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Multi-criteria evaluation and multi-method analysis for appropriately selecting renewable energy sources in Colombia ☆

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ABSTRACT

This research explores the implementation of renewable energy technologies for power generation using multi-criteria decision-making (MCDM) methods, including AHP, FAHP, TOPSIS, and FUZZY-TOPSIS. Ten renewable energy alternatives were evaluated across seven geographic regions in Colombia, revealing variability in preferences depending on the method and scenario. Alternatives 6 and 4 frequently stood out, while others showed varied rankings. This study significantly contributes to the energy sector by offering a rigorous framework for selecting renewable generation technologies, supporting sustainable energy planning, and providing a model for replication in global contexts, some key points are:

- The study applied systematic MCDM approaches to assess renewable energy sources.
- Results demonstrated method-dependent variability and highlighted regional preferences.
- It sets a benchmark for integrating sustainable practices into energy planning worldwide.

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(*continued on next page*)

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Background

The selection of optimal alternatives in complex contexts, such as the evaluation and prioritization of renewable energy sources, demands robust methodological tools that combine analytical precision with the flexibility to address inherent data uncertainties. In this regard, the Fuzzy Analytic Hierarchy Process (FAHP), Analytic Hierarchy Process (AHP), Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), and Fuzzy Technique for Order of Preference by Similarity to Ideal Solution (FTOPSIS) offer complementary capabilities to tackle this challenge [1].

The choice of FAHP and AHP stems from their ability to structure multicriteria problems hierarchically, enabling the decomposition of complex issues into manageable elements. These methodologies facilitate the determination of relative priorities among criteria and alternatives using pairwise comparisons. The inclusion of FAHP is justified by its capacity to incorporate uncertainty and subjectivity in expert judgments through the use of fuzzy numbers. This is particularly relevant in scenarios where available data is ambiguous or incomplete, as is often the case in sustainability studies [2].

Meanwhile, TOPSIS and FTOPSIS were selected for their focus on proximity to ideal solutions, which identifies alternatives that optimize multiple criteria simultaneously. TOPSIS relies on the concept of Euclidean distance and offers a transparent and computationally efficient framework. However, to address the variability and subjectivity inherent in expert judgments during the initial modeling stages, the fuzzy variant, FTOPSIS, was employed. This methodology uses fuzzy numbers to model uncertainties and produce more robust rankings when facing ambiguous data [3].

The integration of these methodologies provides a comprehensive framework for multicriteria decision-making in this research. AHP and FAHP offer a structured, hierarchical approach to prioritize criteria and alternatives, while TOPSIS and FTOPSIS complement the analysis by identifying alternatives closest to an ideal solution. This combined approach effectively integrates quantitative and qualitative data, enabling holistic and flexible evaluations [4]. Multi-criteria analysis has proven to be a versatile and effective tool for decision-making across various sectors, thanks to its ability to integrate multiple factors and criteria when evaluating alternatives. Among the most widely used methods, the Analytic Hierarchy Process (AHP) has been extensively applied in different contexts, ranging from the assessment of indoor environmental quality through the definition of appropriate weighting schemes for evaluating various environmental parameters [5],to the selection of optimal interventions for improving acoustic quality in learning environments [6]. Additionally, in the field of fire safety and prevention, AHP has been employed to identify the most probable fire origin room within a building, facilitating more effective response strategies [7]. These applications highlight the flexibility of multi-criteria analysis and its ability to adapt to complex problems across different disciplines, reinforcing its relevance in the present study.

Our motivation lies in the need to provide decision-makers with a methodological suite that, in addition to being rigorous and adaptable, is replicable across various geographic contexts and similar challenges. These tools not only enhance the ability to evaluate alternatives in energy-related contexts but also contribute to promoting sustainable practices aligned with the United Nations' Sustainable Development Goals (SDGs) [8].

As the last comment, the combination of FAHP, AHP, TOPSIS, and FTOPSIS addresses the need to simultaneously handle complexity, subjectivity, and uncertainty in multicriteria decision-making processes. It provides a robust and flexible framework for evaluating and selecting optimal alternatives in energy projects and beyond.

Method details

This research evaluated seven (7) scenarios corresponding to different geographic regions of Colombia. Ten (10) energy alternatives were used for each scenario. Finally, four (4) decision methods (AHP, FAHP, TOPSIS, and Fuzzy TOPSIS) were used to evaluate the different scenarios and energy alternatives and define the most suitable renewable energy source have contributed to only 28 of the 80 projects progressing smoothly.

The main objective of the AHP method is to find the weights of the criteria by pairwise comparisons of the alternatives and classifying them accordingly. Strengths of the AHP method: simplicity, scalability, and hierarchical approach can be applied to many issues besides not being too sensitive to data changes. In the literature, the AHP method has been used both to calculate criterion weights and to classify alternatives [9]. One significant disadvantage of the AHP method depends on the opinions of the experts. When experts are used who, if they do not have enough experience, can give erroneous results, such results loaded with high subjectivity are mitigated by implementing a second method called FAHP [10].

In this study, to avoid this disadvantage of the AHP method, the experts were chosen among those who have a lot of experience in their fields according to what is relevant in this research, it is observed that the opinions of the experts collected through the questionnaire carried out differ significantly from each other [11]. The decision problem criteria table was normalized to classify the alternatives for calculating the AHP. The normalization matrix is calculated by dividing the value of each cell by the sum of all the numbers in its column; for each scenario, the priorities were calculated, and the classifications were obtained. In the TOPSIS method,

Table 1
Implementation of the Saaty scale according to the degree of importance [16].

Value	Definition
1	Equal importance
2	Moderate importance
5	Great importance
7	Very important
9	Extreme importance
2, 4, 6 and 8	Intermediate values

Table 2
Example of a comparison matrix.

	A1	A2	A3
A1	1	A12	A13
A2	A21	1	A23
A3	A31	A32	1

the positive ideal solution is first, then the negative perfect solution and the distance of the solution are calculated. According to calculation, the closest alternative to the perfect positive solution, or, in other words, the furthest from the negative [11].

The ideal solution is the first; this study's alternatives are ordered with the same logic. Microsoft Excel software was used to solve the problem with the TOPSIS and Fuzzy TOPSIS methods. First, there's the normalized decision matrix. Here, the value of the square root of the sum of the squares of the elements in each column in the last row is used in the second step to construct the standard decision matrix [11]. The "Weighted Standard Decision Matrix" was obtained in the third step by multiplying the criterion weights by the standard decision matrix. In the fourth step, the positive and negative ideal solutions are calculated through a weighted standard decision matrix. In the fifth step, the Euclidean distances of all the points from the positive, negative, and positive ideal points are calculated, and the negative ideal distances are found. In the sixth step, the relative closeness of all the alternatives is calculated and classified, and the classification of the other options is obtained [12].

AHP methodology

The Hierarchical Analytical Process is a versatile tool that is applied in various areas, from project and risk management to strategic planning and public policy design [13] [4]. Its ability to decompose complex problems and evaluate alternatives in a systematic and structured way makes it a valuable resource for informed and effective decision-making. The methodology used in the application of the hierarchical analytical process is presented below [14].

Step 1: Modeling. In this phase, the hierarchical sequence of problems is implemented, and the objectives, criteria, and alternatives to be implemented are defined according to the requirements of the experts. Next, the alternatives through which the criteria to be evaluated are established. These criteria should take into account the problem and identify attributes that help make good decisions. These criteria should be measured at the level, which is the fundamental goal we must achieve to solve the problem, and at the second level, the requirements will be positioned according to a descending hierarchy of one or more variables for each criterion. The third and final layer will be the alternatives in decision-making.

Step 2: Reviews. Once the alternatives are understood and the criteria defined, each criterion is classified and weighted when selecting the alternatives. This process intends to measure the importance that decision-makers assign to each criterion or alternative i, compared to each criterion or alternative j. A baseline scale of 1 to 9 was used to assess the relative preference of the items, Table 1.

In this way, we proceed to construct the matrix of paired comparisons, where we obtain a square matrix Anxn = [aij], with $1 \leq i, j \leq n$.

For the construction of the matrix, the following axioms must be considered [15]:

Axiom of reciprocity: If A is a matrix of paired comparisons, then it is true that if $aij = x$ then $aji = 1/x$ with $1/9 \leq x \leq 9$

For the property of reciprocity, only n(n-1)/2 comparisons are made [16]:

Axiom of homogeneity: The elements that are compared with each other will be of the same order of magnitude and hierarchy.

Axiom of independence: When the decision-maker makes the comparisons, it is assumed that the criteria do not depend on the different alternatives.

By complying with the above axioms, it is possible to determine the desired comparison matrix, Table 2.

Step 3. Prioritization and synthesis. After comparing the paired matrices, we calculate since this is a priority part to be made. This underscores the importance that decision-makers attach to each element.

Table 3
Comparison between the obtained consistency index (CI) and the random CI [18].

Die Size (n)	1	2	3	4	5	6	7	8	9	10
Random consistency	0	0	0.52	0.89	1.11	1.25	1.35	1.4	1.45	1.49

The priority is represented as a vector or vector, assuming that it is a matrix A (nxn), as obtained by comparing in pairs. We call the solution of the equation eigenvalues or eigenvectors of A (λ1, λ2, λn): det (A- λI) = 0. The principal eigenvalue (λ_{max}) of the matrix is the maximum value obtained.

The associated eigenvector is the principal eigenvalue of {A} and {a}. The eigenvectors associated with the value of probabilities are the weighting vectors that must be achieved.

Thus, the eigenvector achieved is that of the criteria matrix, which we call Vc, which represents the relative importance of each criterion selected in the joint evaluation of the alternatives we work on. When the eigenvector obtained is the eigenvector of the surrogate matrix for a given criterion, we call it *Vai* (column vector), which represents the relative importance of each surrogate matrix for criterion *i*, where we obtain as many eigenvectors as standard. Remember that the final decision is the consistency of the decision-maker's decision when completing the matching matrix [17].

In this way, the insured's decision is a personal judgment, which leads to an inconsistency that is evaluated to determine if the limits are below what corresponds.

Step 4. Consistency Analysis. This analysis considers the subjectivity of manufacturing decisions. When comparing matrices in pairs, subjectivity is as real and objective as possible because the different elements of one matrix are compared with those of another matrix.

On the other hand, there is a procedure for calculating it. If acceptable, the decision-making process can continue, but if not, more in-depth analysis is required, as it can review judgments about peer comparisons. Calculate the consistency ratio using Eq. (1); see Table 3.

Standard Matrix A:

$$Anormalized\left[\frac{a_y}{\sum_{k-1}^{n} a_{kj}}\right] \tag{1}$$

The sum of the rows is obtained from Eq. (2) [24].

$$\begin{aligned}
&\frac{a_{11}}{\sum_{n-1}^{n} a_{n1}} + \frac{a_{12}}{\sum_{n-1}^{n} a_{n2}} + \ldots\ldots\ldots\ldots + \frac{a_{1n}}{\sum_{n-1}^{n} a_{nn}} = b_1\\
&\frac{a_{11}}{\sum_{n-1}^{n} a_{n1}} + \frac{a_{12}}{\sum_{n-1}^{n} a_{n2}} + \ldots\ldots\ldots\ldots + \frac{a_{1n}}{\sum_{n-1}^{n} a_{nn}} = b_2\\
&\frac{a_{11}}{\sum_{n-1}^{n} a_{n1}} + \frac{a_{12}}{\sum_{n-1}^{n} a_{n2}} + \ldots\ldots\ldots\ldots + \frac{a_{1n}}{\sum_{n-1}^{n} a_{nn}} = b_n
\end{aligned} \tag{2}$$

The priority vector B that is formed is given by Eq. (3).

$$\left[\frac{b_1}{n}, \frac{b_2}{n}, \ldots\ldots\ldots . \frac{b_n}{n},\right]^T \tag{3}$$

The product of the original matrix A and the priority vector B forms a matrix of column C, Eq. (4).

$$A*B = C = \left[c_{1,}c_{2\ldots\ldots\ldots\ldots\ldots}c_n\right]^T \tag{4}$$

Consequently, the quotient between the column of matrix C and the priority vector B is calculated, obtaining another vector of column D, Eq. (5).

$$\frac{C}{B} = D \tag{5}$$

By adding and averaging its elements, the value of the consistency index (CI), Eq. (6), is obtained.

$$CI = \frac{\lambda_{max-n}}{n-1} \tag{6}$$

Subsequently, the CI obtained is compared with the random CI in Table 3.

The random consistency (CI) value as a function of the matrix size represents the CI value that would have been obtained if the numerical judgments of the scale had been entered into the comparison matrix in a completely random manner.

Therefore, the CI is divided by random consistency, thus obtaining the Inconsistency Index (IR), Eq. (7).

$$IR = \frac{CI}{Random\ consistency} \tag{7}$$

Finally, a consistent matrix is considered when the values stipulated for the size of each matrix are not exceeded. If a matrix exceeds the consistency coefficient, the valuations performed are checked and modified.

Table 4
FAHP methodology.

Definition of the problem	• Identify and clearly define the decision-making problem. • Establish the objectives and criteria for evaluating the alternatives.
Hierarchization	• Decompose the problem into a hierarchy of criteria and sub-criteria. • Identify and organize the key factors influencing the decision.
Peer-to-peer comparison	• Perform peer-to-peer comparisons to assess the relative importance of criteria and sub-criteria. • Assign numerical values that represent the preferences of the experts
Comparison matrix	• Build a matrix that reflects the preferences of the experts. • Collect the comparisons between pairs to calculate the weights.
Standardization	• Normalize the comparison matrix to ensure that the weights add up to one. • Ensure the consistency of the weights.
Calculation of global weights	• Calculate the overall weights based on comparisons and normalization. • Determine the contribution of each element to the final decision.
Consistency	• Evaluate the consistency of comparisons using the consistency index. • Adjust in case of inconsistencies in the matrix.
Multicriteria analysis	• Use the calculated weights to evaluate the alternatives. • Conduct a multi-criteria assessment to determine the most appropriate option
Synthesis of Results	• Synthesize the results of the evaluation. • Present the alternatives ordered according to their performance in relation to the criteria
Sensitivity	• Perform a sensitivity analysis to assess the impact of changes in preferences. • Determine how variations in judgments affect decisions.
Decision-making	• Use FAHP analysis results with fuzzy logic for informed decisions. • Select the best alternative, considering the uncertainty.

FAHP methodology

The Hierarchical Analytic Process with Fuzzy Logic (FAHP) methodology extends the AHP (Hierarchical Analytic Process) that incorporates fuzzy logic to address uncertainty and ambiguity in multi-criteria decision-making. However, the exact history of its development is not as widely documented as that of the AHP [19]. Fuzzy logic, developed in the 1960s, provides a framework for representing and managing uncertainty in data and judgments. To combine the advantages of AHP with fuzzy logic's ability to deal with uncertainty, researchers began exploring the extension of AHP with fuzzy logic [20]. Throughout the 1990s and 2000s, there was significant growth in research and literature related to FAHP. Researchers from various disciplines, such as engineering, management, and artificial intelligence, contributed to developing and adapting FAHP methods for specific applications. As the FAHP methodology gained popularity, specific variants and extensions were designed to address problems [21].

These variants are tailored to the needs of various applications and industries, including project management, engineering decision-making, and strategic planning. Although there is no specific event or prominent figure behind the development of the FAHP, as in the AHP case, its evolution is a testament to the adaptability and versatility of multi-criteria decision-making methods in response to decision-making needs in uncertain environments [22]. The FAHP methodology has proven to be valuable in addressing complex problems in which uncertainty and ambiguity are vital elements.

In the same way that the steps for the AHP methodology were explained, the steps to achieve the implementation of the fuzzy hierarchical analytical process FAHP are now summarized, see Table 4.

This section presents the fundamental concepts that guided this study. The intention is not to cover all topics but to provide essential support information to understand the objective of the research, the context, and the results perfectly; in this research, initially a characterization of a specific population, I seek to evidence the social, economic, environmental and energy reality of this. The different existing government and research databases were consulted to carry out this characterization [23].

It happens that the characterizations of the population nature manage to obtain as results information on the structure and a large number of identity attributes of various groups of people with evolutionary continuity over time, which, according to their differences, configure particular ways of being and being in a territory, in this research, it was taken to the department of La Guajira in the country of Colombia because this area is a territory very rich in natural resources, which makes it a potential in the implementation of renewable energy sources, however despite this natural disposition, this area of that country is one where its inhabitants suffer from a poor quality of life [24].

These studies that characterize a population's energy potential also allow us to focus attention on guaranteeing or restoring the effective enjoyment of the rights of population groups, the recognition of their diversity and multiculturalism as social wealth, the particularities and inequalities that hinder or enable their access to the dynamics and benefits of social and territorial development. The importance of correctly directing the appropriate forms of population characterization exercises lies in the fact that they allow the design, adjustment, and implementation of public policies to be based with a view to transforming situations considered problematic and offering goods and services that satisfactorily respond to the needs and interests of population groups [25].

On the other hand, the hierarchical analytical method with fuzzy logic was implemented to prioritize the barriers that may arise in implementing energies with renewable sources in the study area. This methodology's explanation was separated into sections for a better understanding.

Fuzzy assembly operations

The complementary set of a fuzzy set $\overline{A}$ One is one whose characteristic function is defined by [26].

$$m_A = (x) \; - m_A(x) \tag{8}$$

The union of two fuzzy sets A and B is a fuzzy set A ∪ B in U whose membership function is,

$$m_{\mathrm{A\ U\ B}}(x) = m\acute{a}x\ m_A(x),\ m_B(x) \tag{9}$$

The intersection of two fuzzy sets A and B is a fuzzy set A ° B in U
With feature function:

$$m_{\mathrm{A} \cap \mathrm{B}}(x) = m\acute{i}n\ m_A(x),\ m_B(x) \tag{10}$$

The main operators that meet the conditions for t-conorms are the maximum operator and the algebraic sum.

$$m_{\mathrm{A\ U\ B}}(x) = m_A(x) + m_B(x) \; - \; m_A(x)\ m_B(x) \tag{11}$$

And the main operators that meet the conditions to be t-standards are the minimum operator and the algebraic product.

$$m_{\mathrm{A} \cap \mathrm{B}}(x) = m_A(x)\ m_B(x) \tag{12}$$

Fuzzy relationships

$$R(U, V) = \left((x, y), m_R(x, y)\right) | (x, y) \epsilon U x V \tag{13}$$

Suppose, $R(x,\ y)$ and $S(x,\ y)$

They are relationships in the same product space $U x V$ The intersection or union between R and S, which are compositions between the two relations, are defined as [2]:

$$m_{\mathrm{R} \cap \mathrm{S}}(x, y) = \; m_R(x,\ y) * m_S(x) \tag{14}$$

$$m_{\mathrm{R\ U\ S}}(x) = m_R(x,\ y) * m_{\mathrm{S}}(x,\ y) \tag{15}$$

If R ° S, R and S belong to discrete universes of discourse. It is defined as a fuzzy relationship in UxW whose membership function is given by [27]:

$$m_{\mathrm{R} \circ \mathrm{S}}(x, z) = \; sup_{y \epsilon V} \left[\mu_R(x,\ y) * \mu_s(y, z)\right] \tag{16}$$

Where the SUP operator is the maximum and the operator* can be any T-standard. Depending on the t-standard chosen we can obtain different compositions. The two most used compositions are the maximum-minimum composition and the maximum composition of the product [28]:

The max-min composition of the fuzzy relations R (U, V) and S (V, W), is a fuzzy relationship R ∘ S in UxW defined by the membership function

$$\mu_{\mathrm{R} \circ \mathrm{S}}(x, z) = \; m\acute{a}x_{y \epsilon V} min \left[\mu_R(x,\ y) * \mu_s(y, z)\right] \tag{17}$$

Where $(x, z) \epsilon\ U x W$

The composition of the maximum product of the fuzzy relations R (U, V) and S (V, W), is a fuzzy relation to R ∘ S in UxW defined by characteristic function,

$$\mu_{\mathrm{R} \circ \mathrm{S}}(x, z) = \; m\acute{a}x_{y \epsilon V} \left[\mu_R(x,\ y) * \mu_s(y, z)\right] \tag{18}$$

Where $(x, z) \epsilon\ U x W$

Fuzzy implication

As we have already seen, in the fuzzy logic theory, the proposition "if you are A, then v is B," where u ε you and v ε V, has an associated characteristic function that takes values in the interval [29]. Examples of possible associated characteristic functions drawn from the application of the analogies between operators and the tautology above are,

$$m_{A \to B}(x, y) = 1 - \mu_{A \cap B}(x, y) = 1 - min\left[\mu_A(x), 1 - \mu_B(y)\right] \tag{19}$$

$$m_{A \to B}(x, y) = max\left[1 - \mu_A(x), \mu_B(y)\right] \tag{20}$$

$$m_{A \to B}(x, y) = 1 - \mu_A(x)\left(1 - \mu_B(y)\right) \tag{21}$$

In fuzzy logic, the Modus Ponens extends to what is called Generalized Modus Ponens and can be summarized as follows [30],

Premise 1: "u is A*"
Premise 2: "if you are A THEN v is B"
Consequence: "v is B*"

Where the fuzzy set A* does not necessarily have to be the same as the fuzzy set A of the rule's antecedent and the fuzzy set B* does not necessarily have to be the same as the fuzzy set B that appears in the rule's consequence.

Thus, the generalized Modus Ponens is a fuzzy composition in which the first fuzzy relation is the fuzzy set A* and which can be expressed,

$$\mu_{B*}(y) = sup_{x\epsilon A*1}\left[\mu_{A*}(x) * \mu_{A \to B}(x, y)\right] \tag{22}$$

Considering that, in the applications of fuzzy logic to engineering, the characteristic function of the implication is built with the minimum and product operators, which in addition to being the simplest preserve the cause-effect relationship, we will have two options to choose from,

$$\mu_{A \to B}(x, y) = min\left[\mu_A(x), \mu_B(y)\right] \tag{23}$$

$$\mu_{A \to B}(x, y) = \mu_A(x).\mu_B(y) \tag{24}$$

Methods of organizing

Maximum Method: The output variable for which the characteristic function of the fuzzy output set is maximum is chosen. In general, it is not an optimal method, as this maximum value can be reached by several outputs [17].

Centroid method: Uses the center of gravity of the output characteristic function as the output of the system.

$$y = \left(\int y\mu_A(y)dy\right) \Big/ \left(\int y\mu_B(y)dy\right) \tag{25}$$

It is the most widely used method in applications ranging from fuzzy logic to engineering as a single solution is obtained, although it is sometimes difficult to calculate.

Height method: The center of gravity of the diffuse output set Bm is calculated for each ruler and then the system output is calculated as the weighted average:

$$y_h = \left(\int \bar{y}_m \mu_{B_m}\left(\bar{y}_m\right)dy\right) \Big/ \left(\int \mu_{B_m}\left(\bar{y}_m\right)dy\right) \tag{26}$$

Fuzzy logic analysis

If it is a set of objects and a set of objectives, according to extended analysis method, the extended analysis is developed for each of the values of the objects; In this way they can be obtained for each objective$X = \{x_1, x_2, x_3, \ldots\ldots x_n\}$ $U = \{u_1, u_2, u_3, \ldots\ldots u_n\}$. Therefore, the extended analysis values of m can be obtained with the following notation [31],

$$M_{gi}^1, M_{gi}^2, \ldots\ldots, M_{gi}^m = 1, 2, 3, \ldots\ldots n. \tag{27}$$

Where everything is fuzzy triangular numbers.$M_{gi}^1 (j = 1, 2, 3, \ldots\ldots m)$

Key steps of the model proposed by,

Step 1: The value of the object – th of the extended analysis is defined as: i

$$S_i = \sum_{j=1}^{m} M_{gi}^j \otimes \left[\sum_{i=1}^{n}\sum_{j=1}^{m} M_{gi}^j\right]^{-1} \tag{28}$$

Table 5
Fuzzy triangular conversion scale [34].

Linguistic scale	Triangular Diffuse Triangular
Just the same	(0,0,0)
Degradable important	(0,1,3)
Important	(1,3,5)
Much more important	(3,5,7)
Very strongly more important	(5,7,9)
Absolutely more important	(7,9,9)

To obtain, the fuzzy addition operation of m values of the extended analysis is performed for a particular matrix, such that:$\sum_{j=1}^{m} M_g^j$

$$\sum_{j=1}^{m} M_{gi}^{j} = \left(\sum_{j=1}^{m} l_j \sum_{j=1}^{m} m_j \sum_{j=1}^{m} u_j \right) \tag{29}$$

To get perform the fuzzy sum of values operation, so that:$[\sum_{i=1}^{n} \sum_{j=1}^{m} M_{gi}^{j}]^{-1} M_{gi}^{1} (j = 1,\ 2,\ 3,\ \ldots\ldots\ m)$

$$\sum_{i=1}^{n} \sum_{j=1}^{m} M_{gi}^{j} = \left(\sum_{i=1}^{n} l_i \sum_{i=1}^{m} m_i \sum_{i=1}^{m} u_i \right) \tag{30}$$

Then the inverse vector of the equation is calculated, as follows [32]:

$$\left[\sum_{i=1}^{n} \sum_{j=1}^{m} M_{gi}^{j} \right]^{-1} = \left(\frac{1}{\sum_{i=1}^{n} u_i},\ \frac{1}{\sum_{i=1}^{n} m_i},\ \frac{1}{\sum_{i=1}^{n} l_i} \right) \tag{31}$$

Step 2: The degree of chance of it occurring is defined as:$M_2 = (l_2,\ m_2,\ u_2) \geq M_1 = (l_1,\ m_1,\ u_1)$

$$V\ \left(M_2 \geq M_1\right)\ = sup_{y \geq x}\ \left[min\left(\mu_{M1}(x),\ \mu_{M2}(y)\right)\right] \tag{32}$$

And it can be expressed equivalently as follows:

$$V\ (M_2 \geq M_1)\ = hgt(M_1 \cap\ M_2) = \mu_{M2}(d) = f\ (d) \tag{33}$$

Yes $m_2 \geq m_1$

$$\text{Yes } l_1 \geq u_2 = \begin{cases} 1, \\ 0, \\ \frac{l_1 - u_2}{(m_2 - u_2) - (m_1 - l_1)} \end{cases} \tag{34}$$

Where d is the ordinate of the highest point of intersection D between and To compare and the values of y are required $\mu_{M1}\mu_{M2} M_1 M_2\ V\ (M_2 \geq M_1)\ V\ (M_1 \geq M_2)$ [33].

Step 3: The degree of chance that a fuzzy convex number is greater than k

Convex numbers are defined as:

$$V\ \left(M \geq M_1,\ M_2,\ \ldots\ldots,\ M_k\right)\ = V\ \left[\left(M \geq M_1\right)\ y\ \left(M \geq M_2\right)\ y\ \left(M \geq M_k\right)\right] = min\ V\left(M \geq M_i\right),\ i = 1,\ 23,\ \ldots\ldots,\ k$$

Therefore, assuming that:

$$d'\ \left(A_i\right))\ min\ V\ \left(S_i \geq S_k\right) \tag{35}$$

For. The weight of the vector is given by:$k\ = 1,\ 2,\ 3,\ \ldots\ldots, n;\ k\ \neq\ iW' = (d'\ (A_1),\ d'\ (A_2),\ \ldots\ldots,\ d'\ (A_n))^T$
Where are n elements?$A_i (i = 1,\ 2,\ 3,\ \ldots\ldots,\ n)$

Step 4: Vector normalization is presented as follows:

$$W =\ \left(d\ \left(A_1\right),\ d\ \left(A_2\right),\ \ldots\ldots,\ d\ \left(A_n\right)\right)^T \tag{36}$$

Where W is not a fuzzy number, but the set of weights of each matrix.
In this case, it must be considered that W are no longer fuzzy numbers, but vectors with the final weights. Table 5 shows the values used in the conversion of the linguistic syntax used by the experts and their respective assessment into fuzzy triangular and triangular numbers.

TOPSIS methodology

Implementing the Technique for Order Preference by Similarity to the Ideal Solution (TOPSIS) method involves systematically evaluating and prioritizing alternatives based on multiple criteria. The following are the key steps to apply the TOPSIS method effectively [35]:

Problem Identification and Definition of Criteria and Alternatives: The first step is to clearly define the decision problem and determine the criteria that will be used to evaluate the alternatives. These criteria must be relevant and measurable. Likewise, the alternatives that will be evaluated must be identified.

Construction of the Decision Matrix: A decision matrix is created where the rows represent the alternatives, and the columns represent the criteria. The matrix elements are the values that indicate the performance of each alternative concerning each criterion.

Decision Matrix Normalization: Because criteria can have different units of measurement, it is necessary to normalize the decision matrix values to be comparable. This is done using the normalization Expression.

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{k=1}^{m} x_{kj}^2}} \tag{37}$$

Where you govern the normalized value, *xijes* the original value, and m is the number of alternatives.

Construction of the Normalized Weighted Matrix: The normalized values are multiplied by the corresponding weights of the criteria to obtain the normalized weighted matrix. The weights reflect the relative importance of each criterion and must be determined in advance.

$$Vij = wj \cdot rij \tag{38}$$

Where you see the normalized weighted value and *wjes* the weight of criterion j.

Determination of Ideal and Anti-Ideal Solutions: The positive ideal solutions (best value for each criterion) and negative ideal (worst value for each criterion) are identified.

$$A+ = \{max(Vij) \mid j \in J\}, min(Vij) \mid j \in J\prime\} \tag{39}$$

$$A- = \{min(vij) \mid j \in J\}, max(Vij) \mid j \in J\prime\} \tag{40}$$

Where JJ is the set of criteria to be maximized and J′J′ is the set of criteria to be minimized.

Calculation of the Distances to the Ideal Solutions: The Euclidean distance of each alternative to the positive and negative ideal solutions is calculated.

$$\mathrm{Di}+ = \sqrt{\sum_{j=1}^{n} v_{ij} + A_j^{+2}} \tag{41}$$

$$\mathrm{Di}- = \sqrt{\sum_{j=1}^{n} v_{ij} - A_j^{-2}} \tag{42}$$

Where Di+ is the distance to the positive ideal solution and Di− is the distance to the negative ideal solution.

Calculation of the Coefficient of Similarity to the Ideal Solution: The coefficient of similarity for each alternative is determined, which indicates how close each alternative is to the positive ideal solution.

$$\mathrm{Ci}* = \frac{D_i^-}{D_i^+ + D_i^-} \tag{43}$$

Where Ci∗ varies between 0 and 1, with 1 being the positive ideal solution.

Hierarchy of Alternatives: Alternatives are ranked according to their similarity coefficients Ci∗. The alternative with the highest coefficient is considered the best option.

Fuzzy set theory

A fuzzy set over the universal set is defined as: $\tilde{F}G$

$$\tilde{F} = \left\{g,\ \mu_{\tilde{F}}(g) \mid g \in G\right\} \tag{44}$$

Where represents the degree of membership of element $\mu_{\tilde{F}}(g) : G[0,\ 1]\ g$ To $\tilde{F}$ such that for all FST allows partial membership of an element in a set. The element belongs entirely to, if the degree of membership value equals one. On the other hand, the degree of membership value is zero if it does not belong to the set [12]. The element is a partial membership of the fuzzy set if the degree of membership is between 0 and 1. Different fuzzy numbers have been used to model linguistic variables like triangular fuzzy numbers (TFNs), trapezoidal fuzzy numbers, Gaussian fuzzy numbers, bell-shaped fuzzy numbers, etc. Among these numbers, we have used TFNs because of their simplicity in understanding and representing the decision-maker's linguistic information. Among these numbers, we have used TFNs because of its simplicity in understanding and representing the decision makers linguistic information $\mu_{\tilde{F}}(g) \in [0,\ 1]\ g \in G$ [36].

A TFN is a normal, convex fuzzy subset of, with a piecewise linear relationship function, defined by $\widetilde{F} = (c,\ p,\ d)\ G\mu_{\widetilde{F}}$.

$$(S) = \begin{cases} 0\ for\ g < c, \\ \frac{g-c}{p-c}\ for\ c\ \leq g\ \leq p, \\ \frac{d-g}{d-p}\ for\ p\ \leq g\ \leq d, \\ 0\ for\ g > d \end{cases} \tag{45}$$

In which and are real numbers with. Let and be TFNs.$c,\ p\ d c\ <\ p\ <\ d \widetilde{E}\ =\ (c_{1,}\ p_1,\ d_1)\widetilde{F}\ = (c_{2,}\ p_2,\ d_2)$ [37]
Then, (a) Addition:

$$\widetilde{F}\ (+)\ \widetilde{E}\ = \left(c_1\ +\ c_{2,}\ \ p_1 +\ p_2,\ d_1 +\ d_2\right)\ c_1\ \geq 0,\ c_2\ \geq 0 \tag{46}$$

(b) Multiplication:

$$\widetilde{F}\ (\times)\ \widetilde{E}\ = \left(c_1\ \times\ c_{2,}\ \ p_1 \times\ p_2,\ d_1 \times\ d_2\right)\ c_1\ \geq 0,\ c_2\ \geq 0 \tag{47}$$

(c) Subtraction:

$$\widetilde{F}\ (-)\ \widetilde{E}\ = \left(c_1\ -\ c_{2,}\ \ p_1 -\ p_2,\ d_1 -\ d_2\right)\ c_1\ \geq 0,\ c_2\ \geq 0 \tag{48}$$

(d) Division:

$$\widetilde{F}\ (\widetilde{A.})\ \widetilde{E}\ =\ (c_1\ \widetilde{A.}\ d_2,\ p_1\ \widetilde{A.}\ p_2,\ d_1\ \widetilde{A.}\ c_2)\ c_1\ \geq 0,\ c_2\ \geq 0 \tag{49}$$

(e) Inverse:

$$\widetilde{E}^{-1} = \left(\frac{1}{d_1},\ \frac{1}{p_1},\ \frac{1}{c_1}\right) \geq 0 \tag{50}$$

Fuzzy TOPSIS

[38] proposed the fuzzy TOPSIS method to solve the MCDM problems under uncertainty. Decision-makers use linguistic variables to evaluate the weights of the NFRs and the ranking of the FRs. The weights of the NFR is represented by and it is given by the decision maker $M =\ (i = 1,\ \cdots,\ r)\ b^{th} D_b =\ (b = 1,\ \cdots,\ p)\ \tilde{Y}_i^b i^{th}$ [39]. The rating is represented with respect to NFR b, and the decision maker specifies it. This method includes the following steps $a^{th} FRFR_a = (a = 1,\ \cdots,\ q)\widetilde{S}^{i}_{ab} i^{th}$.

(i) Aggregate the weights of NFRs and ratings of FRs specified by decision makers, as expressed in Equations and respectively r [40].

$$\tilde{y}_b = \frac{1}{r}\left[\tilde{y}^1_b\ +\ \tilde{y}^2_b +\ \cdots +\ \tilde{y}^r_b\right] \tag{51}$$

$$\tilde{s}_{ab} = \frac{1}{r}\left[\tilde{s}^1_{ab}\ +\ \tilde{s}^i_{ab} +\ \cdots +\ \tilde{y}^r_{ab}\right] \tag{52}$$

(ii) Construct the fuzzy decision matrix (FDM) of the FRs ($\widetilde{M}$) and the NFR, according to Eqs. (52) and (53), ($\widetilde{Y}$)$D_1\ D_2\ D_b\ D_p$

$$\widetilde{M}\ =\ \begin{array}{c} FR_1 \\ FR_a \\ FR_q \end{array}\begin{bmatrix} \tilde{s}_{11} & \tilde{s}_{12} & \tilde{s}_{1b} & \tilde{s}_{1p} \\ \vdots & \vdots & \vdots & \vdots \\ \tilde{s}_{q1} & \tilde{s}_{q2} & \tilde{s}_{qb} & \tilde{s}_{qp} \end{bmatrix} \tag{53}$$

$$\widetilde{Y}\ =\ \left[\tilde{y}_1 +\ \tilde{y}_2 +\ \cdots + \tilde{y}_p\right] \tag{54}$$

(iii) Normalize the FDM of FRs using linear scale transformation. The normalized FDM is given by $(\widetilde{M}\ )\widetilde{I}$

$$\widetilde{I}\ =\ \left[\tilde{i}_{ab}\right]_{p\times q} \tag{55}$$

$$\tilde{i}_{ab} = \left(\frac{\tilde{c}_{ab}}{\tilde{d}^+_b},\ \frac{\tilde{p}_{ab}}{\tilde{d}^+_b},\ \frac{\tilde{d}_{ab}}{\tilde{d}^+_b}\right) \tag{56}$$

Table 6
Implemented Likert scale [41].

1	Very Low
3	Low
5	Average
7	High
9	Very High

And (benefit criteria) $\tilde{d}_b^+ = max_a \tilde{d}_{ab}$

$$\tilde{i}_{ab} = \left(\frac{\tilde{c}_b^-}{\tilde{d}_{ab}}, \frac{\tilde{c}_b^-}{\tilde{p}_{ab}}, \frac{\tilde{c}_b^-}{\tilde{c}_{ab}} \right) \quad (57)$$

And (cost criteria) $\tilde{c}_b^- = max_a \tilde{c}_{ab}$

(iv) Compute the weighted normalized FDM, by multiplying the weights of NFRs, by the elements of the normalized FDM $\widetilde{W}$ $\tilde{y}_b \tilde{i}_{ab}$ [17].

$$\widetilde{W} = \left[\tilde{w}_{ab}\right]_{p\times q} \quad (58)$$

Where $\tilde{w}_{ab}$is given by Eq. (59).

$$\tilde{w}_{ab} = \widetilde{s}_{ab} \times \tilde{y}_b \quad (59)$$

(v) Define the Fuzzy Positive Ideal Solution (FPIS) and the Fuzzy Negative Ideal Solution (FNIS), as: $F^+ F^-$

$$F^+ = \tilde{w}_1^+, \tilde{w}_b^+, \cdots, \tilde{w}_p^+ \quad (60)$$

$$F^- = \tilde{w}_1^-, \tilde{w}_b^-, \cdots, \tilde{w}_p^- \quad (61)$$

(vi) Compute the distances and of each FR using the following Eqs. (62) and (63),

$$m_a^+ = \sum_{b=1}^{q} m_w\left(\tilde{w}_{ab}, \tilde{w}_b^+\right) \quad (62)$$

$$m_a^- = \sum_{b=1}^{q} m_w\left(\tilde{w}_{ab}, \tilde{w}_b^-\right) \quad (63)$$

Where represents the distance between two fuzzy numbers. The vertex method is used to compute the distance between two fuzzy numbers $m\ (\cdots)$ [18]:

$$m\left(\widetilde{s}, \widetilde{u}\right) = \sqrt{\frac{1}{3}\left[\left(c_s - c_u\right)^2 + \left(p_s - p_u\right)^2 + \left(d_s - d_u\right)^2\right]} \quad (64)$$

(vii) The ranking order of the FRs are determined by the closeness coefficient value. The is computed as:$(clos\_coff_a)$ $clos\_coff_a$

$$clos\_coff_a = \frac{m_a^-}{m_a^+ + m_a^-} \quad (65)$$

The best FR is nearby to the FPIS and furthest to the FNIS

For the evaluation of the variables or criteria that were used in this research, such as the environmental impact, the analysis of the structure in installation and operation, and finally, the possible conflicts with other economic actors, a Likert scale structure was used. The experts consulted should give their appreciation or degree of importance according to their experience and knowledge. The nomenclatures used are seen in Table 6.

Identification of alternatives and criteria

In the process of selecting renewable energy sources to implement in Colombia, it is essential to consider a variety of criteria that cover social, political, economic, and environmental aspects; these criteria provide a comprehensive framework to evaluate the implications and impacts of each energy alternative on society, the environment and the economy of the country. The criteria and alternatives considered in this research arose from basic research, such as previous studies that have been carried out on the choice of criteria and sub-criteria for energy generation projects by conventional and non-conventional sources [3].

Firstly, social criteria are essential to ensure that the implementation of new energy sources considers the well-being and needs of local communities; this includes aspects such as equitable access to energy, local job creation, and community participation in the

Table 7
List of alternatives.

A1	Small-Scale Hydroelectric Power Plants
A2	Undimotriz Energy
A3	Tidal Energy
A4	Biomass
A5	General Wind Energy
A6	Photovoltaic (PV)
A7	Offshore Wind Energy
A8	Onshore Wind Energy
A9	Large-Scale Hydroelectric Power Plants
A10	Geothermal Energy

Table 8
Methodology Implementation scenarios.

Scenarios (SC)	Regions of Colombia
SC1	Caribbean Region
SC1.1	Caribbean Region 2
SC2	Pacific Region 1
SC2.1	Pacific Region 2
SC3	Andean Region
SC4	Amazon Region
SC5	Orinoquia Region

decision-making process. It is crucial to consider political stability and the willingness to support the transition to more sustainable energy sources [42].

Economic criteria play a vital role in the financial viability of new investments in renewable energy. This includes assessing the initial investment required, operation and maintenance costs, and the impact on consumer energy prices. In addition, it is essential to consider the potential for income generation and the contribution to long-term economic growth. Environmental criteria are critical to ensure that implementing new energy sources does not cause irreparable ecological damage; this involves assessing the impact on air, water, and soil quality, mitigating greenhouse gas emissions, and protecting biodiversity [43].

In addition to these criteria, it is also crucial to consider the initial investment required for each energy source, as well as the analysis of the infrastructure necessary for its installation, operation, and maintenance; this includes evaluating the availability of natural resources, the capacity of the electricity grid and the transport infrastructure. Regarding specific energy sources, each offers unique advantages and challenges that must be considered in the Colombian context. Tidal energy, for example, takes advantage of the movement of tides to generate electricity and could be especially relevant in coastal regions such as the Colombian Caribbean. Biomass, on the other hand, uses organic matter to produce energy and can help reduce dependence on fossil fuels [44].

Solar photovoltaic (PV) and wind, both offshore and onshore, offer great potential in Colombia due to its abundant solar and wind resources. Hydroelectric plants, both large-scale and small-scale, have traditionally been influential in the Colombian energy matrix and can continue to play an essential role. In addition, geothermal energy harnesses heat from the earth's interior to generate electricity and could be especially relevant in volcanic regions such as southwestern Colombia. Finally, wave energy uses wave movement to generate electricity and could be a promising option for the country's coastal areas [45].

The criteria selected for each of the methodologies were as follows:

AHP and FAHP methodologies: Social, economic, environmental, and technical.

TOPSIS, Fuzzy TOPSIS methodologies: Meteorological, system performance, environmental, economic, and demographic (Table 7).

Colombia has a great diversity of natural and climatic resources that make it possible to generate electricity in all its geographic regions using renewable sources. By taking advantage of these resources in a sustainable and responsible manner and making the right decisions, the percentage of success in the planning, execution and implementation of energy generation projects with non-conventional sources would increase. Table 8 shows the scenarios (SC) analyzed in this research according to the different regions of Colombia.

Caribbean Region (SC1, SC1.1): Colombia's Caribbean region, known for its rich culture and coastline, offers great potential for renewable energy generation. With a tropical climate, this region has abundant solar resources, making it ideal for installing photovoltaic solar energy systems. In addition, its extensive coastline provides opportunities for offshore wind energy, taking advantage of the winds that blow over the Caribbean Sea. Biomass is also a promising source in this region, given the availability of agricultural and forestry residues for energy production [46].

Pacific Region (SC2, SC2.1): Colombia's Pacific region, known for its biodiversity and coastline on the Pacific Ocean, has great potential for renewable energy generation. Its dense forests and humid climate offer optimal conditions for producing energy from biomass and biogas, taking advantage of organic waste and agricultural residues. In addition, its coastline is exposed to Pacific winds, which makes it ideal for offshore wind energy, taking advantage of the strong winds that blow over the ocean [40].

Table 9
Analysis of alternatives for scenario 1.

SCENARIO 1 (SC1)						
METHODOLOGY/ALTERNATIVE	A1	A2	A3	A4	A5	A6
AHP	14.35 %	16.22 %	12.19 %	17.62 %	17.95 %	21.66 %
FAHP	4.00 %	11.00 %	5.00 %	19.00 %	27.00 %	34.00 %
TOPSIS	7.82 %	4.20 %	10.54 %	24.46 %	22.78 %	30.19 %
FUZZY TOPSIS	28.00 %	2.00 %	3.00 %	17.00 %	21.00 %	29.00 %

Andean Region (SC3): The Andean Region of Colombia, characterized by its mountainous topography and fertile valleys, presents great potential for various renewable energy sources. Its high mountains offer opportunities for large-scale hydroelectric power, taking advantage of the mighty rivers that descend from the Andes Mountains. In addition, it's temperate climate and high altitude make it conducive to photovoltaic and wind-solar energy in mountainous areas [41].

Amazon Region (SC4): Colombia's Amazon region, known for its lush rainforest and unique biodiversity, offers great potential for renewable energy generation. Its dense vegetation and humid climate make it ideal for energy production using biomass and biogas, taking advantage of organic waste and forest residues. In addition, its extensive network of rivers, such as the Amazon River and the Caquetá River, offers opportunities for large-scale hydropower, harnessing the flow and energy of these waterways [42].

Orinoquia Region (SC5): Colombia's Orinoquia Region, characterized by its vast plains and rushing rivers, offers great potential for renewable energy generation. Its large lowland areas and tropical climate make it ideal for installing large-scale solar photovoltaic systems. In addition, its many rivers, such as the Meta River and the Orinoco River, offer opportunities for hydroelectric power and biomass from agricultural and forestry residues.

In Resource availability you will find more detailed information on how to replicate the implemented methodologies, you will find excel files with data, programming of methodologies and explanatory videos

Method validation

The discrepancy in the results between the different multicriteria decision methods highlights the importance of understanding each methodology's inherent differences. While AHP and FAHP mainly favor Alternative 6, TOPSIS highlights Alternative 4, and Fuzzy TOPSIS shows a preference for Alternatives 1 and 6.

These findings emphasize the need for further analysis and consideration of other relevant factors before selecting the best renewable generation technology alternative for the given scenario. Understanding the various methodologies and proper weighting of criteria is critical to making informed and effective decisions in the context of renewable energy source selection.

Comparison of results for scenario 1

Table 9 shows the analysis of the results for each methodology associated with Scenario 1, in which there is significant variability in the preferences of renewable generation technology alternatives. According to the AHP Method, Alternative 6 emerges as the most favorable, with a preference percentage of 21.66 %, followed closely by Alternative 5, which reaches 17.95 %. These results suggest that, within the framework of weightings and criteria used in the AHP, Alternative 6 is the preferred alternative.

On the other hand, the FAHP Method shows an even more pronounced preference for Alternative 6, with a 34 % preference, although Alternative 5 also receives significant consideration with 27 %. These results indicate an alignment with the preferences observed in the AHP Method. In contrast, the TOPSIS Method highlights Alternative 4 as the most favorable, with a preference value of 24.46 %; despite this, Alternative 6 still obtains a significant value of 30.19 %. This finding highlights the influence of the TOPSIS method in determining the best alternative. Finally, the Fuzzy TOPSIS Method presents a different perspective, showing a significant preference for Alternative 1 with 28 %, followed closely by Alternative 6 with 29 %. These results underline the influence of uncertainty and vagueness in decision-making, as considered in the fuzzy approach.

Comparison of results for scenario 1.1

In Scenario 1.1, there is significant variability in the preferences of alternatives for selecting renewable energy generation technologies according to the different multi-criteria decision methods (MCDM) applied. First, according to the AHP method, Alternative 6 is the most favorable, with a preference percentage of 36 %, followed closely by Alternative 5 with 22 %. This result suggests that, within the framework of weights and criteria used in the AHP, Alternative 6 is preferred. On the other hand, the FAHP Method shows a clear preference for Alternative 7, which obtains the highest percentage of preference with 24 %, followed by Alternative 6 with 35 %. This result indicates an alignment with the preferences observed in the AHP Method, Table 10.

As for the TOPSIS Method, Alternative 4 stands out as the most favorable, with a preference value of 22 %, followed closely by Alternative 7 with 23 %; this finding highlights the influence of the TOPSIS Method in determining the best alternative. Finally, the Fuzzy TOPSIS Method shows a more even distribution of preferences, with Alternative 1 and Alternative 6 being the most preferred, both with 25 %. This indicates a more significant ambiguity in the final decision under the fuzzy approach of the Fuzzy TOPSIS method.

Table 10
Analysis of alternatives for scenario 1.1.

SCENARIO 1.1 (SC1.1)						
METHODOLOGY/ALTERNATIVE	A1	A7	A3	A4	A8	A6
AHP	4.00 %	20.00 %	0.00 %	18.00 %	22.00 %	36.00 %
FAHP	2.00 %	24.00 %	0.00 %	21.00 %	18.00 %	35.00 %
TOPSIS	8.00 %	23.00 %	0.00 %	22.00 %	21.00 %	27.00 %
FUZZY TOPSIS	25.00 %	18.00 %	0.00 %	15.00 %	17.00 %	25.00 %

Table 11
Analysis of alternatives for scenario 2.

SCENARIO 2 (SC2)						
METHODOLOGY/ALTERNATIVE	A1	A2	A3	A4	A5	A6
AHP	14.61 %	15.69 %	10.63 %	17.36 %	18.83 %	22.88 %
FAHP	15.00 %	10.00 %	6.00 %	20.00 %	21.00 %	28.00 %
TOPSIS	7.51 %	6.51 %	12.02 %	25.69 %	22.71 %	25.56 %
FUZZY TOPSIS	30.00 %	2.00 %	4.00 %	19.00 %	22.00 %	23.00 %

Table 12
Analysis of alternatives for scenario 2.1.

SCENARIO 2.1 (SC2.1)						
METHODOLOGY/ALTERNATIVE	A1	A7	A3	A4	A8	A6
AHP	7.00 %	21.00 %	0.00 %	24.00 %	23.00 %	25.00 %
FAHP	5.00 %	25.00 %	0.00 %	18.00 %	25.00 %	27.00 %
TOPSIS	7.30 %	23.64 %	0.00 %	23.27 %	21.50 %	24.28 %
FUZZY TOPSIS	27.00 %	19.00 %	0.00 %	16.00 %	17.00 %	20.99 %

Comparison of results for scenario 2

For Scenario 2, there is significant variability in the preferences of the renewable generation technology alternatives according to the different multi-criteria decision methods (MCDM) applied. According to the AHP Method, Alternative 6 is the most favorable, with a preference percentage of 22.88 %, followed by Alternative 5 with 18.83 %. This suggests that, under the framework of weights and criteria used in AHP, Alternative 6 is the most preferred. On the other hand, the FAHP Method shows a clear preference for Alternative 6, which obtains the highest percentage of preference with 28 %, followed by Alternative 5 with 21 %; these results indicate an alignment with the preferences observed in the AHP Method, Table 11.

Regarding the TOPSIS Method, Alternative 4 stands out as the most favorable, with a preference value of 25.69 %, followed closely by Alternative 6 with 25.56 %. This finding highlights the influence of the TOPSIS Method in determining the best alternative. Finally, the Fuzzy TOPSIS method shows a clear preference for Alternative 1, which obtains the highest preference percentage with 30 %, followed by Alternative 6 with 23 %, Table 11.

Comparison of results for scenario 2.1

Table 12 analyzes the results of scenario 2.1. We can see significant variability in the percentages of preference for each renewable generation technology alternative according to the different multi-criteria decision methods (MCDM) applied. If we compare the AHP vs. FAHP method, we can observe that in both methods, Alternative 6 is the preferred one, although FAHP shows a slight preference, with 27 % vs. 25 % of AHP.

When comparing the AHP vs. TOPSIS method we appreciate that, although Alternative 6 is preferred in both methods, in TOPSIS this Alternative has a slightly lower percentage (24.30 %) compared to AHP (25 %). In addition, the AHP method compared to Fuzzy TOPSIS shows that Fuzzy TOPSIS has a higher preference for Alternative 1 (27 %) compared to AHP (7 %), Table 12.

The FAHP and TOPSIS methods show a preference for Alternative 6, but in FAHP, this preference is more notable at 27 %, while in TOPSIS, it is 24.30 %. Furthermore, when the FAHP and Fuzzy TOPSIS methods were compared, a significant difference in preferences was observed between them, with Alternative 1 being the most preferred in Fuzzy TOPSIS, with 27 %, while in FAHP, it is Alternative 7 with 25 %. Finally, although the TOPSIS and Fuzzy TOPSIS methods have similar results for most of the alternatives, there is a notable difference in the preference for Alternative 1, with 27 % in Fuzzy TOPSIS and 7.30 % in TOPSIS, Table 12.

Table 13
Analysis of alternatives for scenario 3.

SCENARIO 3 (SC3)						
METHODOLOGY/ALTERNATIVE	A1	A10	A4	A5	A6	A9
AHP	15.00 %	11.00 %	16.00 %	18.00 %	19.00 %	21.00 %
FAHP	7.00 %	6.00 %	19.00 %	19.00 %	23.00 %	26.00 %
TOPSIS	21.38 %	0.00 %	21.46 %	3.15 %	24.46 %	29.55 %
FUZZY TOPSIS	26.00 %	0.00 %	18.00 %	0.00 %	26.00 %	30.00 %

Table 14
Analysis of alternatives for scenario 4.

SCENARIO 4 (SC4)					
METHODOLOGY/ALTERNATIVE	A5	A1	A9	A4	A6
AHP	13.00 %	17.00 %	20.00 %	24.00 %	26.00 %
FAHP	17.00 %	19.00 %	20.00 %	22.00 %	22.00 %
TOPSIS	12.50 %	23.87 %	23.82 %	15.93 %	23.87 %
FUZZY TOPSIS	4.00 %	21.00 %	21.00 %	31.00 %	23.00 %

Table 15
Analysis of alternatives for scenario 5.

METHODOLOGY/ALTERNATIVE	A1	A5	A6	A4
AHP	24.00 %	20.00 %	22.00 %	24.00 %
FAHP	25.00 %	25.00 %	23.00 %	27.00 %
TOPSIS	22.61 %	21.97 %	22.71 %	32.71 %
FUZZY TOPSIS	17.00 %	15.00 %	34.00 %	34.00 %

Comparison of results for scenario 3

For this scenario, a comparative analysis is made between alternatives and scenarios. Table 13 shows that the AHP and FAHP methods prefer Alternative 9, with 21 % and 26 %, respectively. When comparing the AHP and TOPSIS methods, it is evident that, although the preferences differ, both highlight Alternative 9 as the most preferred, with 21 % and 29.55 %, respectively. In addition, the AHP and Fuzzy TOPSIS methods prefer Alternative 9, with 21 % in AHP and 30 % in Fuzzy TOPSIS, respectively.

The FAHP and TOPSIS methods show a similar preference for Alternative 9, with 26 % and 29.55 % respectively. The comparison between the FAHP and Fuzzy TOPSIS methods shows that both prefer Alternative 9, although Fuzzy TOPSIS shows a slightly higher preference with 30 % versus 26 % for FAHP. On the other hand, the TOPSIS and Fuzzy TOPSIS methods show a similar preference for Alternative 9, although Fuzzy TOPSIS shows a slightly higher preference with 30 % versus 29.55 % for TOPSIS, Table 13.

Comparison of results for scenario 4

Table 14 presents the results of the analysis performed in Scenario 4. According to these results, the AHP method prioritizes Alternative 6 with 26 % and Alternative 4 with 24 %, while in the FAHP method, Alternatives 4 and 6 also prevail with 22 % each. Furthermore, in the TOPSIS method, Alternatives 1 and 6 emerge as the preferred ones with a value of 23.87 %, followed closely by Alternative 9 with 23.82 %, indicating a strong preference for these three alternatives. Finally, in the Fuzzy TOPSIS method, Alternative 4 prevails over the remaining alternatives with a value of 31 %. As seen in this scenario, although there are some differences among the methods, Alternatives 4, 6, and 9 seem to be consistently preferred in most cases.

Comparison of results for scenario 5

In the analysis of the results for Scenario 5, Table 15, the AHP and FAHP methods reflect a similar distribution of weights among the alternatives, with A1 and A4 standing out slightly. This pattern suggests that both AHP and FAHP value most of the alternatives relatively balanced, which could reflect well-balanced criteria in this scenario. However, FAHP shows a slight additional preference toward A4 (27 %), indicating that fuzzy logic introduces variation that emphasizes this alternative compared to AHP. On the other hand, the results obtained using TOPSIS and Fuzzy TOPSIS show a stronger preference towards A4, with a weighting of 32.71 % and 34 %, respectively, followed by A6 in both cases. This consistency between TOPSIS and its Fuzzy version in favoring A4 and A6 could indicate that, in this particular scenario, these alternatives are the most viable when considering proximity factors to the positive ideal. The Fuzzy TOPSIS version reinforces this trend, assigning more weight to these two alternatives. In general terms, although each methodology's results vary, there is a consensus on positioning A4 as an outstanding alternative.

Table 16
Results of Spearman's coefficient application.

A/A	SC1	SC1.1	SC2	SC2.1	SC3	SC4	SC5
AHP-FAHP	1.000	1.000	0.792	0.792	0.865	−0.262	0.786
AHP-TOPSIS	0.875	0.875	0.786	−0.833	0.875	0.262	0.750
AHP-FUZZY TOPSIS	0.875	0.875	0.292	0.875	0.708	−0.833	0.917
FAHP-TOPSIS	0.792	−0.542	0.667	0.875	0.786	0.750	0.917
FAHP-FUZZY TOPSIS	0.667	0.958	0.917	0.542	0.875	0.667	0.833
TOPSIS-FUZZY TOPSIS	0.958	−0.792	0.708	−0.833	−0.750	−0.917	0.875

The results obtained by applying Spearman's coefficients reveal essential findings on the correlation between the different multi-criteria decision methods (MCDM) in each of the scenarios evaluated. In general, a high positive correlation is observed between the methods' results in most of the scenarios, suggesting consistency in the preferences for the alternatives analyzed. This indicates that, in general terms, the different MCDM methods tend to favor the same alternatives in each scenario. However, negative correlations are also observed in some cases, indicating discrepancies in preferences between methods. These discrepancies may be due to differences in each method's evaluation criteria or their respective weighting structures.

It is important to note that correlation coefficients vary between scenarios, indicating that consistency in preferences between methods may depend on the specific context of each scenario. Thus, these results underscore the importance of using multiple MCDM methods and carefully considering the context of each situation when making decisions in the energy sector.

The analysis of Spearman's coefficients highlights the usefulness and relevance of MCDM methods in selecting renewable generation technologies in the energy sector. It also highlights the importance of adopting a holistic and multidisciplinary approach to evaluate alternatives and make informed decisions in transitioning to a more sustainable energy system. In Spearman correlation analysis, all ranking methods are compared in pairs, and the Spearman correlation coefficient (Rs) is determined using Eq. (66). The calculated correlation coefficients are shown in Table 16.

$$\mathrm{Rs} = 1 - \frac{6* \sum di^2}{n*\left(n^2 - 1\right)} \tag{66}$$

Where RS is the Spearman correlation coefficient, di is the difference between the ordinal numbers of the ranking method, and n is the number of alternatives.

Limitations

The limitations that were found in this investigation were: in the first instance the acceptance of the experts to be participants of this investigation and as a second the programming and correct revision in excel of each of the implemented methods.

Ethics statements

This work did not involve human subjects, animal experiments data, and data collected from social media platforms.

CRediT author statement

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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