APPLICATION OF TYPE-2 FUZZY TOPSIS METHOD FOR ESTIMATING RENEWABLE ENERGY SOURCES

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Abstract

As global energy demands rise and the adverse effects of climate change become increasingly evident, the need for clean, sustainable energy sources has never been more critical. Renewable energy options, which harness natural processes like sunlight, wind, water, and geothermal heat, offer promising solutions to reduce dependence on fossil fuels and mitigate environmental damage. Estimating renewable energy options involves evaluating various energy sources to determine their suitability based on several criteria. Renewable energy potential varies significantly across different regions, influenced by factors such as natural resources, technological development, and policy support. Some regions are naturally more suited for certain types of renewable energy due to their climate, geography, and resources. The efficiency and cost-effectiveness of renewable technologies can vary based on how advanced technology is in each region. Government policies and incentives play a huge role in determining how much potential renewable energy can be developed. The key objective is to choose the most viable renewable energy sources for a given region or application by considering factors like efficiency, flexibility, and reliability. The TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) method helps decision-makers identify the preferred alternatives by evaluating the relative proximity of each alternative to an ideal solution. Unlike traditional type-1 fuzzy numbers, type-2 fuzzy numbers provide an additional layer of uncertainty by representing a fuzzy set with both primary and secondary membership functions. This allows capturing more detailed and complex uncertainties. Type-2 fuzzy numbers can be integrated into TOPSIS to handle the inherent uncertainty and imprecision in decision-making, particularly in the context of renewable energy options, where data is often uncertain or vague. This paper offers the integration of spectrum selection optimization algorithms based on the evaluation of the characteristics of various renewable energy options using the TOPSIS fuzzy method.

Keywords: Renewable energy options, type-2 fuzzy numbers, multi-criteria decision making, TOPSIS method

I. Introduction

As global energy demands rise and the adverse effects of climate change become increasingly evident, the need for clean, sustainable energy sources has never been more critical. Renewable energy options, which harness natural processes like sunlight, wind, water, and geothermal heat, offer promising solutions to reduce dependence on fossil fuels and mitigate environmental damage. The shift toward renewable energy is not only a necessity for environmental sustainability but also presents opportunities for economic growth and energy security. Among the most widely recognized renewable energy sources, solar energy uses photovoltaic cells to convert sunlight directly into electricity. Solar power is abundant, particularly in regions with high levels of sunlight, making it an attractive option for decentralized power generation. Technology has advanced significantly, with the cost of solar panels decreasing over the past decade, making solar power more affordable and accessible to both individual and large-scale projects. Wind power harnesses the kinetic energy of wind through turbines to generate electricity. Onshore and offshore wind farms are becoming an increasingly common sight across the globe. Wind energy is particularly effective in areas with strong and consistent wind currents, such as coastal regions and open plains. Hydropower, one of the oldest and most established renewable energy sources, generates electricity by harnessing the energy of flowing water. Large-scale hydropower projects typically involve dams that store water in reservoirs, which are then released to drive turbines. Smaller, run-of-river projects have also been developed to reduce the environmental impacts associated with damming rivers. Geothermal energy taps into the Earth's natural heat, often through hot springs, geysers, or geothermal reservoirs found deep beneath the surface. This energy source can be used for heating or converting it into electricity. Geothermal power plants are particularly effective in regions with significant tectonic activity. Biomass energy comes from organic materials such as wood, agricultural residues, and waste. Biomass can be burned directly for heat or converted into biofuels like ethanol and biodiesel for transportation. Biomass energy is considered carbon-neutral because the carbon dioxide released during combustion is offset by the carbon dioxide absorbed by plants during their growth. Ocean energy encompasses both tidal and wave energy, harnessing the power of the oceans to generate electricity. Tidal energy relies on the rise and fall of tides, while wave energy captures the motion of the ocean's surface. Although still in the early stages of development, ocean energy holds significant potential. As the world confronts the challenges of climate change, energy security, and environmental degradation, the need to transition to renewable energy sources has become more urgent. The selection of the most suitable renewable energy option depends on a variety of factors such as cost, efficiency, flexibility, reliability, environmental impact, technological maturity, etc. However, these factors often involve uncertainties that make decision-making difficult. Governments, businesses, and individuals must work together to promote the growth of renewable energy, develop innovative solutions to overcome challenges, and ensure that future generations can enjoy the benefits of a healthier, more sustainable planet.

MCDM (Multi-Criteria Decision Making) techniques are widely used to evaluate and rank renewable energy alternatives based on multiple criteria [1]. Traditional decision-making methods like Weighted Sum Model (WSM) [2], Analytic Hierarchy Process (AHP) [3], and Elimination and Choice Expressing Reality (ELECTRE) [4] have been applied to renewable energy selection. These methods are effective in aggregating various factors, but they often fail to handle the vagueness and uncertainty associated with real-world data. For instance, cost estimations, environmental impact assessments, and efficiency measures of renewable energy systems are typically subject to uncertainty, making it difficult to apply crisp values in traditional methods. The use of fuzzy sets in MCDM allows decision-makers to express uncertainty in criteria, where each value is represented by a fuzzy number instead of a precise number [5]. Type-1 fuzzy numbers are commonly used to model such uncertainties, but they still do not fully capture the complexity of the decision-making process, especially when the degree of uncertainty itself is uncertain [6]. This limitation has prompted the exploration of type-2 fuzzy sets, which provide a more sophisticated representation of uncertainty. TOPSIS is a popular MCDM method for ranking alternatives based on their distance from an ideal and a negative ideal solution. Hwang and Yoon (1981) introduced TOPSIS as a technique to determine the best option by minimizing the distance from the ideal solution and maximizing the distance from the negative ideal solution [7]. The method involves constructing a decision matrix, normalizing the data, calculating the weighted normalized decision matrix, and then computing the separation measures (i.e., Euclidean distance) from the ideal and negative ideal solutions [8]. In the context of renewable energy, TOPSIS has been applied in several studies to compare and evaluate different energy sources (e.g., solar, wind, hydropower) based on criteria such as cost, efficiency, environmental impact, and reliability. Sengul et al. applied fuzzy TOPSIS for the evaluation of renewable energy alternatives in Turkey, ranking solar, wind, and biomass energy based on economic, environmental, and technical factors [9]. Similarly, Kaya and Kahraman used the fuzzy TOPSIS method to assess the sustainability of various renewable energy technologies [10]. However, one limitation of TOPSIS in its classical form is its inability to handle uncertain or imprecise data. This is particularly important when evaluating renewable energy options, as many of the data points used in these evaluations are subject to variability. This has led to the incorporation of fuzzy logic into TOPSIS, with researchers proposing fuzzy-TOPSIS models to address these issues [11]. Goumas and Lygerou used the PROMETHEE method to assess the sustainability of various renewable energy technologies [12]. Similarly, Ramanathan employed fuzzy AHP to assess the suitability of various renewable energy resources (e.g., wind, solar, biomass) [13]. It used fuzzy numbers to express vagueness in evaluating factors like environmental impact, social acceptance, and availability of resources. Levitin et all. used genetic algorithm for open-loop distribution system design [14]. Mamlook and et all. used neuro-fuzzy program approach for evaluating electric power generation systems [15]. The integration of TOPSIS with type-2 fuzzy numbers enhances the robustness of the decision-making process by allowing for more precise handling of uncertainty [16].

Type-2 fuzzy TOPSIS provides more reliable results compared to traditional methods, especially when the decision data are uncertain or imprecise. This methodology is widely used for multi-criteria decision-making problems, where a set of alternatives needs to be ranked based on multiple conflicting criteria in deeply uncertain conditions. The application of the TOPSIS method combined with type-2 fuzzy numbers offers a powerful framework for evaluating and selecting renewable energy options. This approach offers more reliable decision-making than traditional methods by tackling the uncertainty in energy costs, efficiency, and environmental impact data. The literature shows increasing interest in using this hybrid approach for selecting renewable energy, with promising outcomes in several case studies. This paper explores how the TOPSIS method, when applied with type-2 fuzzy numbers, can improve decision-making in renewable energy selection. Paper is structured as follows. In section 2 literature review is given. Section 2 represents the major definitions of type-2 fuzzy numbers and the TOPSIS steps that are utilized for estimation problems. In section 3, the TOPSIS methodology using type-2 fuzzy numbers is applied to solve the problem of estimating the renewable energy options. Conclusion represents the main results developed in this paper.

II. Preliminaries

Definition 1. A type-1 fuzzy set A in the universe X is characterized by a membership function and is expressed in figure 1 [17]:

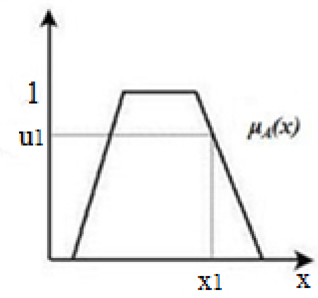

Figure 1: *Type-1 fuzzy set*

$$A = \{(x, \mu_A(x)) \mid \forall x \in X, \mu_A(x) \in [0,1]\} \tag{1}$$

Definition 2. A type 2 fuzzy set $\tilde{A}$ is characterized by a fuzzy membership function $\mu_{\tilde{A}}(x,u)$ in the universe X where $x \in X$ and $u \in J_X, J_X \subseteq [0,1]$ is shown in figure 2 [17]:

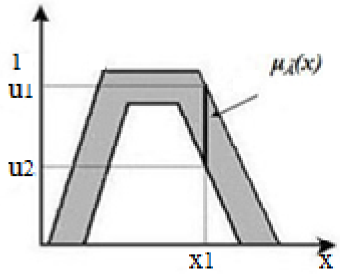

Figure 2: *Type-2 fuzzy set*

$$\tilde{A} = \{(x, u, \mu_{\tilde{A}}(x,u)) \mid \forall x \in X, u \in [0,1]\} \tag{2}$$

Definition 3. In classical mathematics, functions operate on precise (crisp) inputs and produce crisp outputs. But in fuzzy logic, inputs and/or outputs can be fuzzy sets (i.e., sets with degrees of membership between 0 and 1). The extension principle provides a way to apply a function $f : X \to Y$ to fuzzy inputs and obtain a fuzzy output. Suppose that $\tilde{A} = \sum_i \mu_{\tilde{A}}(x_i)/x_i$ and $\tilde{B} = \sum_j \mu_{\tilde{B}}(x_j)/x_j$ are fuzzy sets included in the set X . According to Zadeh extension principal [18]

$$\tilde{A} * \tilde{B} = \left(\sum_i \mu_{\tilde{A}}(x_i)/x_i\right) * \left(\sum_j \mu_{\tilde{B}}(x_j)/x_j\right) = \sum_{i,j} \left(\mu_{\tilde{A}}(x_i) \wedge \mu_{\tilde{B}}(x_j)\right) / \left(x_i * x_j\right) \tag{3}$$

Extension principle allows to extend classical function f from a set X to a fuzzy set A on X. For each element x in A, the degree of membership in the fuzzy set $f(A)$ is determined by applying the function f to the degree of membership of x in A.

$$\mu_{f(A)}(y) = \sup_{x \in X, f(x) = y} \mu_A(x) \tag{4}$$

This means the membership function of the fuzzy set $f(A)$ at y is maximum membership degree of all elements x in A such that $f(x) = y$. The Extension Principle also applies to set operations. The union of two fuzzy sets A and B is given below.

$$\mu_{A \cup B}(x) = \max(\mu_A(x), \mu_B(x)) \tag{5}$$

The intersection is given below.

$$\mu_{A \cap B}(x) = \min(\mu_A(x), \mu_B(x)) \tag{6}$$

The complement of a fuzzy set is given below.

$$\mu_{\neg} A(x) = 1 - \mu_A(x) \tag{7}$$

Definition 4. If $\mu_{\tilde{A}}(x)$ and $\mu_{\tilde{B}}(x)$ are membership degrees of type-2 fuzzy sets $\tilde{A}$ and $\tilde{B}$ of the fuzzy set $J \in [0,1]$, then

$$\mu_{\tilde{A}}(x) = f(u_1)/u_1 + f(u_2)/u_2 + \cdots + f(u_n)/u_n = \sum_i f(u_i)/u_i, \quad u_i \in J \tag{8}$$

$$\mu_{\tilde{B}}(x) = g(w_1)/w_1 + g(w_2)/w_2 + \cdots + g(w_m)/w_m = \sum_j f(w_j)/w_j, \quad w_j \in J \tag{9}$$

where f and g are membership functions.

Definition 5. The union and intersection of type-2 fuzzy sets are defined as below [18]:

$$\begin{aligned} \tilde{A} \cup \tilde{B} \Leftrightarrow \mu_{\tilde{A}\cup\tilde{B}}(x) = \mu_{\tilde{A}}(x) \cup \mu_{\tilde{B}}(x) = \left(\sum_i f(u_i)/u_i\right) \cup \left(\sum_i f(w_j)/w_j\right) = \\ = \sum_{i,j} \left(f(u_i) \vee g(w_j)\right)/\left(u_i \vee w_j\right) \end{aligned} \tag{10}$$

$$\begin{aligned} \tilde{A} \cap \tilde{B} \Leftrightarrow \mu_{\tilde{A}\cap\tilde{B}}(x) = \mu_{\tilde{A}}(x) \cap \mu_{\tilde{B}}(x) = \left(\sum_i f(u_i)/u_i\right) \cap \left(\sum_i f(w_j)/w_j\right) = \\ = \sum_{i,j} \left(f(u_i) \wedge g(w_j)\right)/\left(u_i \wedge w_j\right) \end{aligned} \tag{11}$$

Definition 6. The defuzzification process for type-2 fuzzy numbers is more complicated than for type-1 fuzzy sets due to the two-dimensional nature of type-2 fuzzy sets. However, the most common defuzzification methods for type-2 fuzzy numbers are represented below.

Center of gravity (COG) method: Calculates the centroid of the type-2 fuzzy number considering both the primary and secondary membership functions.

$$\tilde{x} = \frac{\int_X \int_0^1 x \cdot \mu_A(x,u)\,du\,dx}{\int_X \int_0^1 \mu_A(x,u)\,du\,dx} \tag{12}$$

where $\int_X$ is the integration over the universe of discourse X, $\int_0^1 x$ is the integration over the secondary membership values, $\mu_A(x,u)$ is the membership function of the type-2 fuzzy number at x, u. Formula gives the crisp value x, which represents defuzzified center of the type-2 fuzzy set.

Alpha-cut method: Cuts the fuzzy number at different levels of α, treats each cut as a type-1 fuzzy set, defuzzifies each cut, and then averages the results.

$$\tilde{x}_\alpha = \frac{\int_X x \cdot \mu A_\alpha(x)\,dx}{\int_X \mu A_\alpha(x)\,dx} \tag{13}$$

Weighted average of the defuzzified values for each α-cut is taken, where the weight is based on the membership grade α:

$$\tilde{x} = \int_0^1 \tilde{x}_\alpha \cdot \alpha\,d\alpha \tag{14}$$

Mean of Maxima (MOM) method: Computes the average of the points where the membership function is maximized. For type-2 fuzzy numbers, this involves finding the values of x that correspond to the maximum membership degree for each possible secondary membership u, and then averaging these values.

$$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{15}$$

where x_i are the values corresponding to the maximum degree of membership at each u.

III. Case Study Example: Renewable energy sources estimation problem

Suppose that there are three possible alternatives - A (wind), B (hydropower), C (solar) for estimation renewable energy sources with three criteria's: C_1 - efficiency (refers to how efficient each energy source is in converting the natural resource into usable energy), C_2 - flexibility (refers to the ability of an energy system or resource to adapt to changing demand, supply, or operational conditions), C_3 - reliability (the consistency and dependability of each energy source in providing power, especially considering factors like intermittency and weather dependence). Wind energy (A) is a key player in the transition to a cleaner, more sustainable energy future. While it faces challenges like intermittency, space requirements, and environmental impact concerns, its advantages - such as zero emissions, low operating costs, and abundant availability - make it one of the most promising renewable energy sources. Technological advancements in turbine efficiency, energy storage, and offshore wind development will likely overcome many of these challenges, making wind energy an even more integral part of the global energy mix in the coming years. Hydropower (B) remains a cornerstone of the renewable energy landscape due to its reliability, efficiency, and scalability. While it faces challenges, such as environmental impacts and high upfront costs, it offers significant benefits, including clean energy generation, energy storage capabilities, and long operational lifespans. As technology advances, hydropower is becoming more efficient and less intrusive, ensuring its role in the global transition to a sustainable and low-carbon energy future. Solar energy (C) is an essential part of the global transition to a sustainable, cleaner future. While it faces challenges such as intermittency and space requirements, advances in technology and policy support are making solar energy more viable and affordable. As the cost of solar energy continues to decrease and storage solutions improve, solar power will play an increasingly significant role in reducing dependence on fossil fuels and mitigating climate change.

The efficiency (C_1) of converting the resources (wind, sunlight, water flow, etc.) into usable energy is crucial. For example, modern photovoltaic solar panels can have efficiencies ranging from 15% to 22%, while wind turbines have efficiencies of 35-45%. Flexibility (C_2) in renewable energy selection refers to how adaptable and scalable an energy source is, both in terms of installation and integration into an existing grid or energy system. Flexibility also includes the ability to adjust power output based on changing demands, technological advancements, and regional or local conditions. Hybrid systems combining different energy sources, for example, wind and solar or integrating with traditional power sources can offer greater flexibility in maintaining stable energy output. The reliability (C_3) of an energy source depends on its ability to provide consistent power. Wind and solar can be intermittent (i.e., depending on weather), while biomass energy may be more reliable due to its consistent fuel source. Weights of criteria are w_1 = (0.2,0.3,0.4,0.4; 0.3,0.4,0.5;0.5), w_2 = (0.4,0.5,0.6,0.6; 0.5,0.6,0.7;0.7), w_3 = (0.4,0.5,0.6,0.6; 0.5,0.6,0.7;0.7). Linguistic values of type-2 fuzzy sets of linguistic terms are shown below:

Absolutely low - (0,0,0;0), Very low - (0.1,0.2,0.3;0.3), Low - (0.2,0.3,0.4;0.4), Slightly low - (0.25,0.35,0.45;0.45), Medium - (0.3,0.4,0.5;0.5), Slightly high - (0.4,0.5,0.6;0.6), High - (0.5,0.6,0.7;0.7), Very high - (0.6,0.7,0.8;0.8), Absolutely high - (0.7,0.8,0.9;0.9).

The detailed steps of the solution of estimation problem type-2 fuzzy TOPSIS modification are shown below [19]:

Step 1: Determining a decision matrix. A decision matrix is essentially a table where each alternative is evaluated based on several criteria. Determining a decision matrix using linguistic terms and corresponding type-2 fuzzy numbers based on the decision maker's preferences involves a structured approach for evaluating alternatives under uncertainty. The idea is to represent the decision maker's qualitative judgments expressed in linguistic terms and convert them into fuzzy numbers that account for uncertainty and vagueness, allowing for a more flexible and accurate decision-making process. Decision matrix applying type-2 fuzzy numbers given in table 1.

Table 1: *Type-2 fuzzy decision matrix*

	C_1	C_2	C_3
A	(0.4,0.5,0.6;0.6), (0.5,0.6,0.7;0.7)	(0.3,0.4,0.5;0.5), (0.4,0.5,0.6;0.6)	(0.5,0.6,0.7;0.7) (0.6,0.7,0.8;0.8)
B	(0.6,0.7,0.8;0.8), (0.7,0.8,0.9;0.9)	(0.5,0.6,0.7;0.7), (0.6,0.7,0.8;0.8)	(0.5,0.6,0.7;0.7) (0.6,0.7,0.8;0.8)
C	(0.3,0.4,0.5;0.5), (0.5,0.6,0.7;0.7)	(0.3,0.4,0.5;0.5) 0.5,0.6,0.7;0.7)	(0.6,0.7,0.8;0.8), (0.7,0.8,0.9;0.9)

Step 2: Determining the weighted decision matrix. The weighted decision matrix is used to evaluate and compare different alternatives across multiple criteria, considering both the relative importance (weights) of each criterion values of the performance scores. Determining the weighted decision matrix $V = \left(v_{ij}\right)_{n\times m}$ by employing the next formula is represented in table 2.

$$v_{ij} = w_j r_{ij}; i = 1,\cdots,n; \ j = 1,\cdots,m \tag{16}$$

Table 2: *Weighted decision matrix*

	C_1	C_2	C_3
A	(0.08,0.15,0.24;0.24), (0.15,0.24,0.35;0.35)	(0.12,0.2,0.3;0.3), (0.2,0.3,0.42;0.42)	(0.2,0.3,0.42;0.42), (0.3,0.42,0.56;0.56)
B	(0.12,0.21,0.32;0.32), (0.21,0.32,0.45;0.45)	(0.2,0.3,0.42;0.42), (0.3,0.42,0.56;0.56)	(0.2,0.3,0.42;0.42), (0.3,0.42,0.56;0.56)
C	(0.06,0.12,0.2;0.2), (0.15,0.24,0.35;0.35)	(0.12,0.2,0.3;0.3) 0.25,0.36,0.49;0.49)	(0.24,0.35,0.48;0.48), (0.35,0.48,0.63;0.63)

Step 3: Determining positive and negative optimal solutions: In the TOPSIS methodology, the concept of the positive ideal solution (PIS) and the negative ideal solution (NIS) play a very important role in ranking the options. These two concepts represent the best and worst possible outcomes for each criterion. The PIS (A^*) is the best possible set of values for all criteria where possible. It represents the ideal or most desirable scenario for each alternative, based on the given decision criteria. For benefit criteria where higher values are better, the PIS will have the maximum values for each criterion. For cost criteria where lower values are better, the PIS will have the minimum values. The NIS (A^-) is the worst possible set of values for all criteria. It represents the least desirable scenario for each alternative. For benefit criteria, the NIS will have the minimum values for each criterion. For cost criteria, the NIS will have the maximum values. So, PIS is the ideal best - closest to what we would want to achieve, NIS is the ideal worst - farthest from what we want. Positive and negative optimal solutions are calculated as below.

$$A^* = \left\{v_1^*,\cdots,v_m^*\right\} = \left\{\max v_{ij}^* \mid j \in \Omega_b, \quad \min v_{ij}^* \mid j \in \Omega_b\right\} \tag{17}$$

$$A^- = \left\{v_1^-,\cdots,v_m^-\right\} = \left\{\max v_{ij}^- \mid j \in \Omega_b, \quad \min v_{ij}^- \mid j \in \Omega_b\right\} \tag{18}$$

$A^{*}=\{\ (0.12,0.21,0.32;0.32),(0.21,0.32,0.45;0.45);(0.2,0.3,0.42;0.42),(0.3,0.42,0.56;0.56);$
$(0.24,0.35,0.48;0.48),(0.35,0.48,0.63;0.63)\ \}$

$A^{-}=\{\ (0.06,0.12,0.2;0.2),(0.15,0.24,0.35;0.35);(0.12,0.2,0.3;0.3)0.25,0.36,0.49;0.49);$
$(0.2,0.3,0.42;0.42),(0.3,0.42,0.56;0.56)\ \}$

Step 4: Determining separation measure and proximity to the optimal solution. The separation measure refers to the distance between each alternative and the positive ideal solution (PIS) and the negative ideal solution (NIS). The separation measure quantifies how far each alternative is from the best and worst possible outcomes. The smaller the distance to the PIS (the ideal best), the better the alternative. Conversely, the larger the distance to the NIS (the ideal worst), the better. The Euclidean distance formula is commonly used to calculate the separation between an alternative and the ideal solutions. Separation measures and proximity to the optimal solutions are determined by employing Euclidean distance as shown below [19]:

$$D^{*}=\sqrt{\sum_{i=1}^{m}\left(v_{ij}-v_{j}^{*}\right)^{2}};\ i=1,\cdots,n \tag{19}$$

$$D^{-}=\sqrt{\sum_{i=1}^{m}\left(v_{ij}-v_{j}^{-}\right)^{2}};\ i=1,\cdots,n \tag{20}$$

Negative and positive separation measure for each option calculated as below:

$D_{A}^{*}=(0.03,0.02,0.1;0.01,0.16,0.034)$ $\quad D_{A}^{-}=(0.016,0.025,0.036;0.0025,0.0036,0.0049)$

$D_{B}^{*}=(0.016,0.025,0.036;0.025,0.036,0.049)$ $\quad D_{B}^{-}=(0.014,0.018,0.028;0.061,0.01,0.015)$

$D_{C}^{*}=(0.01,0.018,0.028;0.061,0.01,0.015)$ $\quad D_{C}^{-}=(0.014,0.018,0.028;0.0025,0.0036,0.0049)$

Step 5: Ranking the options by computing the relative closeness of each alternative to the optimal solution. After calculating the separation measures, proximity to the optimal solution is represented by the closeness coefficient. The Closeness coefficient quantifies the relative closeness of each alternative to the ideal solution. It is a ratio that measures how near an alternative is to the positive ideal (PIS) and how far it is from the negative ideal (NIS). Closeness coefficient (CC) of the option is determined by applying calculations shown below:

$$CC_{i}=\frac{D_{i}^{-}}{D_{i}^{*}+D_{i}^{-}};\ i=1,\cdots,n \tag{21}$$

where, D_{i}^{-} is separation distance of alternative i to the negative ideal solution (NIS), D_{i}^{*} is separation distance of alternative i to the positive ideal solution (PIS).
The relative closeness for each option calculated as below:

$$C_{A}^{*}=\frac{(0.016,0.025,0.036;0.0025,0.0036,0.0049)}{(0.03,0.02,0.01;0.01,0.016,0.034)+(0.016,0.025,0.036;0.0025,0.0036,0.0049)}=$$
$$=\frac{(0.016,0.025,0.036;0.0025,0.0036,0.0049)}{(0.046,0.045,0.046;0.0185,0.0286,0.0389)}=(0.3478,0.5556,0.7826;0.0643,0.1254,0.2649)$$

$$C_B^* = \frac{(0.014, 0.018, 0.028; 0.061, 0.01, 0.015)}{(0.016, 0.025, 0.036; 0.025, 0.036, 0.049) + (0.014, 0.018, 0.028; 0.061, 0.01, 0.015)} =$$

$$= \frac{(0.014, 0.018, 0.028; 0.061, 0.01, 0.015)}{(0.030, 0.043, 0.064; 0.086, 0.046, 0.064)} = (0.2188, 0.4186, 0.9333; 0.9531, 0.2174, 0.2344)$$

$$C_C^* = \frac{(0.01, 0.018, 0.028; 0.061, 0.01, 0.015)}{(0.01, 0.018, 0.028; 0.061, 0.01, 0.015) + (0.014, 0.018, 0.028; 0.061, 0.01, 0.015)} =$$

$$= \frac{(0.01, 0.018, 0.028; 0.061, 0.01, 0.015)}{(0.024, 0.036, 0.056; 0.086, 0.046, 0.064)} = (0.25, 0.5, 1.1667; 0.3906, 0.7826, 0.5698)$$

Comparing all three alternatives (wind, hydropower, and solar energy) we determine that option wind energy (A) source is the best alternative.

IV. Conclusion

Renewable energy options refer to the various sources of energy that are naturally replenished on a human timescale and have minimal environmental impacts compared to traditional fossil fuels. These energy sources are crucial for reducing greenhouse gas emissions, improving energy security, and contributing to sustainability. Estimation renewable energy options require a thorough assessment of available resources, technological capabilities, economic viability, environmental impacts, social factors etc. By considering factors like energy potential, costs, storage needs, and regulatory frameworks, it can be identified the most suitable renewable energy options for a specific area or project. Estimating renewable energy options using type-2 fuzzy numbers is a powerful way to handle uncertainty and imprecision in renewable energy decision-making - especially when expert opinions or environmental data are vague, conflicting, or incomplete. Using the TOPSIS method with type-2 fuzzy numbers is a great way to rank renewable energy options under uncertainty. Type-2 fuzzy TOPSIS helps when expert judgments are imprecise or ambiguous, as is common in energy planning. This approach is especially helpful in multi-stakeholder, data-uncertain environments like energy planning, policy development, or rural electrification. For making decisions on renewable energy sources estimation in this article is applied fuzzy TOPSIS methodology with type-2 fuzzy numbers to consider high uncertainty in estimation problem. In this paper three options A (wind), B (hydropower), C (solar) with three criteria's C_1 - efficiency, C_2 - flexibility, and C_3 - reliability are used for renewable energy options estimation. By employing offered method it was identified that wind energy (A) source is more appropriate for selection.

V. Discussion

The decision-making process for selecting renewable energy sources is inherently complex and involves several challenges due to the numerous factors that must be considered. These challenges arise from the interplay of environmental, social, and economic factors that influence the feasibility and sustainability of renewable energy projects. Given the complexity and uncertainty involved in selecting renewable energy sources, Multi-Criteria Decision-Making (MCDM) methods are crucial for a systematic and comprehensive evaluation process. MCDM methods like type-2 fuzzy TOPSIS, can model and account for uncertainties in decision-making. For instance, fuzzy logic methods can deal with imprecise or incomplete data, which is common in renewable energy planning, especially when predicting variables such as energy production or costs over time. By using fuzzy sets, decision-makers can incorporate varying degrees of uncertainty into their evaluations. Type-2 fuzzy logic introduces a second layer of fuzziness to the membership functions. This means that rather than assigning a single value to represent an element's degree of membership, type-2 fuzzy sets assign a range of values for each input. In the case of renewable energy, this allows the model to represent uncertainties in environmental variables, such as cloud cover or wind speed, that are difficult to quantify precisely. For example, instead of assigning a crisp membership value of 0.8 for solar panel efficiency, a type-2 fuzzy set could represent a range of possible values, for example, between 0.75 and 0.85, reflecting the uncertainty in weather conditions over time. In the context of renewable energy, TOPSIS is useful because it allows decision-makers to consider multiple factors, such as cost, efficiency, reliability, environmental impact, and availability of resources, while providing a clear ranking of the alternatives. By comparing the alternatives to the ideal and anti-ideal solutions, it helps identify the most suitable energy source for a specific region or project. While the type-2 fuzzy TOPSIS method offers significant advantages in handling uncertainty and providing more accurate results in complex decision-making scenarios, it also comes with several challenges. These challenges primarily revolve around the complexity of constructing decision matrices, the computational requirements for processing large datasets, and the difficulty in defining appropriate membership functions.

The type-2 fuzzy TOPSIS method for renewable energy estimation is a powerful tool, but there is significant room for future improvements. Integrating this method with machine learning for predictive accuracy, optimization algorithms for better decision-making, and real-time data for dynamic and adaptive responses could substantially enhance its applicability and usefulness. Additionally, improving its ability to handle multiple uncertainties and developing user-friendly decision support systems would make it more accessible and effective for a broader range of decision-makers in the renewable energy sector. These improvements will lead to more accurate, efficient, and responsive decision-making, ultimately helping to accelerate the transition to sustainable and reliable energy systems. The type-2 fuzzy TOPSIS method holds immense potential for improving decision-making in renewable energy planning by accounting for uncertainty and providing a more nuanced evaluation of alternatives. However, there are several exciting avenues for future research and potential improvements that can enhance its applicability, accuracy, and efficiency. Machine learning (ML) models, particularly supervised learning algorithms like regression or classification, can be integrated with the type-2 fuzzy TOPSIS method to predict or estimate fuzzy membership values based on historical or real-time data. For example, predictive models could be developed to estimate the efficiency of solar panels, wind turbines, or other renewable energy sources based on environmental factors such as weather patterns, geographical features, and technological advancements. Machine learning can improve the prediction accuracy of fuzzy membership functions by learning from historical data, reducing the subjective assumptions often involved in manually defining the fuzziness levels. For example, rather than relying on expert-defined fuzzy sets, ML algorithms could automatically learn the optimal fuzzy sets based on real-world observations. Optimization algorithms, such as genetic algorithms (GA), particle swarm optimization (PSO), or simulated annealing, can be integrated with the type-2 fuzzy TOPSIS method to automate and optimize the selection of the best renewable energy sources. These algorithms can help identify the optimal energy portfolio that minimizes costs, maximizes efficiency, or meets other specific goals e.g., environmental sustainability. In addition to environmental factors like weather and geography, renewable energy systems are influenced by factors such as policy shifts e.g., subsidies or tariffs, economic conditions e.g., fuel price fluctuations, and technological innovations e.g., breakthroughs in storage technology. Incorporating these uncertainties into the decision-making process can make the type-2 fuzzy TOPSIS method more robust. Future research could extend the type-2 fuzzy TOPSIS method to include not just environmental uncertainties but also economic and policy-related uncertainties. Fuzzy logic could be used to model uncertain variables such as the potential for future price changes of renewable energy technologies or the impact of upcoming government regulations on energy production. By incorporating various uncertainty scenarios e.g., future energy prices, technological advancements, policy shifts, type-2 fuzzy TOPSIS could be used for scenario-based decision-making, allowing decision-makers to explore different potential futures and make choices that are resilient to a wide range of possible outcomes.

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