method.

		Lifecycle Stage				Criteria			
Reference	**Method**	**Analysis**	**Installation**	**Operation**	**Disposal**	**Technical**	**Economic**	**Environment**	**Social**
This research	Morphological matrix and fuzzy TOPSIS	x	x	x	x	x	x	x	x
[33]	GIS-based Fermatean Fuzzy TOPSIS	x	x			x	x		x
[38]	Fuzzy TOPSIS	x	x	x		x			x
[34]	Fuzzy AHP-TOPSIS	x		x		x	x	x	x
[39]	Fuzzy AHP-TOPSIS	x	x	x		x	x		x
[35]	SWOT-based AHP, fuzzy VIKOR and fuzzy TOPSIS	x	x	x		x	x	x	x
[40]	Delphi method, fuzzy AHP, fuzzy VIKOR and TOPSIS	x		x		x	x	x	x
[42]	Fuzzy AHP-TOPSIS	x		x		x	x		x
[41]	Fuzzy AHP-TOPSIS	x		x	x		x	x	x
[36]	AHP and fuzzy TOPSIS	x	x	x		x	x	x	x
[37]	Fuzzy AHP-TOPSIS	x	x			x		x	

Regarding the fuzzy TOPSIS method, except for Ranganath et al. (2022) [38], all the studies combined the method with other MCDM methods, mainly with AHP, since the combination of AHP and fuzzy TOPSIS can provide a more comprehensive and robust decision-making framework and can effectively deal with the complexity of MCDM problems [52].

This proposal considers the complete lifecycle of PV systems, since each stage is essential because it contributes to the overall success, efficiency, and sustainability of the system. Furthermore, the analysis of each stage ensures that the system is well located, complies with regulations, is efficient in its operation and safe for personnel, and it is environmentally responsible throughout its lifecycle. Regarding the other proposals, as observed in Table 17, all the studies focus on the analysis stage, where the technical and economic viability of the project can be assessed. The second most considered stage is operation phase. During this stage, the system generates electricity, which involves monitoring to ensure it continues to function optimally, meeting economic, environmental, and social goals. The installation stage is addressed by six proposals, taking into account the structure, safety precautions, component compatibility, and proper documentation. Among all the studies reviewed, only Ligus and Peternek (2018) [41] address the disposal stage for waste management purposes. The fact that only one study considers disposal stage is critical because this stage is essential for environmental responsibility and regulatory compliance.

On the other hand, the two most considered criteria in the revised proposals were technical and social. The former primarily ensures the system's effectiveness, while the latter is essential for compliance with legal requirements. The economic criterion, focused on analyzing the economic viability of the project, was the third most considered. Finally, environmental criteria were addressed in only six studies, covering subcriteria such as waste management, GHG emissions, and impact on land and on flora and fauna.

While methods like AHP or Delphi could provide structured ways of determining weights, fuzzy TOPSIS was selected due to its ability to directly incorporate uncertainty and linguistic judgements, making it particularly suited to the complex, multi-criteria environment of industrial PV selection.

Decision making constitutes a critical process in the deployment and operation of solar energy systems, as corroborated by the findings of this study. The employment of morphological matrices enables a broader understanding of the system requirements and potential solutions, as well as the possible solution combinations. The application of a multi-criteria methodology, specifically fuzzy TOPSIS, in consideration of the S4 features and criteria, provides a holistic evaluation of solar energy systems, tailored to the distinct needs of manufacturing enterprises. This evaluation covers the complete lifecycle and takes into account essential technical, economic, environmental, and social factors at each stage.

However, it is essential for decision makers to meticulously analyze the needs and judiciously select potential solutions, thereby ensuring the effective achievement of the objectives of the decision-making tools proposed in this study. Conclusively, a strategy predicated on the previous results is proposed for the current and future operations of the company, as illustrated in Table 18.

Table 18. Strategy for present and future actions for the manufacturing company.

Present Actions	Future Actions
1. Install appropriate sensors (e.g., panel surface temperature, solar radiation, voltage, current, air/ambient temperature, battery voltage, tilt angle, wind speed, wind direction, and humidity) to collect accurate and reliable data for efficient solar panel operation and maintenance. 2. Implement a smart meter system to monitor energy production and consumption, enabling better energy management and facilitating grid integration. 3. Implement a solar tracking system to maximize solar energy capture by adjusting the panels' orientation according to the sun's position. 4. Develop a monitoring system to track and manage the performance of solar panels and related components in real time. 5. Implement a battery management system to optimize battery charging/discharging cycles, prolonging battery life and ensuring efficient energy storage.	1. Expand data storage and analytics capabilities to process and analyze sensor data, enabling the identification of trends and optimization opportunities. 2. Implement predictive analysis techniques to forecast solar energy production, allowing for better grid management and integration. 3. Utilize intelligent modelling techniques for forecasting solar energy to improve the accuracy of solar energy predictions, thus enhancing overall system efficiency. 4. Implement a smart inverter system to manage energy production, consumption, and storage more effectively and to provide grid support when needed. 5. Continuously monitor and evaluate solar panels' and inverters' total CO_2 emissions to assess and improve their environmental sustainability. 6. Implement land use strategies that minimize the environmental impact of solar panel installations, such as using previously disturbed lands or integrating solar panels into building designs. 7. Advocate for and adhere to a comprehensive legal and regulatory framework that promotes solar energy adoption and ensures responsible practices. 8. Monitor and consider economic parameters such as costs, incentives, and market trends to ensure the financial viability of solar panels installation and operation.

5.3. Practical Implications

The proposed morphological matrix + fuzzy TOPSIS framework provides a structured, data-driven approach for decision making in industrial solar PV deployment, offering manufacturing firms a systematic way to explore, evaluate, and select optimal system configurations based on multiple lifecycle-based criteria. By integrating technical, economic, environmental, and social factors, the methodology ensures that PV system adoption aligns with both operational efficiency and sustainability goals. The framework is highly adaptable, allowing companies to customize criteria weights based on strategic priorities, regulatory constraints, or financial considerations; thus, the proposed methodology can be customized for diverse industrial sectors beyond manufacturing, including automotive, textiles, and food processing industries, as well as firms of varying sizes and geographical locations.

While this proposed decision-making framework facilitates the optimal selection of solar PV configuration, manufacturing companies may face several other implementation challenges beyond the decision-making stage. Regulatory barriers often present significant hurdles, including unclear permitting procedures, grid access limitations, and complex compliance requirements, which can delay or deter solar PV adoption. Additionally, financial risks stemming from high initial investment costs, limited financing options, or uncertain payback periods could restrict companies' willingness to pursue renewable energy projects. Technical constraints, such as integration difficulties with existing power infrastructure and the availability of trained personnel to manage PV systems, may also pose substantial barriers. Addressing these practical challenges through targeted policies, financial incentives, streamlined regulatory frameworks, and specialized training programs is crucial to successfully implementing solar PV projects in industrial settings.

Mexico has experienced significant fluctuations in renewable energy policies over recent years, impacting solar PV adoption. Notably, reforms and regulatory changes have introduced uncertainty into the market. Initiatives such as the Electric Industry Law (Ley de la Industria Eléctrica-LIE) and recent changes proposed by the federal government have prioritized state-owned utilities and fossil fuel-generated power, indirectly creating barriers to renewable energy expansion and investment.

Conversely, supportive policy frameworks like net-metering, distributed generation incentives, and renewable energy auctions have historically encouraged solar adoption among industrial and commercial sectors. For instance, distributed generation policies allow industrial companies to offset energy costs by selling surplus solar-generated power back to the grid. However, regulatory uncertainties surrounding grid access, unclear permitting procedures, and the lack of consistent financial incentives have created significant hurdles for manufacturing firms aiming to adopt solar technologies.

Thus, to bolster solar PV adoption in Mexico's industrial sector, stable and transparent policy frameworks, clear regulations for renewable integration, financial incentives, streamlined permitting processes, and comprehensive renewable energy standards are critical. Policymakers should address these barriers proactively to unlock Mexico's considerable solar energy potential fully.

5.4. Limitations of the Proposed Methodology

Despite its advantages, the proposed methodology has certain limitations. First, the selection of criteria weights and linguistic variable assignments in fuzzy TOPSIS relies on expert judgement, which may introduce subjectivity and bias into the decision-making process in real-world scenarios. While sensitivity analysis helps mitigate this concern, further validation through larger expert panels or machine learning-based optimization techniques could enhance objectivity. Second, the computational complexity increases as the number of decision criteria and solution paths grows, making it less scalable for highly complex industrial applications with hundreds of potential configurations. Finally, the methodology has been tested in a single case study in a Mexican manufacturing company, and additional case studies across different industries and geographic regions would be needed to generalize its applicability further.

6. Conclusions

This research proposes a hybrid methodology integrating a morphological matrix with fuzzy TOPSIS, supported by the S4 Framework (sensing, smart, sustainable, and social), to select optimal PV configuration for manufacturing firms. The morphological matrix visually represents all possible PV system configurations based on identified requirements, while fuzzy TOPSIS effectively ranks these alternatives, managing uncertainty and incorporating multiple decision criteria.

A case study involving a Mexican manufacturing firm validated the proposed methodology. Five decision makers analyzed company-specific needs and established the morphological matrix, generating multiple solution paths. Fuzzy TOPSIS ranked these solutions, identifying Solution Path 5 as optimal based on decision-maker inputs. However, upon evaluation against the S4 requirements, it was found that this selection failed to cater to the Sustainable and Social needs of the company, thus rendering it unfit as the best possible alternative. Sensitivity analysis confirmed the stability and robustness of the ranking results, even when criteria weights and fuzzy logic inputs were varied.

Although the proposed methodology proves effective in identifying the best combination of S4 features for manufacturing companies considering the implementation of photovoltaic systems, the role of decision makers is paramount in the evaluation of S4 requirements and the selection of the features that best satisfy them. This is crucial to ensure that the selected alternative is indeed the most suitable.

This study emphasizes the practical importance of informed, multi-criteria decision making for industrial solar PV adoption, advocating for comprehensive understanding and customization based on sustainability goals, cost-efficiency, and unique organizational needs. Future research work includes the integration of discrete event simulation to optimize solar energy systems and energy consumption in the manufacturing process, leading to cost reduction, extended system lifespan, and maintenance savings by simulating real-time performance and operational variability, providing dynamic feedback to refine system configurations and decision-making processes. Furthermore, future studies should include detailed lifecycle cost analyses and comprehensive environmental impact assessments to further strengthen the decision-making framework's completeness and robustness. Incorporating artificial intelligence and optimization algorithms could also significantly improve the scalability and automation of the decision-making process, since criteria weighting could be automated based on historical project performance data, while optimization algorithms could rapidly evaluate thousands of configuration alternatives.

Finally, the practical and policy implications suggest the necessity of creating an environment that encourages Mexican manufacturing companies and other industrial sectors to embrace solar PV systems. Effective policies should include financial incentives, educational initiatives, research and development funding, environmental standards, and adaptability and training, encouraging widespread solar PV integration and sustainable industrial growth.

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Abbreviations

The following abbreviations are used in this manuscript:

AHP	Analytic Hierarchy Process
ANP	Analytic Network Process
CC_i	closeness coefficient
CO2	carbon dioxide
DM	decision maker
ELECTRE	Elimination Et Choix Traduisant la Realité
F	fair
FNIS	fuzzy negative ideal solution
FPIS	fuzzy positive ideal solution
G	good
GHG	greenhouse gas
GIS	geographic information system
GMA	General Morphological Analysis
H	high
KPIs	key performance indicators
L	low
M	medium
MADM	Multi-attribute decision making
MCDM	Multi-criteria decision making
MG	medium good
MH	medium—high
ML	medium—low
MODM	Multi-objective decision making
MP	medium poor
P	poor
PV	photovoltaic
ROI	return on investment
R&D	research and development
s1	sensing
s2	smart
s3	sustainable
s4	social
S4	sensing, smart, sustainable, and social
SP	solution path
SWOT	strengths, weaknesses, opportunities, and threats
TOPSIS	Technique for Order of Preference by Similarity to Ideal Solution
VG	very good

VH	very high
VL	very low
VP	very poor
WSN	wireless sensor network

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