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A Fuzzy Analytic Hierarchy Process Based COPRAS Approach for the Evaluation of the Renewable Energy Sources

Yenilenebilir Enerji Kaynaklarının Değerlendirilmesi için Bulanık Analitik Hiyerarşi Süreci Tabanlı COPRAS Yaklaşımı

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Abstract

Renewable energy sources are those that naturally replenish over time and provide an endless supply of energy without the risk of resource exhaustion. Examples include solar power, wind energy, hydropower, geothermal energy, and biomass. These energy sources are crucial due to their sustainable nature, enabling continuous energy production while minimizing environmental harm and preserving natural resources. Unlike conventional fossil fuels, which are limited and heavily pollute the environment, renewable energy significantly reduces carbon emissions, improves air quality, and helps address climate change challenges. Embracing renewable energy is vital for building a sustainable future. This study evaluates renewable energy sources using a hybrid fuzzy multi-criteria decision-making approach. The proposed method integrates two techniques: the fuzzy analytic hierarchy process and the fuzzy-based COPRAS method. The fuzzy analytic hierarchy process is first applied to determine the relative importance of criteria and create a fuzzy decision matrix. Then, the COPRAS method processes this matrix, incorporating the calculated weights, to systematically assess and rank renewable energy options.

Özet

Yenilenebilir enerji kaynakları, doğal olarak zamanla kendini yenileyen ve tükenme riski olmadan sınırsız enerji sağlayan kaynaklardır. Örnekler arasında güneş enerjisi, rüzgar enerjisi, hidroelektrik enerji, jeotermal enerji ve biyokütle bulunur. Bu enerji kaynakları, sürdürülebilir yapıları sayesinde sürekli enerji üretimini mümkün kılar ve çevresel zararları en aza indirirken doğal kaynakların korunmasına yardımcı olur. Geleneksel fosil yakıtların aksine, yenilenebilir enerji karbon emisyonlarını önemli ölçüde azaltır, hava kalitesini iyileştirir ve iklim değişikliğiyle ilgili zorlukların üstesinden gelinmesine yardımcı olur. Yenilenebilir enerjiye yönelmek, sürdürülebilir bir gelecek inşa etmek için hayati önem taşımaktadır. Bu çalışma, yenilenebilir enerji kaynaklarını hibrit bir bulanık çok kriterli karar verme yaklaşımı kullanarak değerlendirmektedir. Önerilen yöntem, iki tekniği birleştirmektedir: bulanık analitik hiyerarşi süreci ve bulanık temelli COPRAS yöntemi. İlk olarak, bulanık analitik hiyerarşi süreci, kriterlerin göreceli önemini belirlemek ve bulanık bir karar matrisi oluşturmak için uygulanmıştır. Ardından COPRAS yöntemi, hesaplanan ağırlıkları içeren bu matrisi işleyerek yenilenebilir enerji seçeneklerini sistematik bir şekilde değerlendirmiş ve sıralamıştır.

Introduction

The increasing demand for energy, driven by population growth, industrialization, and urbanization, has led to a pressing need for sustainable and environmentally friendly energy solutions. Traditional energy sources, such as fossil fuels, are finite and contribute significantly to environmental challenges, including global warming, air pollution, and resource depletion. These challenges are exacerbated by the rapid pace of development and consumption, which place immense pressure on natural resources and ecosystems. The environmental consequences of relying on fossil fuels are severe, leading to rising sea levels, more frequent and intense weather events, and a loss of biodiversity. Such impacts pose a direct threat to global ecosystems, economies, and human well-being, underscoring the urgent need for alternative energy strategies.

The harmful effects of conventional energy sources have spurred a global transition toward renewable energy, which offers a sustainable, clean, and virtually inexhaustible alternative. Unlike fossil fuels, renewable energy sources such as solar, wind, and hydropower produce minimal greenhouse gas emissions, making them a crucial component of climate change mitigation efforts. Beyond their environmental benefits, renewable energy sources also contribute to economic growth by fostering innovation, generating new industries, and creating employment opportunities. Moreover, they enhance energy security by reducing dependence on imported fuels and providing decentralized energy solutions that can be tailored to local needs. Addressing these energy challenges is essential to ensure long-term environmental health and energy security, paving the way for a future where the growing energy demands of society are met sustainably without jeopardizing the planet's ecological integrity.

1. Renewable Energy Sources

Renewable Energy Sources (RES) are derived from natural processes that are replenished continuously, making them a critical element in the transition toward a sustainable energy future. Among the various renewable energy options, five prominent sources stand out: Solar Energy, Wind Energy, Hydroelectric Energy, Geothermal Energy, and Biomass Energy. Each of these sources has unique characteristics, advantages, and challenges that influence their applicability and feasibility in different regions and scenarios.

Solar Energy, often regarded as one of the most abundant and accessible renewable resources, is harnessed using technologies such as photovoltaic panels and concentrated solar power systems. These systems work by converting sunlight into usable electricity, with photovoltaic cells capturing sunlight and turning it directly into electricity, while concentrated solar power systems use mirrors or lenses to focus sunlight onto a small area, generating heat to drive turbines (Kolamroudi et al., 2022). Solar energy is versatile, applicable in both large-scale power plants and decentralized residential installations. It offers a clean, emission-free way to generate electricity and heat, making it a cornerstone of global renewable energy strategies. Additionally, solar power systems have been steadily improving in efficiency and affordability, contributing to their growing adoption worldwide.

Wind Energy, a rapidly growing and highly promising renewable resource, harnesses the power of moving air to generate electricity. Modern wind turbines are designed to capture the kinetic energy of the wind, converting it into mechanical energy through rotating blades, which is then transformed into electrical power (Sharma et al., 2022). This technology has evolved significantly over the years, with innovations in turbine design, efficiency, and energy storage systems, allowing for more consistent and reliable power generation. Wind farms, both onshore and offshore, are being developed across the globe in regions with strong and predictable wind patterns, such as coastal areas, mountain ridges, and open plains. Offshore wind farms, in particular, are gaining traction due to the higher and more consistent wind speeds found at sea, making them ideal for large-scale energy production. Wind energy offers a clean, renewable alternative to fossil fuels, significantly reducing greenhouse gas emissions and helping combat climate change.

Hydroelectric Energy, one of the oldest and most widely used forms of renewable energy, harnesses the power of flowing water to generate electricity. This energy is typically captured by building dams on rivers, where water stored at a higher elevation is released to flow through turbines, converting its kinetic energy into mechanical energy, which is then transformed into electrical power (Yaseen et al., 2020). Hydroelectric power plants can vary in size, from large-scale dams capable of generating significant amounts of electricity to small-scale systems designed for localized use. This resource offers several advantages, including the ability to provide a constant, reliable power supply, as water flows are generally predictable and can be managed to meet demand. Additionally, hydroelectric energy systems have a relatively low environmental impact compared to fossil fuels, producing no direct emissions. However, large-scale dams can have ecological consequences, such as disrupting local ecosystems and affecting water quality and fish migration patterns. Hydroelectric energy is a crucial component of the global energy mix, particularly in regions with abundant water resources, contributing to energy security and helping reduce reliance on fossil fuels. With ongoing advancements in technology and efficiency, hydroelectric power remains a cornerstone of sustainable energy solutions, supporting the transition towards a greener, low-carbon future.

Geothermal Energy, a powerful and sustainable renewable resource, harnesses the heat stored beneath the Earth's surface to generate electricity and provide direct heating. This heat originates from the natural radioactive decay of elements in the Earth's core, as well as residual heat from the planet's formation. Geothermal power plants use wells to tap into this thermal energy, bringing hot water or steam to the surface to drive turbines connected to electricity generators (Kabeyi and Olanrewaju, 2022). Geothermal systems can also be used for direct heating in residential and commercial applications, providing a reliable and energy-efficient alternative to conventional heating methods. One of the key advantages of geothermal energy is its ability to provide a consistent and stable power source, as the Earth's internal heat is available year-round, regardless of weather conditions. This makes it an ideal resource for base-load power generation, complementing other renewable sources like wind and solar, which can be intermittent. Geothermal energy has a relatively low environmental impact, with minimal greenhouse gas emissions compared to fossil fuel-based energy production. However, geothermal power plants are most effective in regions with high geothermal activity, such as tectonic plate boundaries or volcanic areas. Advances in drilling technology and enhanced geothermal systems are expanding the potential for geothermal energy, making it feasible in a broader range of locations.

Biomass Energy, a versatile and renewable resource, derives from organic materials such as plant matter, wood, agricultural residues, and even certain types of waste. These materials are converted into usable energy through processes such as combustion, anaerobic digestion, or gasification. Biomass can be used to produce electricity, heat, and biofuels, making it a flexible component of the renewable energy mix (Lenz and Ortwein, 2017). The combustion of biomass in power plants or industrial facilities generates heat, which is used to produce steam to drive turbines, thereby generating electricity. Alternatively, biomass can be processed into biofuels like ethanol or biodiesel, which serve as cleaner alternatives to gasoline and diesel for transportation. One of the significant advantages of biomass energy is its ability to utilize organic waste, reducing landfill waste and providing an environmentally friendly way to recycle material. Additionally, as plants grow, they absorb carbon dioxide from the atmosphere, which is released when the biomass is burned, creating a closed carbon cycle that is considered more sustainable than fossil fuel combustion. Biomass energy is particularly valuable in rural areas, where agricultural waste or forestry byproducts can be used locally for energy production. However, the sustainability of biomass depends on factors such as land use practices and the sourcing of materials, as overharvesting of resources or using land for biofuel crops instead of food production can lead to environmental challenges.

While renewable energy offers undeniable advantages, there are still obstacles to its development and integration. Issues such as fluctuations in resource availability, substantial upfront costs, technological limitations, and environmental concerns require careful consideration and resolution. Additionally, the successful implementation of renewable energy depends on well-informed decisions that account for various factors, including economic feasibility, environmental sustainability, technical practicality, and societal acceptance.

To address these challenges, systematic methods are essential for evaluating and ranking RES. Multi-criteria decision-making (MCDM) techniques are particularly effective in this regard, as they enable the analysis of diverse and sometimes conflicting factors. In this research, a hybrid fuzzy-based MCDM approach is utilized to analyze and prioritize Solar Energy, Wind Energy, Hydroelectric Energy, Geothermal Energy, and Biomass Energy. This methodology combines the fuzzy analytic hierarchy process (FAHP) and the fuzzy-based COPRAS (Complex Proportional Assessment) method, ensuring a thorough evaluation that incorporates uncertainties and subjective preferences.

The process begins with the FAHP, which is used to determine the relative importance of criteria set and to create a weighted fuzzy decision matrix. Next, the fuzzy based COPRAS method evaluates and ranks RES by comparing their performance against these weighted criteria. By integrating these two methods, the approach ensures a comprehensive and transparent evaluation process capable of addressing the complexities involved in renewable energy assessments.

The results of this study aim to provide actionable insights for the strategic prioritization of RES. By identifying the most suitable energy options for specific scenarios, the research seeks to guide policymakers, industry leaders, and stakeholders in developing effective energy strategies. Ultimately, widespread adoption of renewable energy will not only reduce greenhouse gas emissions and combat climate change but also foster a more sustainable and equitable global energy future.

In summary, RES hold significant potential to play a pivotal role in the shift toward more sustainable and environmentally friendly energy systems. Their adoption can help reduce dependence on fossil fuels, mitigate greenhouse gas emissions, and promote a cleaner and more equitable energy landscape for future generations. Recognizing their importance, this study evaluates five distinct RES options under a comprehensive framework consisting of 11 carefully selected criteria. The criteria set used in the evaluation, presented in Table 1, was obtained through an in-depth process involving expert consultations and a thorough review of the relevant literature. References such as Wang et al. (2009), Kahraman et al. (2009), Doukas et al. (2010), Kaya and Kahraman (2010), Barry et al. (2011), Tasri and Susilawati (2014), and Şengül et al. (2015) were instrumental in identifying and refining the criteria set. These criteria encompass a broad range of factors, including economic, environmental, technical, and social dimensions, ensuring a holistic analysis of renewable energy alternatives. By integrating expert knowledge with established research, this study aims to provide valuable insights into the prioritization of RES, ultimately supporting the development of sustainable energy strategies. For the detailed usage and review of MCDM methods in power and energy systems, the article of Bohra and Anvari-Moghaddam (2022) can be checked. Both the MCDM methods and literature on energy systems are reviewed in detail in their study.

Table 1. Evaluation Criteria Set for RES

Symbol	Criterion	Reference	Explanation
C1	Sustainability	Lu et al., 2020	Sustainability of RES.
C2	Effectiveness	Bundschuh et al., 2021	Efficiency of RES.
C3	The variety of the usage areas	Kebede et al., 2022	Wide utilization and applicability of RES in various sectors and systems.
C4	Storability	Ilbahar et al., 2020	Effective storage and preservation of energy obtained.
C5	Efficiency of conveyance	Sharma et al., 2022	Minimal energy loss during the transportation process.
C6	Initial investment cost	Steffen, 2020	Low initial investment costs associated with RES.
C7	Simplicity of the facility	Karatop et al., 2021	Simple and straightforward facility design for RES.
C8	Technology requirement	Lu et al., 2023	Minimal technological infrastructure requirements for RES.
C9	Maintenance Requirements	Si et al., 2023	Infrequent maintenance needs after the construction of RES facilities.
C10	Accident risk and their effects	Kim et al., 2021	Low accident risk and minimal operational damage potential of RES facilities.
C11	Detriment to nature and human	Moldan et al., 2021	Negligible environmental and human impact from operations.

2. The Proposed Fuzzy AHP Based COPRAS Approach

In this section, the proposed FAHP based COPRAS approach is presented in detail for the evaluation of RES. The proposed method consists two main parts. The first part is calculation of the weights and priorities by applying FAHP method. And hen in the second part, fuzzy-based COPRAS is applied for the ranking and evaluation of RES alternatives. In the following figure, the calculation steps of the proposed approach are given step by step in detail. Afterwards, both methods are given in two different subsections in detail for the calculations of them.

Because FAHP based COPRAS effectively handle the uncertainty and vagueness inherent in decision-making processes, the proposed method is more suitable for evaluating RES. Renewable energy evaluation involves multiple conflicting criteria, such as cost, efficiency, environmental impact, etc, which often include subjective judgments. FAHP allows for a more flexible and accurate pairwise comparison by incorporating linguistic variables, reducing the impact of human bias. Meanwhile, Fuzzy based COPRAS enhances the ranking process by considering both the significance and utility of alternatives under uncertain conditions. This combination ensures a more reliable and robust decision-making framework for selecting the most appropriate RES.

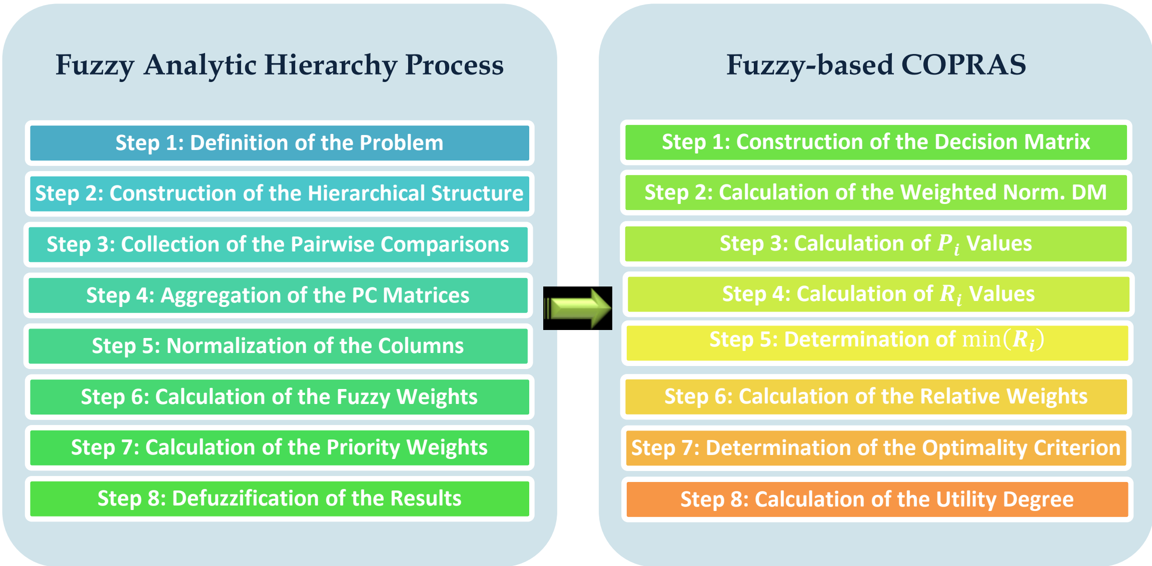

Figure 1. The Step-by-Step calculation Process of the proposed FAHP based COPRAS

2.1. The proposed fuzzy analytic hierarchy process

The Fuzzy Analytic Hierarchy Process (FAHP) (Çelikbilek et al., 2016), which is fundamentally an extension of the traditional Analytic Hierarchy Process (AHP), was first introduced by Saaty in 1979 (1979). While the classic AHP utilizes crisp sets and precise numerical values for decision-making processes, FAHP incorporates the principles of fuzzy logic by employing fuzzy sets and fuzzy numbers. This modification enhances the method's ability to handle uncertainties and vagueness often present in real-world decision-making scenarios. Instead of relying solely on exact numerical values, pairwise comparisons in FAHP are conducted using linguistic scales, which are then represented by fuzzy numbers to better capture the ambiguity of subjective judgments. Liu et al. (2020) published a review article on fuzzy AHP methods and their effectiveness and weaknesses. In the study, different FAHP approaches for the decision-making problems with subjective judgements are evaluated and interpreted in detail. In this study, triangular fuzzy numbers, a commonly used type of fuzzy number due to their simplicity and effectiveness, will be employed for pairwise comparisons and subsequent calculations. The linguistic scale and the corresponding triangular fuzzy numbers used in this methodology are given in Table 2, offering a clear framework for how subjective assessments are transformed into quantifiable data. This approach ensures a more flexible and realistic evaluation process, particularly in complex decision-making environments.

Table 2. The Linguistic Scale for the Pairwise Comparisons and their Fuzzy Representations

Crisp Number Evaluation	Linguistic Scale Representation	Fuzzy Number Representation
1	Equally Important (EI)	(1, 1, 2)
3	Weakly Important (WI)	(2, 3, 4)
5	Important (I)	(4, 5, 6)
7	Strongly Important (SI)	(6, 7, 8)
9	Absolutely Important (AI)	(8, 9, 9)

Step 1: Definition of the Problem: Initially, the problem and the associated variables within the problem set are clearly identified and defined. This step involves outlining the scope of the problem, specifying the key elements that influence it, and determining the relevant factors and parameters that need to be considered for analysis. By establishing a comprehensive understanding of the problem and its variables, a solid foundation is created for the subsequent steps in the decision-making or problem-solving process.

Step 2: Construction of the Hierarchical Structure: Once the problem, alternatives, and criteria have been clearly defined, the next step involves constructing the hierarchical structure. This structure organizes the decision-making process by breaking it down into multiple levels, typically starting with the main goal at the top, followed by the criteria and sub-criteria in the middle, and the alternatives at the bottom. The hierarchical framework provides a systematic and logical arrangement, allowing for a clear visualization of how each criterion and alternative contributes to achieving the overall objective.

Step 3: Collection of the Pairwise Comparisons (PC): Depending on the nature of the problem, decision-makers or experts perform pairwise comparisons both among the criteria and among the alternatives. This process involves evaluating each pair of elements to determine their relative importance or preference with respect to the overall goal. These comparisons are crucial for quantifying the relationships between criteria and alternatives, ensuring that the decision-making process reflects expert knowledge and aligns with the priorities of the problem at hand.

Step 4: Aggregation of the PC Matrices: The pairwise comparison matrices, generated through the evaluations of decision-makers or experts, are aggregated using the geometric mean method given in Eq. (1), similar to the classic AHP. However, in FAHP, these calculations incorporate fuzzy numbers instead of crisp values. This approach allows for the inclusion of uncertainty and vagueness in the decision-makers' judgments. By employing fuzzy numbers, the aggregated comparisons reflect a more realistic representation of subjective opinions, enhancing the reliability of the final weightings. This process ensures that the collective assessments of all experts are synthesized into a consistent framework, enabling more robust decision-making.

$$\tilde{x}_{ij} = \sqrt[D]{\prod \tilde{x}_{ij}^{d}} \tag{1}$$

, where $\tilde{x}_{ij}^{d}$ is the evaluation of the decision maker d between criteria/alternative i and criteria/alternative j, D is the number of the decision makers, and $\tilde{x}_{ij}$ is the aggregated matrix of the PC matrices of the decision makers.

Step 5: Normalization of the Columns: In this step, the normalization process for fuzzy numbers, as CFCS (Converting Fuzzy data into Crisp Scores) proposed by Wu and Lee (2017), will be applied. This method ensures that the fuzzy numbers are scaled appropriately, bringing them into a comparable range while preserving their relative significance. Normalization is a critical step in the FAHP as it allows the fuzzy triangular numbers to be standardized, ensuring consistency and accuracy in the subsequent computations. By utilizing the approach introduced by Wu and Lee (2017) given in Eq. (2-4), the method effectively handles the fuzzy data and ensures that the derived weights are both meaningful and interpretable within the context of the problem.

$$nxl_{ij} = \frac{\left(xl_{ij} - \min(xl_{ij})\right)}{\left(\max(xr_{ij}) - \min(xl_{ij})\right)} \tag{2}$$

$$nxm_{ij} = \frac{\left(xm_{ij} - \min(xl_{ij})\right)}{\left(\max(xr_{ij}) - \min(xl_{ij})\right)} \tag{3}$$

$$nxr_{ij} = \frac{\left(xr_{ij} - \min(xl_{ij})\right)}{\left(\max(xr_{ij}) - \min(xl_{ij})\right)} \quad (4)$$

, where $\tilde{x}_{ij} = (xl_{ij}, xm_{ij}, xr_{ij})$, and $\widetilde{nx}_{ij} = (nxl_{ij}, nxm_{ij}, nxr_{ij})$ as the normalized value of $\tilde{x}_{ij}$.

Step 6: Calculation of the Fuzzy Weights: Fuzzy weights are determined by calculating the mean of the rows in the fuzzy PC matrix. This process aggregates the relative importance values for each criterion while accounting for the inherent fuzziness in the data. The calculation of the weights will follow the methodology in Eq. (5), where W is the number of weights. This approach ensures that the derived fuzzy weights are consistent and reflective of the decision-makers' evaluations, providing a solid basis for ranking and prioritization in the decision-making process.

$$\frac{\sum_{j=1}^{W} \tilde{x}_{ij}}{W} \quad (5)$$

Step 7: Calculation of the Priority Weights: After determining the fuzzy weights of the criteria and calculating the fuzzy weight vectors of the alternatives for each criterion, the priority weights for the alternatives are derived using the formula given in Eq. (6). This step involves synthesizing the individual weight vectors of the alternatives with the corresponding criteria weights to obtain an overall ranking. By combining these values, the priority weights reflect the relative importance of each alternative in achieving the main objective, ensuring a comprehensive and balanced evaluation that integrates both criteria and alternatives into the decision-making process.

$$\tilde{x}_i = \sum_{j=1}^{W} w_j \tilde{x}_{ij} \quad (6)$$

Step 8: Defuzzification of the Results: The results of the fuzzy priority weights are defuzzified using the CFCS method proposed by Wu and Lee (2017). This method converts the fuzzy priority weights into crisp values, making them easier to interpret and utilize for decision-making. By applying the CFCS method, the inherent uncertainty in the fuzzy data is effectively reduced, while the core information and relative rankings are preserved. This defuzzification process ensures that the final crisp scores provide a clear and actionable representation of the alternatives' priorities within the decision-making framework.

$$xl_i = \frac{xm_i}{1 + xm_i - xl_i} \quad (7)$$

$$xr_i = \frac{xr_i}{1 + xr_i - xm_i} \quad (8)$$

$$y_i = \frac{xl_i(1 - xl_i) + xr_i xr_i}{1 - xl_i + xr_i} \quad (9)$$

$$z_i = \min(xl_i) + y_i\left(\max(xr_i) - \min(xl_i)\right) \quad (10)$$

2.2. The fuzzy-based COPRAS

The COPRAS (Complex Proportional Assessment) method was first introduced by Zavadskas and Kaklauskas in 1996 (1996). The method is a widely used multi-criteria decision-making (MCDM) approach, designed to evaluate and rank alternatives based on multiple conflicting criteria. It provides a systematic framework to assess the relative importance of each alternative by considering both beneficial and non-beneficial criteria. By using proportional assessments, COPRAS facilitates decision-making processes in various fields, such as project management, resource allocation, engineering, etc. However, the classical COPRAS method, while effective in evaluating alternatives based on multiple criteria, has limitations in addressing uncertainties and subjective judgments during the decision-making process as a group decision-making process with a group of experts. This shortcoming arises from its reliance on precise numerical data, which may not fully capture the complexities of real-world scenarios. In practice, decision-making often involves ambiguity and the need to incorporate expert opinions, preferences, or incomplete information. To overcome these challenges, extended versions of COPRAS have been developed, integrating tools like fuzzy logic or probabilistic approaches to enhance its flexibility and robustness. The study of Sampathkumar et al. (2023) can be checked for a brief review on COPRAS method.

This section aims to provide a step-by-step explanation of the fuzzy-based COPRAS (F-COPRAS) methodology, offering a detailed walkthrough of its computational process derived from the study of Yazdani et al. (2011). A fuzzy-based COPRAS method calculations are easier and more effective for decision maker in the process of complex MCDM problems such as energy systems or sophisticated engineering problems, while considering the subjective judgements and uncertainties if we compare with a totally fuzzy COPRAS system. The stepwise approach ensures that readers gain a thorough understanding of how the method quantitatively evaluates alternatives and identifies the optimal solution.

Step *1: Construction of the Decision Matrix:* In this step, the fuzzy decision matrix, or the defuzzified decision matrix (D), which is initially derived through the application of FAHP or any other suitable method, is constructed. This matrix serves as a foundational element in the main calculations of the F-COPRAS method. The process involves systematically organizing and transforming the data into a structure that can be used for the subsequent evaluation and decision-making phases. This matrix, which encapsulates the decision-makers' preferences and expert evaluations, is crucial for ensuring the accuracy and reliability of the F-COPRAS model's outputs.

$$D = \left[x_{ij}\right]_{mxn} \tag{11}$$

Step 2: Calculation of the Weighted Normalized Decision Matrix: In this step, the decision matrix is normalized by dividing each element by the sum of the corresponding criterion's column as given in Eq. (12). Then, the normalized values are multiplied by their respective weights to obtain the weighted normalized decision matrix as given in Eq. (12), reflecting the relative importance of each criterion in the decision-making process. Let $D = \left[y_{ij}\right]_{mxn}$ be the weighted normalized decision matrix.

$$y_{ij} = w_j \cdot \frac{x_{ij}}{\sum_{j=1}^{n} x_{ij}} \tag{12}$$

Step 3: Calculation of P_i Values: Sums P_i values of attributes, where higher values are considered more preferable (for benefit criteria), are calculated for each alternative represented in a row of the decision-making matrix. This calculation involves summing the values of each criterion for an alternative, ensuring that the preferences align with the goal of maximizing the chosen criteria. By performing this operation for each alternative, we generate a set of aggregated values that reflect the overall performance of each option based on the selected criterion.

$$P_i = \sum_{j=1}^{k} y_{ij} \tag{13}$$

Step 4: Calculation of R_i Values: Sums R_i values of attributes, where lower values are considered more preferable (for cost criteria), are calculated for each alternative represented in a row of the decision-making matrix. This calculation involves summing the values of the cost-related criteria for each alternative in the decision-making matrix. In a cost-focused approach, lower costs are considered more advantageous, so the alternatives with the lowest total cost are prioritized. This step enables the comparison and evaluation of alternatives based on their cost efficiency, helping to identify the most cost-effective solution.

$$R_i = \sum_{j=k+1}^{n} y_{ij} \tag{14}$$

Step 5: Determination of $min(R_i)$: The determination of the minimum R_i value involves identifying the alternative with the lowest performance score for each criterion. This minimum value is critical for evaluating the relative effectiveness of each alternative in comparison to others, particularly when dealing with cost-oriented criteria.

$$R_{min} = min(R_i) \tag{15}$$

Step 6: Calculation of the Relative Weights: The calculation of the relative weight (Q_i) of each alternative involves evaluating the performance of each alternative. This step aims to determine the importance of each alternative relative to the others by considering how well they satisfy the given criteria. The relative weight is calculated by applying Eq. (16). The result is a set of relative weights that reflect the overall performance of each alternative, which can then be used to rank and make decisions based on the comparative effectiveness of each criterion.

$$Q_i = P_i + \frac{R_{min} \sum_{i=1}^{n} R_i}{R_i \sum_{i=1}^{n} \frac{R_{min}}{R_i}} \tag{16}$$

$$Q_i = P_i + \frac{\sum_{i=1}^{n} R_i}{R_i \sum_{i=1}^{n} \frac{1}{R_i}} \tag{17}$$

Step 7: Determination of the Optimality Criterion: The determination of the optimality criterion involves identifying the maximum Q_i value for the calculation of utility degree. This criterion guides the final ranking and selection of the most optimal alternative.

$$Q_{max} = \max_i(Q_i) \tag{18}$$

Step 8: Calculation of the Utility Degree: The calculation of the utility degree of each alternative involves assessing how well each alternative meets the predefined criteria based on its relative weight and performance score. The utility degree is calculated by using the optimality criterion and relative weight of each alternative in Eq. (19). The result, utility degree, reflects the overall desirability or effectiveness of the related alternative in comparison to others. The result is a utility score that provides a clear measure of the alternative's overall performance, allowing for a straightforward ranking of alternatives according to their utility degrees.

$$N_i = \frac{Q_i}{Q_{max}} \tag{19}$$

3. The Evaluation of Renewable Energy Sources

The fuzzy MCDM approach proposed in this study is specifically designed for evaluating RES alternatives from a subjective perspective, utilizing linguistic scales to capture the preferences and judgments of experts. The alternatives to be evaluated were carefully selected after extensive discussions with professionals in the field, ensuring that the choices were well-informed and relevant. The evaluation process involved 11 experts from Türkiye, each with notable experience and a background in renewable energy systems. To maximize the objectivity and reliability of the results, the experts were chosen from a diverse range of departments within the Faculty of Engineering, representing various fields of expertise. This multidisciplinary approach helped mitigate bias and ensured a more comprehensive analysis of the alternatives.

The criteria set used to assess RES alternatives were gathered from both literature and expert insights, providing a balanced and up-to-date perspective on the factors influencing RES evaluation. In this study, five major RES alternatives —Solar Energy, Wind Energy, Hydroelectric Energy, Geothermal Energy, and Biomass Energy—were evaluated under 11 criteria, which are introduced in the first section. The selection of these specific RES reflects the current relevance and importance of each within the context of sustainable energy development. The evaluation process is presented in a structured, step-by-step manner in the following subsections, with each step elaborating on the methodology and providing the corresponding results of the analysis. This detailed approach ensures clarity and transparency in the evaluation process, allowing for a comprehensive understanding of how the proposed method was applied to each alternative.

3.1. Calculating the weights and constructing the decision matrix

In this sub-section, the weights of the evaluation criteria for RES alternatives are calculated, and the fuzzy decision matrix and defuzzified decision matrix of the problem are constructed. After applying FAHP given in Section 2.1 to the fuzzy pairwise comparisons of the experts for each criterion and alternatives one by one, the fuzzy decision matrix and the weights given in Table 3 are obtained. Each column and the weight vector in Table 3 is a separate FAHP calculation process, which means that FAHP given in Section 2.1 is applied 11 times in total to construct Table 3. Therefore, not all pairwise comparisons and tables with their calculations could be listed here step by step in detail.

Table 3. The Aggregated Fuzzy Decision Matrix for the Evaluation of RES

	C1	C2	C3	C4	C5	C6
Wj	**0.033**	**0.101**	**0.029**	**0.119**	**0.094**	**0.068**
Solar E.	(0.131, 0.181, 0.252)	(0.132, 0.194, 0.276)	(0.221, 0.323, 0.445)	(0.091, 0.137, 0.190)	(0.076, 0.115, 0.156)	(0.206, 0.303, 0.428)
Wind E.	(0.072, 0.098, 0.142)	(0.078, 0.110, 0.164)	(0.106, 0.157, 0.228)	(0.058, 0.084, 0.121)	(0.053, 0.074, 0.110)	(0.235, 0.337, 0.472)
Hydroelectric E.	(0.194, 0.271, 0.371)	(0.263, 0.370, 0.516)	(0.170, 0.238, 0.344)	(0.325, 0.453, 0.623)	(0.385, 0.527, 0.706)	(0.132, 0.187, 0.269)
Geothermal E.	(0.188, 0.265, 0.364)	(0.137, 0.197, 0.280)	(0.059, 0.086, 0.125)	(0.073, 0.098, 0.153)	(0.064, 0.086, 0.134)	(0.054, 0.076, 0.110)
Biomass E.	(0.135, 0.185, 0.261)	(0.091, 0.128, 0.192)	(0.141, 0.196, 0.292)	(0.163, 0.228, 0.322)	(0.142, 0.198, 0.282)	(0.074, 0.097, 0.146)

	C7	C8	C9	C10	C11
Wj	**0.088**	**0.259**	**0.030**	**0.120**	**0.059**
Solar E.	(0.099, 0.148, 0.212)	(0.176, 0.270, 0.403)	(0.137, 0.218, 0.318)	(0.206, 0.317, 0.453)	(0.119, 0.193, 0.256)
Wind E.	(0.242, 0.355, 0.521)	(0.179, 0.276, 0.412)	(0.153, 0.239, 0.361)	(0.146, 0.218, 0.330)	(0.093, 0.142, 0.200)
Hydroelectric E.	(0.177, 0.260, 0.379)	(0.087, 0.132, 0.191)	(0.092, 0.135, 0.213)	(0.104, 0.156, 0.234)	(0.122, 0.176, 0.255)
Geothermal E.	(0.067, 0.099, 0.149)	(0.074, 0.111, 0.173)	(0.086, 0.129, 0.196)	(0.078, 0.119, 0.185)	(0.168, 0.240, 0.368)
Biomass E.	(0.095, 0.139, 0.210)	(0.144, 0.212, 0.337)	(0.187, 0.279, 0.436)	(0.130, 0.189, 0.304)	(0.182, 0.249, 0.382)

The aggregated fuzzy decision matrix given in Table 3 undergoes a defuzzification process, as outlined in Step 8 of Section 2.1, to transform the fuzzy values into crisp values. This crucial step helps in eliminating the inherent uncertainty and vagueness of the initial fuzzy data, providing a more precise set of values that can be further analyzed by F-COPRAS. Specifically, the defuzzified matrix, as given in Table 4, becomes the input decision matrix used in the F-COPRAS. F-COPRAS method application with Table 4 ensure that the decision-making process is both systematic and accurate, allowing for a reliable comparison of the alternatives under consideration.

Table 4. The Defuzzified Decision Matrix for the Evaluation of RES

	C1	C2	C3	C4	C5	C6
Wj	**0.033**	**0.101**	**0.029**	**0.119**	**0.094**	**0.068**
Solar E.	0.1749	0.1935	0.3578	0.1132	0.0855	0.3361
Wind E.	0.0466	0.0584	0.1433	0.0388	0.0308	0.3783
Hydroelectric E.	0.3023	0.4597	0.2560	0.5409	0.6299	0.1884
Geothermal E.	0.2938	0.1990	0.0413	0.0619	0.0490	0.0327
Biomass E.	0.1823	0.0894	0.2017	0.2452	0.2048	0.0645

	C7	C8	C9	C10	C11
Wj	**0.088**	**0.259**	**0.030**	**0.120**	**0.059**
Solar E.	0.1244	0.3013	0.2266	0.3670	0.1774
Wind E.	0.4189	0.3091	0.2639	0.2318	0.0958
Hydroelectric E.	0.2899	0.0960	0.0964	0.1333	0.1602
Geothermal E.	0.0523	0.0666	0.0829	0.0746	0.2748
Biomass E.	0.1144	0.2270	0.3302	0.1933	0.2919

3.2. Evaluating and prioritizing the renewable energy sources

After obtaining and constructing the decision matrix as given in the first part of Figure 1 and Section 2.1, RES can be evaluated by applying fuzzy based COPRAS method to this decision matrix given in Table 4. In other words, the first step of F-COPRAS method is completed with the first part of this section by applying FAHP. The fuzzy decision matrix can also be constructed using other techniques from the literature, such as expert judgment, survey results, historical data, the Delphi method, direct rating, etc., to determine criteria weights and evaluate the performance of alternatives instead of FAHP. These methods provide flexibility in capturing uncertainty and subjective preferences, making them suitable for complex decision-making environments. Additionally, integrating multiple techniques can enhance the robustness of the evaluation process by mitigating the biases associated with any single approach. However, FAHP is often preferred due to its systematic pairwise comparison approach, which effectively incorporates expert knowledge while reducing inconsistencies and enhancing the reliability of the final decision. The second step of F-COPRAS is calculation of the weighted normalized decision matrix by applying Eq. (12) to the decision matrix. The weighted normalized decision matrix of the problem is given in Table 5 after the calculations.

Table 5. The Weighted Normalized Decision Matrix for the Evaluation of RES

	C1	C2	C3	C4	C5	C6
Solar E.	0.0058	0.0195	0.0104	0.0135	0.0080	0.0229
Wind E.	0.0015	0.0059	0.0042	0.0046	0.0029	0.0257
Hydroelectric E.	0.0100	0.0464	0.0074	0.0644	0.0592	0.0128
Geothermal E.	0.0097	0.0201	0.0012	0.0074	0.0046	0.0022
Biomass E.	0.0060	0.0090	0.0058	0.0292	0.0193	0.0044

	C7	C8	C9	C10	C11
Solar E.	0.0109	0.0780	0.0068	0.0440	0.0105
Wind E.	0.0369	0.0801	0.0079	0.0278	0.0057
Hydroelectric E.	0.0255	0.0249	0.0029	0.0160	0.0095
Geothermal E.	0.0046	0.0172	0.0025	0.0090	0.0162
Biomass E.	0.0101	0.0588	0.0099	0.0232	0.0172

The relative weights of RES alternatives are calculated in step 6 by applying Eq. (17) after obtaining P_i values, R_i values and $\min(R_i)$ in step 3, step 4 and step 5 of F-COPRAS. Q_i values of RES alternatives are given in the second column of Table 6 and N_i values, which are utility degrees as relative performance scores, are given in the third column of Table 6. The final ranking of RES alternatives is given in the fourth column of Table 6. According to the F-COPRAS results, the best RES alternative is Hydroelectric energy with 0.2519 Q_i value and 100 performance score. Following it, the second-best alternative is Solar Energy with 0.2021 Q_i value and 80 performance score. Wind Energy is the third RES alternative with 0.1771 Q_i value and 70 performance score. Biomass energy is the fourth RES alternative with 0.1700 Q_i value and 67 performance score. The fifth and the last RES alternative is Geothermal Energy with 0.0853 Q_i value and 34 performance score.

Table 6. The Weighted Normalized Decision Matrix for the Evaluation of RES

	Q_i	N_i	Ranking	FAHP	Ranking	FMOORA	Ranking
Solar E.	0.2303	83	2	0.018	2	0.116	2
Wind E.	0.2031	73	3	0.016	3	0.135	3
Hydroelectric E.	0.2789	100	1	0.023	1	0.115	1
Geothermal E.	0.0947	34	5	0.008	5	0.200	5
Biomass E.	0.1929	69	4	0.015	4	0.136	4

3.3. Sensitivity Analysis

In this section, the results of the sensitivity analysis, conducted by modifying the weights of the criteria set, are presented in detail. The sensitivity analysis table provides a structured representation of these results. The first row of the table displays the results of the main case of this study, where the initial weight assignments remain unchanged. The subsequent rows contain results from two distinct sets of alternative weighting scenarios, designed to examine how variations in criterion importance affect the ranking of RES.

The first set of 11 cases involves scenarios where each criterion is individually assigned a weight of 0.7, while the remaining 10 criteria are each assigned a weight of 0.03. This allows an evaluation of the dominant influence of a single criterion in determining the overall ranking. In contrast, the last 11 cases follow a different approach: each criterion is assigned a weight of 0.35, while the remaining 10 criteria receive a weight of 0.065. This alternative scenario provides insight into how moderate changes in weighting affect the ranking dynamics.

For example, in Case 1, Criterion C1 is given a weight of 0.7, while the other 10 criteria are each assigned a weight of 0.03. Similarly, in Case 13, Criterion C2 is assigned a weight of 0.35, with the remaining criteria receiving a weight of 0.065. By analyzing the results of each case, the strengths and weaknesses of various RES become apparent. If, for instance, a particular energy source moves from the lower ranks to the top position when a criterion is weighted at 0.7, it signifies that this energy source exhibits a strong performance concerning that specific criterion.

A practical example of this phenomenon can be observed in Biomass Energy. In the baseline scenario, Biomass Energy is ranked fourth. However, when the weighting is adjusted, as in Case 9 and Case 11, it rises to the first position. A closer examination of Table 4 and Table 5, which present detailed criterion-based analyses, further confirms that Biomass Energy demonstrates superior performance for the two criteria emphasized in these cases. Similar assessments can be performed for each RES and criterion individually to better understand their relative advantages.

To facilitate a holistic evaluation, column-wise averages have been calculated and presented at the bottom of the table. These average values provide an overall ranking of RES when all scenarios are taken into account. Based on these averaged rankings, Hydroelectric Energy emerges as the most preferred option, followed by Solar Energy in second place, Biomass Energy in third, Wind Energy in fourth, and Geothermal Energy in the last position.

Comparing these results to the baseline scenario reveals an interesting shift: Biomass Energy and Wind Energy have switched places in the ranking, with Biomass Energy moving ahead of Wind Energy. This change is believed to stem from the fact that Wind Energy performs significantly better than other sources in certain scenarios where it has a competitive advantage, resulting in substantial score differences. This observation underscores the importance of sensitivity analysis in understanding the impact of weight variations on energy source rankings and highlights how different weighting approaches can lead to shifts in prioritization.

Table 7. Sensitivity Analysis Results

	Solar E.			Wind E.			Hydroelectric E.			Geothermal E.			Biomass E.		
	Q_i	N_i	R.	Q_i	N_i	R.	Q_i	N_i	R.	Q_i	N_i	R.	Q_i	N_i	R.
This Case	0.230	83	2	0.203	73	3	0.279	100	1	0.095	34	5	0.193	69	4
Case 1	0.191	64	3	0.092	31	5	0.297	100	1	0.234	79	2	0.186	63	4
Case 2	0.203	51	2	0.100	25	5	0.403	100	1	0.170	42	3	0.124	31	4
Case 3	0.313	100	1	0.156	50	4	0.266	85	2	0.065	21	5	0.199	64	3
Case 4	0.150	33	3	0.086	19	4	0.457	100	1	0.078	17	5	0.229	50	2
Case 5	0.131	25	3	0.081	16	4	0.517	100	1	0.070	13	5	0.202	39	2
Case 6	0.299	95	2	0.314	100	1	0.221	70	3	0.059	19	5	0.108	34	4
Case 7	0.157	46	3	0.341	100	1	0.289	85	2	0.072	21	5	0.141	41	4
Case 8	0.276	100	1	0.268	97	2	0.159	58	4	0.081	30	5	0.216	79	3
Case 9	0.226	79	3	0.237	83	2	0.159	56	4	0.092	32	5	0.286	100	1
Case 10	0.320	100	1	0.216	68	2	0.184	58	4	0.087	27	5	0.194	61	3
Case 11	0.193	74	4	0.125	48	5	0.202	78	3	0.221	85	2	0.260	100	1
Case 12	0.210	72	2	0.144	50	5	0.291	100	1	0.164	56	4	0.191	66	3
Case 13	0.215	64	2	0.148	44	4	0.336	100	1	0.137	41	5	0.165	49	3
Case 14	0.262	94	2	0.172	62	4	0.278	100	1	0.092	33	5	0.197	71	3
Case 15	0.192	53	3	0.142	40	4	0.359	100	1	0.098	27	5	0.209	58	2
Case 16	0.184	48	3	0.140	36	4	0.384	100	1	0.094	24	5	0.198	51	2
Case 17	0.256	99	2	0.239	92	3	0.259	100	1	0.089	34	5	0.158	61	4
Case 18	0.195	68	3	0.250	87	2	0.288	100	1	0.095	33	5	0.172	60	4
Case 19	0.246	100	1	0.219	89	3	0.232	95	2	0.099	40	5	0.204	83	4
Case 20	0.224	96	3	0.206	88	4	0.232	100	2	0.104	44	5	0.234	100	1
Case 21	0.264	100	1	0.197	75	3	0.243	92	2	0.101	38	5	0.194	74	4
Case 22	0.210	84	3	0.158	63	4	0.251	100	1	0.158	63	5	0.223	89	2
Mean	0.223	74.8	2.318	0.183	61.9	3.409	0.287	89.8	1.818	0.112	37.3	4.591	0.195	64.7	2.864
Ranking	2	2	2	4	4	4	1	1	1	5	5	5	3	3	3

The findings of the sensitivity analysis highlight the significant impact of criterion weighting on the ranking of RES. By systematically varying the importance assigned to each criterion, the analysis has demonstrated how different renewable energy alternatives respond to changes in evaluation priorities. The observed shifts in rankings, particularly the interchange between Biomass Energy and Wind Energy, emphasize the necessity of considering multiple scenarios in decision-making processes. Additionally, the results reinforce the importance of Hydroelectric and Solar Energy, which consistently occupy the top positions, suggesting their overall robustness across different weighting schemes.

These insights underscore the critical role of sensitivity analysis in energy planning and policy formulation. Decision-makers must recognize that the ranking of RES is not static but rather highly dependent on the prioritization of specific criteria, such as cost efficiency, environmental impact, or reliability. Therefore, integrating a dynamic, criterion-sensitive evaluation approach will enable more informed and adaptable energy investment strategies. Future studies may further enhance this analysis by incorporating additional criteria, real-world constraints, or expert-driven weight assignments to refine the decision-making framework for sustainable energy development.

4. Interpreting the Results

The results of the study indicate that among the evaluated RES, Hydroelectric Energy ranks first, followed by Solar Energy, Wind Energy, Biomass Energy, and finally, Geothermal Energy. This ranking provides valuable insights into the relative performance and investment potential of each energy source, highlighting Hydroelectric Energy as the most favorable alternative within the given criteria. The use of FAHP and FMOORA methodologies has further validated these findings, as both techniques yielded identical rankings. The comparison among this study, FAHP and FMOORA is particularly insightful, as these methods share similar foundational steps in MCDM process. This consistency across different decision-making tools strengthens the reliability and robustness of the results.

The first-place ranking of Hydroelectric Energy can be attributed to its established infrastructure, high energy efficiency, and consistent performance in generating electricity. Despite its dependency on geographical and climatic conditions, Hydroelectric Energy has demonstrated significant economic and operational benefits, making it a top choice for investment and performance optimization.

Solar Energy, ranking second, reflects its growing importance due to technological advancements, cost reductions in photovoltaic systems, and its global availability. However, limitations such as dependency on sunlight intensity and the need for efficient energy storage solutions slightly reduce its overall score compared to hydropower.

Wind Energy, placed third, showcases its potential as a clean and sustainable source of power. Nevertheless, factors such as variability in wind patterns, high initial investment costs, and challenges related to land use and noise pollution may have contributed to its relatively lower ranking.

Biomass Energy, ranked fourth, demonstrates moderate potential but is often limited by high operating costs, challenges in sourcing raw materials sustainably, and concerns about emissions when compared to other RES.

Finally, Geothermal Energy's placement at the bottom of the ranking may be influenced by its site-specific nature, high exploration and development costs, and long payback periods. Although it is a reliable and stable energy source, these factors likely hinder its competitiveness against the other RES alternatives.

In conclusion, the alignment of the results obtained through FAHP and FMOORA underscores the robustness of the analysis and provides confidence in the prioritization of RES. This study not only offers valuable insights for policymakers and investors but also emphasizes the importance of integrating advanced decision-making methodologies in evaluating sustainable energy projects.

Conclusion and Evaluation

This study highlights, evaluates and prioritizes the critical importance of renewable energy sources under 11 important criteria as sustainable alternatives to traditional fossil fuels. By utilizing a hybrid fuzzy multi-criteria decision-making approach, five most important and used RES were evaluated based, ensuring a comprehensive and systematic assessment. The integration of FAHP and F-COPRAS method proved to be an effective approach in determining the relative importance of criteria and in ranking the energy alternatives. FAHP method allowed for an accurate representation of the inherent uncertainties in decision-making, particularly when dealing with subjective judgments about the importance of different criteria. This helped create a robust fuzzy decision matrix that reflects the complexity of renewable energy decision-making. Following this, F-COPRAS method efficiently processed the fuzzy matrix and provided a clear ranking of RES, offering valuable insights into which alternatives are most beneficial based on the defined criteria.

The results of this study underscore the significant advantages of RES both together and individually in promoting sustainability. By reducing carbon emissions, improving air quality, and offering a virtually inexhaustible supply of energy, RES are pivotal in addressing climate change and ensuring a cleaner, greener future. The hybrid approach adopted in this study provides decision-makers with a powerful tool for evaluating and selecting the most appropriate RES alternative in line with both environmental and economic goals.

One of the distinguishing features of this study is the application of a hybrid fuzzy multi-criteria decision-making method, which combines the strengths of both FAHP and F-COPRAS methods. This approach not only accommodates the inherent uncertainty in the decision-making process but also ensures a more objective, well-rounded evaluation of energy alternatives. By incorporating fuzzy logic, the methods provide a more realistic analysis compared to traditional crisp-based methods, which may not fully capture the nuances of subjective judgments. The advantages of this methodology are evident, particularly in its ability to handle complex, multi-criteria problems in uncertain environments. The hybrid approach allows for a detailed, adaptable analysis that can be applied to various renewable energy alternatives across different regions and contexts. Additionally, the integration of fuzzy logic ensures that decision-makers can consider a range of potential outcomes, enhancing the robustness and reliability of the results.

In conclusion, the adoption of renewable energy is crucial for a sustainable future. This study's findings emphasize the necessity of integrating advanced decision-making techniques, such as the fuzzy-based hybrid methods, to evaluate energy alternatives. By incorporating these techniques, decision-makers can make more informed choices that account for the complex, uncertain nature of renewable energy assessments. The results highlight the potential of such methods to guide policy development and investment in the renewable energy sector, ensuring optimal energy solutions for both environmental and economic sustainability.

Future studies could further explore the inclusion of additional criteria such as social, political, or technological factors to enrich the decision-making process. Additionally, a comparative analysis with other decision-making methods could be conducted to evaluate the relative effectiveness and robustness of the proposed hybrid approach. It would also be beneficial to apply this methodology to specific geographic regions, accounting for local renewable energy resources, infrastructure, and policy considerations. Furthermore, future research could examine the long-term sustainability and financial viability of selected energy sources to provide a more comprehensive framework for decision-makers in the renewable energy sector.

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