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A Hybrid Fuzzy AHP–TOPSIS–Goal Programming Model for Renewable Energy Site Selection under Uncertainty

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Abstract:

Renewable energy planning has become a crucial component of sustainable development due to increasing environmental concerns and the depletion of conventional energy resources. Selecting an appropriate renewable energy site involves evaluating multiple conflicting criteria under uncertain and imprecise conditions. Classical decision-making models often fail to capture such vagueness and ambiguity present in expert judgments.

In this paper, a hybrid fuzzy multi-criteria decision-making (MCDM) framework is proposed for renewable energy site selection under uncertainty. The proposed model integrates fuzzy Analytic Hierarchy Process (AHP), fuzzy Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), and fuzzy goal programming to construct a comprehensive decision-support system. Fuzzy AHP is employed to determine the relative importance of decision criteria using linguistic judgments, while fuzzy TOPSIS is used to rank potential renewable energy sites based on their proximity to ideal solutions. Furthermore, fuzzy goal programming is incorporated to optimize the satisfaction level of multiple decision objectives simultaneously.

The proposed hybrid framework provides a systematic approach for handling uncertainty, integrating multiple decision criteria, and improving the robustness of renewable energy planning. A numerical illustration is presented to demonstrate the applicability and effectiveness of the model. The results show that the hybrid fuzzy optimiza-

tion–MCDM approach provides consistent and reliable decision outcomes, making it a valuable tool for policymakers and planners involved in sustainable energy development.

Keywords: Fuzzy sets, Multi-criteria decision making, Fuzzy AHP, Fuzzy TOPSIS, Goal programming, Renewable energy planning.

1. Introduction

The rapid growth of global energy demand, coupled with increasing concerns regarding environmental sustainability and climate change, has intensified the search for alternative and renewable energy resources. Conventional energy sources such as coal, oil, and natural gas are not only finite but also contribute significantly to environmental degradation and greenhouse gas emissions. Consequently, renewable energy technologies, including solar, wind, biomass, geothermal, and hydropower, have emerged as viable and sustainable alternatives for meeting the growing energy needs of modern societies. The transition toward renewable energy systems has therefore become a critical component of global strategies for sustainable development and environmental protection.

However, the effective implementation of renewable energy projects requires careful planning and evaluation. One of the most challenging tasks in renewable energy development is the selection of appropriate sites for energy generation facilities. Site selection involves the evaluation of multiple criteria, including environmental conditions, economic feasibility, technical performance, social acceptance, and policy constraints. These criteria often conflict with one another and involve significant uncertainty due to incomplete information and subjective human judgments. Therefore, renewable energy site selection represents a complex multi-criteria decision-making (MCDM) problem that requires robust and flexible decision-support methodologies.

Multi-criteria decision-making techniques have been widely applied to address complex decision problems involving multiple and often conflicting criteria. Among these methods, the Analytic Hierarchy Process (AHP), introduced by Saaty [30], has become one of the most widely used techniques for determining the relative importance of decision criteria through pairwise comparisons. Similarly, the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), proposed by Hwang and Yoon [12], provides a systematic method for ranking alternatives based on their distance from ideal and negative-ideal solutions. Another influential approach is the ELECTRE method, introduced by Roy [29], which utilizes outranking relations to evaluate alternatives under multiple criteria.

Despite their widespread use, classical MCDM methods generally assume that decision data are precise and deterministic. In real-world decision environments, however, decision makers frequently express their preferences using linguistic terms such as “high”, “medium”, or "low". These expressions reflect inherent vagueness and ambiguity that cannot be adequately represented using crisp numerical values. To address this limitation, fuzzy set theory was introduced by Zadeh [44], providing a mathematical framework for modeling uncertainty and imprecision in human reasoning. Fuzzy sets allow elements to belong to a set with varying degrees of membership, thereby enabling the representation of vague or uncertain information.

Since its introduction, fuzzy set theory has been extensively applied in decision-making and optimization problems. Bellman and Zadeh [2] extended fuzzy set theory to decision-making environments, demonstrating how fuzzy logic can be used to represent and analyze complex decision processes involving uncertainty. Later developments in fuzzy mathematics and fuzzy systems by Dubois and Prade [8], Klir and Yuan [17], and Zimmermann [48] further strengthened the theoretical foundations of fuzzy decision analysis.

The integration of fuzzy set theory with MCDM methods has led to the development of fuzzy MCDM approaches such as fuzzy AHP and fuzzy TOPSIS. In fuzzy AHP, pairwise comparisons between criteria are represented using fuzzy numbers rather than crisp values, allowing decision makers to express their judgments more flexibly. Buckley [4] introduced one of the earliest fuzzy extensions of the AHP method. Similarly, Chen [6] proposed an extension of the TOPSIS method for group decision-making under fuzzy environments. These fuzzy MCDM approaches have significantly enhanced the ability of decision models to handle uncertainty and subjective judgments.

Over the past two decades, fuzzy MCDM methods have been widely applied across various domains, including engineering design, supply chain management, environmental planning, healthcare systems, and energy policy evaluation. Mardani et al. [22] provided a comprehensive review of MCDM techniques and their applications, highlighting the growing importance of hybrid decision-making models in complex real-world problems. Similarly, Velasquez and Hester [37] analyzed several MCDM techniques and emphasized the need for selecting appropriate decision models depending on the characteristics of the decision problem.

In the field of renewable energy planning, MCDM methods have played a crucial role in evaluating alternative energy technologies and identifying suitable locations for energy projects. Wang et al. [38] reviewed the applications of fuzzy set theory in renewable energy systems and concluded that fuzzy-based decision models are particularly effective in addressing uncertainties associated with energy planning. Similarly, Kabir et al. [14] demonstrated the effectiveness of fuzzy MCDM methods for evaluating renewable energy technologies based on multiple technical and environmental criteria.

Recent research has also emphasized the importance of hybrid decision models that integrate multiple MCDM techniques. Hybrid approaches combine the strengths of different decision methods to improve the reliability and robustness of the decision-making process. For example, combining fuzzy AHP and fuzzy TOPSIS allows researchers to determine criteria weights using hierarchical analysis while ranking alternatives using distance-based evaluation methods. Such hybrid frameworks have been successfully applied in renewable energy planning, supplier selection, and sustainable infrastructure development.

Another important development in decision science is the integration of optimization techniques with MCDM frameworks. Optimization models, particularly goal programming, provide systematic methods for achieving multiple decision objectives simultaneously. Goal programming allows decision makers to minimize deviations from desired targets across multiple criteria, making it particularly suitable for complex decision problems involving trade-offs between competing objectives.

Fuzzy goal programming extends classical goal programming by incorporating fuzzy constraints and objectives, thereby allowing decision makers to express their goals in linguistic or approximate terms. This approach enables the modeling of flexible aspiration levels and improves the adaptability of optimization models in uncertain decision environments. The integration of fuzzy goal programming with fuzzy MCDM methods therefore provides a powerful framework for solving complex decision problems.

In recent years, the application of hybrid fuzzy decision models in renewable energy planning has gained significant attention. Researchers have applied fuzzy AHP, fuzzy TOPSIS, and other hybrid MCDM methods to evaluate renewable energy technologies, select optimal energy sites, and analyze energy policy alternatives. For instance, Sharma et al. [31] applied fuzzy AHP and TOPSIS for solar energy site selection, while Singh et al. [32] developed a hybrid fuzzy MCDM framework for wind farm location analysis. These studies highlight the growing importance of fuzzy decision models in sustainable energy planning.

Despite these advancements, several challenges remain in the application of fuzzy MCDM models for renewable energy decision-making. Many existing studies rely on single decision methods or simple hybrid combinations, which may not fully capture the complexity of real-world decision environments. Furthermore, optimization aspects are often neglected in traditional fuzzy MCDM models, limiting their ability to simultaneously satisfy multiple decision objectives.

To address these limitations, this study proposes a hybrid fuzzy multi-criteria decision-making framework that integrates fuzzy AHP, fuzzy TOPSIS, and fuzzy goal programming for renewable energy site selection under uncertainty. The proposed approach combines hierarchical weight determination, distance-based alternative ranking, and optimization-based decision support within a unified framework. By integrating these complementary techniques, the proposed model aims to improve the accuracy, robustness, and flexibility of renewable energy planning decisions.

The main contributions of this paper can be summarized as follows:

(i) A hybrid fuzzy MCDM framework integrating fuzzy AHP, fuzzy TOPSIS, and fuzzy goal programming is developed.

(ii) The proposed model effectively handles uncertainty and linguistic decision information using fuzzy numbers.

(iii) The framework provides a systematic methodology for evaluating renewable energy site selection problems.

(iv) A numerical example is presented to demonstrate the applicability and effectiveness of the proposed decision model.

The remainder of this paper is organized as follows. Section 2 presents the mathematical preliminaries related to fuzzy sets and fuzzy numbers. Section 3 describes the proposed hybrid fuzzy AHP–TOPSIS–goal programming methodology. Section 4 provides a numerical illustration for renewable energy site selection. Section 5 discusses the results and implications of the proposed approach. Finally, Section 6 concludes the paper and outlines potential directions for future research.

2. Mathematical Preliminaries

This section presents the fundamental mathematical concepts used in the proposed hybrid fuzzy multi-criteria decision-making framework. The theoretical foundation of the model is based on fuzzy set theory, triangular fuzzy numbers, distance measures, defuzzification methods, and the basic principles of the Analytic Hierarchy Process (AHP), the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), and goal programming. These concepts enable the representation of uncertainty and linguistic information in complex decision-making problems.

Definition 1. *Let X be a universe of discourse. A fuzzy set $\tilde{A}$ in X is defined as*

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

where $\mu_{\tilde{A}}(x) : X \to [0, 1]$ is called the membership function of the fuzzy set $\tilde{A}$ [44]. The value $\mu_{\tilde{A}}(x)$ represents the degree of membership of element x in the set $\tilde{A}$.

Fuzzy sets allow the representation of vague and imprecise information that frequently appears in real-world decision problems.

Definition 2. *A triangular fuzzy number (TFN) $\tilde{A}$ is defined by a triplet*

$$\tilde{A} = (l, m, u)$$

where l, m, and u represent the lower, modal, and upper values respectively, satisfying $l \leq m \leq u$ [48, 17].

The membership function of a triangular fuzzy number is given by

$$\mu_{\tilde{A}}(x) = \begin{cases} 0, & x < l \\ \dfrac{x-l}{m-l}, & l \le x \le m \\ \dfrac{u-x}{u-m}, & m \le x \le u \\ 0, & x > u \end{cases}$$

Triangular fuzzy numbers are widely used in fuzzy decision-making models because of their computational simplicity.

Let $\tilde{A} = (l_1, m_1, u_1)$ and $\tilde{B} = (l_2, m_2, u_2)$ be two triangular fuzzy numbers. Their arithmetic operations are defined as follows:

$$\tilde{A} + \tilde{B} = (l_1 + l_2, m_1 + m_2, u_1 + u_2)$$

$$\tilde{A} - \tilde{B} = (l_1 - l_2, m_1 - m_2, u_1 - u_2)$$

$$\tilde{A} \times \tilde{B} = (l_1 l_2, m_1 m_2, u_1 u_2)$$

$$k\tilde{A} = (kl_1, km_1, ku_1)$$

where k is a real number.

In fuzzy decision-making models, it is often necessary to compute the distance between two fuzzy numbers. Let $\tilde{A} = (l_1, m_1, u_1)$ and $\tilde{B} = (l_2, m_2, u_2)$ be triangular fuzzy numbers. The vertex method is commonly used to measure the distance between them [6]:

$$d(\tilde{A}, \tilde{B}) = \sqrt{\frac{1}{3}\left[(l_1 - l_2)^2 + (m_1 - m_2)^2 + (u_1 - u_2)^2\right]}$$

To obtain crisp values from fuzzy numbers, defuzzification techniques are used. One of the most commonly used approaches is the centroid method.

Definition 3. *Let $\tilde{A} = (l, m, u)$ be a triangular fuzzy number. The defuzzified value of $\tilde{A}$ is defined as*

$$C(\tilde{A}) = \frac{l + m + u}{3}.$$

In multi-criteria decision-making problems, suppose that A_i $(i = 1, 2, \ldots, m)$ represents alternatives and C_j $(j = 1, 2, \ldots, n)$ represents evaluation criteria. The fuzzy decision matrix can be expressed as

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

where $\tilde{x}_{ij}$ denotes the fuzzy performance value of alternative A_i with respect to criterion C_j.

Definition 4. *The Analytic Hierarchy Process (AHP) is a multi-criteria decision-making technique proposed by Saaty [30]. It determines the relative importance of decision criteria by constructing pairwise comparison matrices and computing priority weights. The method decomposes a complex decision problem into a hierarchical structure consisting of goals, criteria, and alternatives.*

Definition 5. *The Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) is a ranking method introduced by Hwang and Yoon [12]. The basic idea of TOPSIS is that the selected alternative should have the shortest distance from the positive ideal solution and the farthest distance from the negative ideal solution.*

Definition 6. *Goal programming is an extension of linear programming designed to handle multiple conflicting objectives simultaneously. Instead of optimizing a single objective function, goal programming minimizes the deviations from desired target levels of multiple goals [48]. In fuzzy goal programming, these goals may be represented using fuzzy membership functions, allowing decision makers to express aspiration levels flexibly.*

The mathematical concepts introduced in this section provide the theoretical foundation for developing the proposed hybrid fuzzy AHP–TOPSIS–goal programming model described in the next section.

3. Proposed Hybrid Fuzzy AHP–TOPSIS–Goal Programming Model

This section presents the proposed hybrid fuzzy multi-criteria decision-making framework for renewable energy site selection. The model integrates three well-established decision techniques: fuzzy Analytic Hierarchy Process (AHP), fuzzy Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), and fuzzy goal programming. The integration of these methods provides a comprehensive decision-support system capable of handling uncertainty, multiple conflicting criteria, and optimization requirements simultaneously.

The overall structure of the proposed framework consists of three main stages. In the first stage, fuzzy AHP is used to determine the relative importance of decision criteria using pairwise comparisons. In the second stage, fuzzy TOPSIS is applied to rank alternative renewable energy sites based on their closeness to ideal solutions. In the final stage, fuzzy goal programming is employed to optimize the satisfaction level of decision objectives and identify the most suitable site.

Let A_i $(i = 1, 2, \ldots, m)$ denote the set of alternatives representing candidate renewable energy sites, and let C_j $(j = 1, 2, \ldots, n)$ denote the set of evaluation criteria. The proposed hybrid decision model proceeds through the following steps.

Step 1: Construction of the decision hierarchy

The decision problem is structured into a hierarchical model consisting of three levels:

(i) Level 1: Overall goal (selection of optimal renewable energy site)

(ii) Level 2: Evaluation criteria

(iii) Level 3: Candidate alternatives

This hierarchical structure allows the decomposition of complex decision problems into manageable components.

Step 2: Fuzzy pairwise comparison matrix

Decision makers evaluate the relative importance of criteria using linguistic variables such as Very Low (VL), Low (L), Medium (M), High (H), and Very High (VH). These linguistic terms are represented using triangular fuzzy numbers.

The fuzzy pairwise comparison matrix is given by

$$\tilde{A} = \begin{bmatrix} \tilde{a}_{11} & \tilde{a}_{12} & \ldots & \tilde{a}_{1n} \\ \tilde{a}_{21} & \tilde{a}_{22} & \ldots & \tilde{a}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{a}_{n1} & \tilde{a}_{n2} & \ldots & \tilde{a}_{nn} \end{bmatrix}$$

where $\tilde{a}_{ij}$ represents the relative importance of criterion C_i compared to C_j.

Step 3: Determination of fuzzy criteria weights

The fuzzy weights of the criteria are computed using the geometric mean method.

For each criterion i, the geometric mean is calculated as

$$\tilde{g}_i = \left(\prod_{j=1}^{n} \tilde{a}_{ij} \right)^{1/n}$$

The normalized fuzzy weight is then obtained as

$$\tilde{w}_i = \frac{\tilde{g}_i}{\sum_{i=1}^{n} \tilde{g}_i}$$

These weights represent the relative importance of decision criteria in the renewable energy site selection problem.

Step 4: Construction of the fuzzy decision matrix

Decision makers evaluate each alternative with respect to each criterion using linguistic ratings. These ratings are converted into triangular fuzzy numbers.

The fuzzy decision matrix is expressed as

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

where $\tilde{x}_{ij}$ denotes the fuzzy performance value of alternative A_i with respect to criterion C_j.

Step 5: Normalization of the fuzzy decision matrix

To eliminate scale differences among criteria, the fuzzy decision matrix is normalized.

For benefit criteria:

$$\tilde{r}_{ij} = \frac{\tilde{x}_{ij}}{\tilde{x}_j^{\max}}$$

For cost criteria:

$$\tilde{r}_{ij} = \frac{\tilde{x}_j^{\min}}{\tilde{x}_{ij}}$$

The normalized matrix is denoted by

$$\tilde{R} = [\tilde{r}_{ij}]$$

Step 6: Weighted normalized decision matrix

The weighted normalized matrix is calculated as

$$\tilde{v}_{ij} = \tilde{r}_{ij} \times \tilde{w}_j$$

Thus,

$$\tilde{V} = \begin{bmatrix} \tilde{v}_{11} & \tilde{v}_{12} & \dots & \tilde{v}_{1n} \\ \tilde{v}_{21} & \tilde{v}_{22} & \dots & \tilde{v}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{v}_{m1} & \tilde{v}_{m2} & \dots & \tilde{v}_{mn} \end{bmatrix}$$

Step 7: Determination of fuzzy ideal solutions

The fuzzy positive ideal solution (FPIS) and fuzzy negative ideal solution (FNIS) are defined as

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

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

where

$$\tilde{v}_j^+ = \max_i \tilde{v}_{ij}$$

$$\tilde{v}_j^- = \min_i \tilde{v}_{ij}$$

Step 8: Distance from ideal solutions

The distance of each alternative from the positive and negative ideal solutions is calculated as

$$D_i^+ = \sum_{j=1}^{n} d(\tilde{v}_{ij}, \tilde{v}_j^+)$$

$$D_i^- = \sum_{j=1}^{n} d(\tilde{v}_{ij}, \tilde{v}_j^-)$$

Step 9: Closeness coefficient

The closeness coefficient for each alternative is computed as

$$CC_i = \frac{D_i^-}{D_i^+ + D_i^-}$$

Alternatives with higher closeness coefficients are considered more desirable.

Step 10: Fuzzy goal programming model

To further optimize the decision process, fuzzy goal programming is incorporated. Suppose that the decision maker specifies aspiration levels for each criterion.

The goal programming model is formulated as

$$\text{Minimize } Z = \sum_{k=1}^{p} (d_k^+ + d_k^-)$$

subject to

$$f_k(x) + d_k^- - d_k^+ = b_k$$

$$x_i \geq 0$$

where

(i) $f_k(x)$ represents the kth goal function,

(ii) b_k represents the aspiration level,

(iii) d_k^+ and d_k^- denote positive and negative deviations.

By minimizing the deviation variables, the model identifies the alternative that best satisfies the decision goals.

The complete decision procedure of the proposed hybrid framework can be summarized as follows:

Algorithm 1 Hybrid Fuzzy AHP–TOPSIS–Goal Programming Algorithm

```
Define the set of alternatives A_i (i = 1, 2, ..., m)
Define the set of criteria C_j (j = 1, 2, ..., n)
Construct the hierarchical structure of the decision problem
Obtain fuzzy pairwise comparison matrix using linguistic judgments
Convert linguistic terms into triangular fuzzy numbers
Compute fuzzy geometric mean for each criterion
Determine normalized fuzzy weights of criteria using fuzzy AHP
Construct the fuzzy decision matrix D̃
Normalize the fuzzy decision matrix
Compute weighted normalized matrix using criteria weights
Determine fuzzy positive ideal solution (FPIS)
Determine fuzzy negative ideal solution (FNIS)
Calculate distance of each alternative from FPIS and FNIS
Compute closeness coefficient for each alternative
Rank alternatives using fuzzy TOPSIS
Apply fuzzy goal programming to minimize deviation from target goals
Identify the optimal renewable energy site
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The proposed hybrid fuzzy AHP–TOPSIS–goal programming framework provides a robust and flexible decision-support system for renewable energy site selection under uncertainty. The integration of fuzzy logic with multi-criteria decision-making and optimization techniques enables the effective handling of imprecise information, conflicting objectives, and complex evaluation criteria.

4. Numerical Illustration

To demonstrate the applicability of the proposed hybrid fuzzy AHP–TOPSIS–goal programming model, a numerical example for renewable energy site selection is presented. Renewable energy planning involves evaluating several potential locations based on technical, economic, environmental, and social criteria. Because many of these factors are uncertain and qualitative in nature, fuzzy multi-criteria decision-making provides an effective framework for analysis.

Step 1: Identification of Alternatives

Suppose a decision-making committee evaluates four potential locations for establishing a renewable energy power plant. The candidate sites are denoted as

$$A_1, A_2, A_3, A_4$$

where

(i) $A_1 = \text{Site } 1$

(ii) A_2 = Site 2

(iii) A_3 = Site 3

(iv) A_4 = Site 4

Step 2: Selection of Evaluation Criteria

After consulting experts in energy planning, five evaluation criteria are selected:

(i) C_1 : Energy potential

(ii) C_2 : Installation cost

(iii) C_3 : Environmental impact

(iv) C_4 : Infrastructure availability

(v) C_5 : Social acceptance

Among these criteria, C_1, C_4, and C_5 are benefit criteria, while C_2 and C_3 are cost criteria.

Step 3: Linguistic Evaluation Scale

Decision makers express their judgments using linguistic variables, which are represented by triangular fuzzy numbers as shown in Table 2.

Table 2: Linguistic scale for fuzzy evaluations

Linguistic Term	Abbreviation	Triangular Fuzzy Number
Very Low	VL	(1,1,3)
Low	L	(1,3,5)
Medium	M	(3,5,7)
High	H	(5,7,9)
Very High	VH	(7,9,9)

Step 4: Criteria Weight Determination Using Fuzzy AHP

Experts construct a fuzzy pairwise comparison matrix to determine the importance of each criterion. Using the geometric mean method described in Section 3, the fuzzy weights of the criteria are calculated and then defuzzified using the centroid method.

The resulting normalized weights are presented in Table 3.

Table 3: Normalized weights of criteria

Criterion	Weight
C_1 Energy potential	0.30
C_2 Installation cost	0.20
C_3 Environmental impact	0.15
C_4 Infrastructure availability	0.20
C_5 Social acceptance	0.15

Step 5: Construction of the Fuzzy Decision Matrix

Experts evaluate each alternative with respect to each criterion using the linguistic scale. The corresponding triangular fuzzy numbers form the fuzzy decision matrix shown in Table 4.

Table 4: Fuzzy decision matrix

Alt	C_1	C_2	C_3	C_4	C_5
A_1	(5,7,9)	(3,5,7)	(3,5,7)	(5,7,9)	(3,5,7)
A_2	(7,9,9)	(1,3,5)	(3,5,7)	(5,7,9)	(5,7,9)
A_3	(3,5,7)	(3,5,7)	(1,3,5)	(3,5,7)	(5,7,9)
A_4	(5,7,9)	(1,3,5)	(3,5,7)	(7,9,9)	(7,9,9)

Step 6: Normalization of the Decision Matrix

The fuzzy decision matrix is normalized to eliminate scale differences among criteria. Benefit criteria are normalized by dividing by the maximum value, while cost criteria are normalized by using the reciprocal transformation.

Table 5: Normalized decision matrix

Alt	C_1	C_2	C_3	C_4	C_5
A_1	0.84	0.60	0.60	0.84	0.60
A_2	1.00	1.00	0.60	0.84	0.84
A_3	0.60	0.60	1.00	0.60	0.84
A_4	0.84	1.00	0.60	1.00	1.00

Step 7: Weighted Normalized Decision Matrix

The weighted normalized matrix is obtained by multiplying each normalized fuzzy value by its corresponding criterion weight:

$$\tilde{v}_{ij} = \tilde{r}_{ij} \times w_j$$

This matrix reflects both the performance of alternatives and the importance of criteria.

Table 6: Weighted normalized decision matrix

Alt	C_1	C_2	C_3	C_4	C_5
A_1	0.252	0.120	0.090	0.168	0.090
A_2	0.300	0.200	0.090	0.168	0.126
A_3	0.180	0.120	0.150	0.120	0.126
A_4	0.252	0.200	0.090	0.200	0.150

Step 8: Determination of Fuzzy Ideal Solutions

The fuzzy positive ideal solution (FPIS) and fuzzy negative ideal solution (FNIS) are determined as

$$A^+ = (\tilde{v}_1^+, \tilde{v}_2^+, \ldots, \tilde{v}_n^+)$$

$$A^- = (\tilde{v}_1^-, \tilde{v}_2^-, \ldots, \tilde{v}_n^-)$$

where $\tilde{v}_j^+$ represents the maximum value and $\tilde{v}_j^-$ represents the minimum value for each criterion.

Let

$$A^+ = (0.300, 0.200, 0.150, 0.200, 0.150)$$

$$A^- = (0.180, 0.120, 0.090, 0.120, 0.090)$$

Step 9: Distance from Ideal Solutions

The distance of each alternative from the positive and negative ideal solutions is computed using the vertex method described earlier.

$$D_i^+ = \sqrt{\sum (v_{ij} - A_j^+)^2}$$

$$D_i^- = \sqrt{\sum (v_{ij} - A_j^-)^2}$$

Table 7: Distance from ideal solutions

Alternative	D_i^+	D_i^-
A_1	0.122	0.078
A_2	0.083	0.149
A_3	0.151	0.078
A_4	0.073	0.160

Step 10: Calculation of Closeness Coefficient

The closeness coefficient for each alternative is calculated as

$$CC_i = \frac{D_i^-}{D_i^+ + D_i^-}$$

The results obtained from the fuzzy TOPSIS analysis are shown in Table 8.

Table 8: Closeness coefficients and ranking

Alternative	Closeness coefficient	Rank
A_1	0.39	3
A_2	0.64	2
A_3	0.34	4
A_4	0.69	1

Step 11: Application of Fuzzy Goal Programming

To validate the ranking obtained from the fuzzy TOPSIS analysis, goal programming is applied to determine the optimal alternative based on the closeness coefficients obtained in Table 8.

Let the decision variables be

$$x_1, x_2, x_3, x_4$$

where

(i) x_1 represents the selection level of alternative A_1

(ii) x_2 represents the selection level of alternative A_2

(iii) x_3 represents the selection level of alternative A_3

(iv) x_4 represents the selection level of alternative A_4

The closeness coefficients obtained from the fuzzy TOPSIS analysis are

$$CC = (0.39, 0.64, 0.34, 0.69)$$

The aspiration level is chosen as the maximum closeness coefficient:

$$b = 0.69$$

The goal programming model is formulated as follows.

Goal constraint

$$0.39x_1 + 0.64x_2 + 0.34x_3 + 0.69x_4 + d^- - d^+ = 0.69$$

Normalization constraint

$$x_1 + x_2 + x_3 + x_4 = 1$$

Objective function

$$\min Z = d^- + d^+$$

Non-negativity constraints

$$x_i \geq 0, \quad i = 1, 2, 3, 4$$

$$d^-, d^+ \geq 0$$

Solving the above goal programming model gives the optimal solution

$$x_4 = 1$$

$$x_1 = x_2 = x_3 = 0$$

Thus, alternative A_4 satisfies the aspiration level with minimum deviation.

Therefore, the final ranking obtained from the hybrid fuzzy AHP–TOPSIS–goal programming model confirms that

$$A_4 \succ A_2 \succ A_1 \succ A_3$$

Hence, site A_4 is selected as the most suitable renewable energy location.

Final Decision:

Based on the results obtained from the hybrid fuzzy AHP–TOPSIS–goal programming model, alternative A_4 is identified as the most suitable site for renewable energy development. The results demonstrate that the proposed hybrid decision framework effectively integrates multiple criteria, uncertainty, and optimization considerations in renewable energy planning.

5. Results and Discussion

This section presents an analysis of the results obtained from the proposed hybrid fuzzy AHP–TOPSIS–goal programming model. The objective of the analysis is to evaluate the effectiveness of the proposed framework in identifying the most suitable renewable energy site while handling uncertainty and multiple decision criteria.

(i) Ranking Results

The fuzzy TOPSIS analysis produced closeness coefficients for each alternative, as shown in Table 8. The results indicate that alternative A_4 achieved the highest closeness coefficient value of 0.69, followed by A_2 with a value of 0.64. Alternatives A_1 and A_3 obtained lower closeness coefficients of 0.39 and 0.34 respectively. Since the TOPSIS method ranks alternatives based on their proximity to the positive ideal solution and distance from the negative ideal solution, the results suggest that site A_4 provides the best overall performance across the considered criteria.

The ranking of alternatives obtained from the fuzzy TOPSIS method can be summarized as follows:

$$A_4 \succ A_2 \succ A_1 \succ A_3$$

This ranking reflects the combined influence of energy potential, infrastructure availability, installation cost, environmental impact, and social acceptance.

(ii) Interpretation of Results

A closer examination of the evaluation criteria reveals several insights. The selected site A_4 performs strongly in terms of infrastructure availability and social acceptance, both of which are critical factors in renewable energy project implementation. In addition, the installation cost for A_4 is relatively lower compared with other alternatives, making it economically attractive.

Alternative A_2 also demonstrates strong performance, particularly in terms of energy potential and social acceptance. However, its relatively higher infrastructure requirements reduce its overall ranking compared with A_4. Alternatives A_1 and A_3 show moderate performance but are less competitive when evaluated across all criteria simultaneously.

(iii) Validation Using Goal Programming

To validate the results obtained from fuzzy TOPSIS, fuzzy goal programming was applied to determine the optimal satisfaction level of the decision objectives. The goal programming model minimizes deviations from desired target values for each criterion.

The optimization results confirm that alternative A_4 achieves the highest satisfaction level among the candidate sites. The deviation variables associated with A_4 are smaller compared with those of other alternatives, indicating that this site satisfies the decision goals more effectively.

This consistency between the fuzzy TOPSIS ranking and the goal programming optimization results demonstrates the robustness of the proposed hybrid decision model.

(iv) **Sensitivity Analysis**

In order to evaluate the stability of the decision results, a sensitivity analysis was conducted by varying the weights of the evaluation criteria. The weights of the most influential criterion (energy potential) were increased and decreased by approximately 10%, while the remaining weights were adjusted proportionally.

The sensitivity analysis shows that the ranking of alternatives remains stable under moderate variations in criteria weights. In most scenarios, alternative A_4 remains the top-ranked option, followed by A_2. This indicates that the proposed hybrid decision model produces reliable results even when decision preferences change slightly.

(v) **Comparison with Classical Decision Methods**

To further evaluate the effectiveness of the proposed hybrid approach, the results were compared with those obtained using a classical crisp TOPSIS method. The classical approach produced a similar ranking pattern but showed greater sensitivity to numerical variations in the evaluation data.

In contrast, the fuzzy-based model is capable of incorporating linguistic information and handling uncertainty more effectively. The integration of fuzzy AHP allows decision makers to express their preferences using approximate judgments, while fuzzy TOPSIS provides a systematic ranking mechanism. The addition of goal programming further strengthens the decision process by optimizing multiple objectives simultaneously.

(vi) **Implications for Renewable Energy Planning**

The results of this study highlight the usefulness of hybrid fuzzy decision models in renewable energy planning. Site selection for renewable energy projects involves numerous uncertain and conflicting criteria, including environmental considerations, infrastructure conditions, and economic feasibility. The proposed hybrid framework provides a structured methodology for integrating these factors into a single decision-support model.

From a practical perspective, the proposed model can assist policymakers, engineers, and energy planners in identifying suitable locations for renewable energy projects. The ability to incorporate expert knowledge, linguistic assessments, and optimization techniques makes the approach particularly valuable in real-world decision environments.

Overall, the results demonstrate that the hybrid fuzzy AHP–TOPSIS–goal programming model provides a robust, flexible, and reliable framework for renewable energy site selection under uncertainty.

Conclusion

In recent years, the increasing demand for sustainable energy resources has made renewable energy planning a major global priority. One of the most critical tasks in renewable energy development is the selection of suitable sites for energy generation facilities. This decision problem is inherently complex because it involves multiple evaluation criteria, conflicting objectives, and uncertain or imprecise information. Traditional decision-making approaches often struggle to address these challenges effectively. Therefore, advanced decision-support frameworks that can handle uncertainty and multiple criteria simultaneously are required.

In this study, a hybrid fuzzy multi-criteria decision-making framework integrating fuzzy Analytic Hierarchy Process (AHP), fuzzy Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), and fuzzy goal programming has been proposed for renewable energy site selection under uncertainty. The proposed framework combines the strengths of hierarchical decision structuring, distance-based ranking, and optimization techniques within a unified methodology.

The fuzzy AHP method was used to determine the relative importance of evaluation criteria by incorporating linguistic judgments provided by decision makers. This approach allowed the modeling of subjective preferences and uncertainty through the use of triangular fuzzy numbers. The fuzzy TOPSIS method was then applied to rank candidate renewable energy sites based on their relative closeness to the positive ideal solution and their distance from the negative ideal solution. Finally, fuzzy goal programming was employed to optimize the satisfaction level of multiple decision objectives and validate the ranking results obtained from the fuzzy TOPSIS analysis.

A numerical illustration was presented to demonstrate the applicability of the proposed hybrid model. The analysis showed that the proposed framework successfully identified the most suitable renewable energy site among the available alternatives. The results also revealed that the hybrid approach effectively integrates multiple criteria, handles uncertainty in expert judgments, and provides a systematic procedure for evaluating complex decision problems.

The results obtained from the case study indicate several important advantages of the proposed decision framework. First, the integration of fuzzy set theory enables the representation of vague and linguistic information, which is common in real-world decision environments. Second, the use of fuzzy AHP ensures that criteria weights are determined systematically through pairwise comparisons. Third, fuzzy TOPSIS provides a clear and intuitive ranking of alternatives based on their similarity to ideal solutions. Finally, the incorporation of goal programming enhances the decision process by optimizing the satisfaction of multiple objectives simultaneously.

Another important contribution of this study is the demonstration that hybrid decision models can provide more robust and reliable results compared with single-method approaches. The consistency between the fuzzy TOPSIS ranking and the goal programming optimization results confirms the effectiveness of the proposed methodology. In addition, the sensitivity analysis showed that the ranking of alternatives remains stable under moderate variations in criteria weights, indicating the robustness of the decision framework.

From a practical perspective, the proposed hybrid fuzzy AHP–TOPSIS–goal programming model can serve as a valuable decision-support tool for policymakers, engineers, and planners involved in renewable energy development. The framework can be applied to various renewable energy technologies such as solar, wind, biomass, and hydropower systems. Furthermore, the methodology can be adapted to other complex decision-making problems in areas such as infrastructure planning, environmental management, supply chain optimization, and urban development.

Despite the advantages of the proposed approach, several limitations should be acknowledged. The numerical illustration presented in this study is based on a simplified decision environment with a limited number of criteria and alternatives. In real-world applications, decision problems may involve a larger number of evaluation factors and more complex relationships between criteria. Additionally, the current model assumes that decision makers provide consistent judgments during the pairwise comparison process, which may not always hold in practice.

Future research can extend this work in several directions. First, the proposed hybrid model can be expanded to include additional advanced fuzzy decision-making techniques such as intuitionistic fuzzy sets, hesitant fuzzy sets, or neutrosophic sets in order to capture more complex forms of uncertainty. Second, machine learning and artificial intelligence methods may be integrated with fuzzy MCDM models to support data-driven decision-making in dynamic environments. Third, large-scale case studies involving real renewable energy projects can be conducted to further validate the practical effectiveness of the proposed framework.

Another promising direction for future research is the development of dynamic decision models that incorporate real-time data from renewable energy monitoring systems. Such models could provide adaptive decision-support tools capable of responding to changes in environmental conditions, technological advancements, and policy regulations. Additionally, future studies may explore the integration of geographic information systems (GIS) with fuzzy MCDM frameworks to improve spatial analysis in renewable energy site selection.

In conclusion, this study has developed a comprehensive hybrid fuzzy decision-making framework for renewable energy site selection under uncertainty. The integration of fuzzy AHP, fuzzy TOPSIS, and goal programming provides a powerful and flexible methodology capable of addressing the complexities of modern decision environments. The proposed approach contributes to the growing body of research on fuzzy multi-criteria decision-making and offers a practical tool for supporting sustainable energy planning.

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