J. Math. Sci. Model., 9(3) (2026) 162-182 https://doi.org/10.33187/jmsm.1946389

Journal of Mathematical Sciences and Modelling

ISSN (Online) 2636-8692
https://dergipark.org.tr/en/pub/jmsm

Research Article

Renewable Energy Sources Selection Analysis with the Maximizing Deviation Method

Murat Kirişci[1,2]

[1]*Istanbul University-Cerrahpaşa, Department of Biostatistics and Medical Informatics, Istanbul, Türkiye*
[2]*Istanbul Commerce University, Information Technologies and Research and Application Center, Istanbul, Türkiye*

Article Info

Keywords: *Fermatean fuzzy environment, Renewable energy, Maximizing deviation, Criterion weighting, COPRAS, Sensitivity analysis*

Received: *7 May 2026*
Accepted: *18 August 2026*
Available online: *19 August 2026*

Abstract

Multi-criteria decision-making (MCDM) methods offer powerful tools for decision-makers to identify the most suitable options in uncertain, complex, and contradictory situations. However, traditional fuzzy sets and Intuitionistic or Pythagorean fuzzy structures restrict the subjective judgment of experts due to mathematical constraints on the sum/sum of squares of membership and non-membership degrees, and are insufficient for modeling complex uncertainties. The main motivation of this research is to integrate the superior uncertainty-representation capability of Interval Fermatean Fuzzy Sets (IVFFS), which expands the flexibility limits of decision-makers with a cubic framework ($u^3+v^3\leq 1$), into MCDM processes. Existing studies reveal a significant research gap: the lack of deviation-maximization mechanisms to objectively optimize criterion weights in an IVFFS environment. To fill this gap, this study develops a novel mathematical optimization model based on the Maximizing Deviation (MD) method for cases in which criterion-weighting information is completely or partially unknown. The biggest advantage of the proposed weighting model is that it objectively maximizes the discrepancies and deviations between expert decisions using Lagrangian multipliers, completely eliminating human bias and subjective errors. The developed IVFF-MD-based methodology was combined with the COPRAS ranking algorithm and applied to the selection of renewable energy sources, a critical step in mitigating global climate change and carbon emissions. v; robustness and sensitivity analyses demonstrated that the proposed framework is highly stable and robust to data fluctuations. This study contributes to the literature by introducing a theoretical weighting-optimization framework and offering a strategic decision-support mechanism for energy investments.

1. Introduction

Energy is essential to human life and greatly influences a nation's economic development. However, overuse of fossil fuels causes major environmental issues, including a rise in greenhouse gas emissions that contribute to climate change and global warming. To address environmental problems, most nations are actively developing renewable energy sources ($\mathscr{RES}$). As seen by the 1997 Kyoto Protocol discussions and the completion of the 2015 Paris Climate Change Conference, many countries are dedicated to cutting carbon emissions and creating a green economy because they understand the serious threat that climate change poses. Therefore, many countries must move away from fossil fuels and toward sustainable energy [1]. Energy is becoming more and more necessary for nations to continue developing.

However, preserving natural systems while generating the necessary energy is equally crucial. Since the 1990s, nations, international organizations, and institutions have emphasized producing energy in an environmentally sustainable manner. With increased environmental awareness, $\mathscr{RE}$ has gained much more importance. During their natural cycle, $\mathscr{RES}$ can either naturally regenerate themselves over time or continuously renew themselves. Until recently, objective conditions and the uncompetitiveness (high cost) of equipment for large-scale applications hindered the integrated utilization of $\mathscr{RES}$. Nevertheless, the difficulty of boosting the effectiveness of employing the current

***Email address*: murat.kirisci@iuc.edu.tr**
Cite as: M. Kirişci, *Renewable energy sources selection analysis with the maximizing deviation method*, J. Math. Sci. Model., 9(3) (2026), 162-182.

This is an open-access article distributed under the terms of the Creative Commons Attribution-NonCommercial 4.0 International License.

renewable resources will escalate as solar cell prices steadily decline and tariffs on organic fuels and energy services increase. The policy of a gradual shift to a carbon-neutral economy further aids this.

The installed capacity of RE is 15.1 GW, and the total investment in 2024 will exceed 728 billion US dollars globally, according to the REN21 Global Status Report 2025. The average yearly growth rate is 0.88% [2]. However, renewable sources accounted for the largest share of the increase in the total energy supply (38%). Only a 1% rise in the energy intensity of the global economy prolonged the recent downturn. The growth in energy-related CO2 emissions was 0.8% lower than the 1.2% increase in 2023 [3]. According to IRENA, $\mathscr{RE}$ will account for roughly 40% of global energy by 2030 due to decreased technology prices. $\mathscr{RE}$ is infinite, pure energy with many benefits over conventional fossil fuel energy, such as plentiful and cost-free. However, because solar rays and wind power are unpredictable, $\mathscr{RE}$ has limitations regarding output and capacity. Specifically, the price of electricity produced using $\mathscr{RES}$s is now higher than that produced using fossil fuels.

The $\mathscr{RE}$ Policy Network for the 21st Century website [2] provides various statistics on this topic. Some of these statistical graphs are shown in Figures 1.1, 1.2, 1.3, and 1.4.

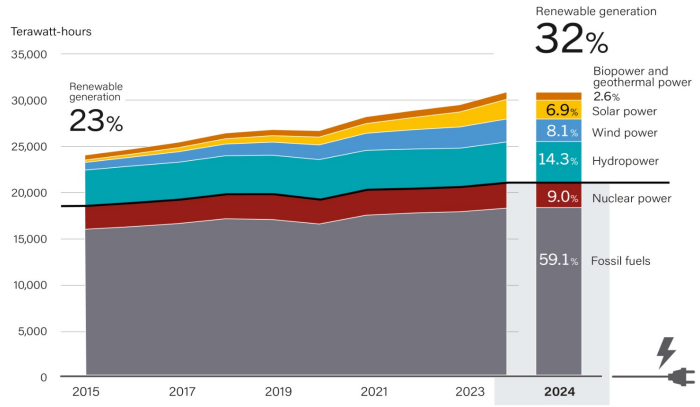


Figure 1.1: Electricity generation by energy source, 2015–2024

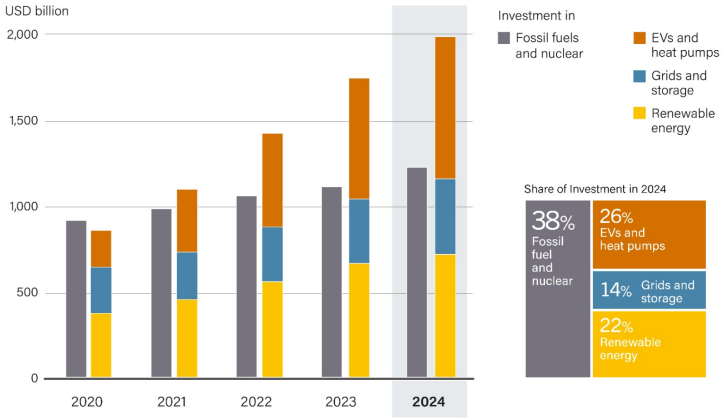


Figure 1.2: Global investment in selected energy technologies, 2020–2024

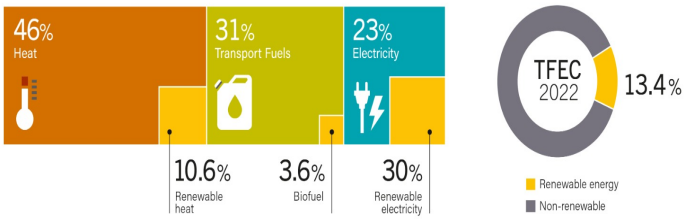


Figure 1.3: Total final energy consumption (TFEC) and share of modern renewable energy, by energy carrier, 2022

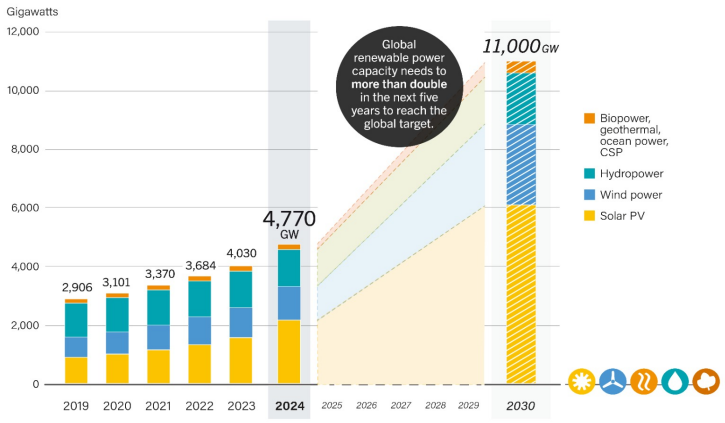


Figure 1.4: Renewable power capacity by technology, 2019–2024, compared to 2030 global tripling target

The selection of $\mathscr{RES}$s is a multi-criteria challenge with several conflicting factors. When deciding on the selection criteria, we must consider the superiority and limitations of each option. To solve this problem, a multi-criteria strategy should be employed. Such criteria provide the evaluation process with more uncertainty and complexity. It can be difficult for decision-makers ($\mathscr{DMR}$) to give whole numerical values for the criteria or attributes, and their evaluations are frequently imprecise in many decision-making($\mathscr{DM}$) scenarios. $\mathscr{DMR}$s usually use language to convey the assessment data of the alternative energy policy's acceptability for many subjective criteria and the weights, because most evaluation factors are difficult to quantify precisely. Fuzzy logic is an effective way to imitate this ambiguity in human preferences. Fuzzy logic is a branch of fuzzy set theory that focuses on handling imprecise input by utilizing membership functions. In 1965, Zadeh formalized fuzzy set theory [4].

Fuzzy assessment information is fused utilizing aggregation operators to help organize all the options in real-world multi-criteria $\mathscr{DM}$($\mathscr{MCDM}$) situations. Assigning the attribute's weight is a crucial issue since we cannot always collect comprehensive information in the complicated $\mathscr{DM}$ environment, and the attribute's weight is always partially or entirely unknown. In several $\mathscr{DM}$ domains, similar multi-criteria $\mathscr{DM}$ ($\mathscr{MCDM}$) problems have been addressed using Wang's [5] maximizing deviation ($\mathscr{MD}$) technique. As we all know, ranking the fused values makes it simple to choose the superior options. When a characteristic significantly affects ranking outcomes, it is evident that this feature is crucial in affecting decision results and should be given significant weight to illustrate the differences between all the options clearly. Conversely, if an attribute minimizes how options are arranged, it is irrelevant to the $\mathscr{DM}$ process and should therefore be given less weight. Put another way, we should give the option that makes a wider deviation more weight and the option that makes a lesser difference less weight.

When many uncertainties and judgments can or should be made sequentially, robustness analysis offers a method for organizing the problem. The robustness analysis focuses on preserving flexibility by using the difference between plans and decisions. Generally speaking, robustness tells us how flexible the options are.

During method development or validation, the robustness check can be performed at any point. Robustness is both a legal requirement and a sign of best practices in method development. Method validation can be supported by robustness data gathered during development. This study will perform robustness analysis using the COPRAS method based on IVFF. The Complex Proportional Assessment (COPRAS) method is one of the $\mathscr{MCDM}$ methods and was developed to help $\mathscr{DMR}$s select the most suitable alternative from a set of alternatives. This methodology is often used to rank and evaluate alternatives that must be assessed based on various criteria. Specifically, COPRAS allows $\mathscr{DMR}$s to evaluate each alternative's relative benefits (or harms) by comparing them against each other. The fundamental superiority of COPRAS is that it can determine both benefit and harm criteria.

1.1. Necessity

By lowering carbon dioxide emissions, $\mathscr{RES}$s contribute to environmental protection, one of their most important features. Because they are domestically sourced, they contribute to reducing external energy dependency and increasing employment. They also attract widespread and strong public support. In other words, $\mathscr{RES}$s possess all the characteristics of accessibility, availability, and acceptability.

The importance of $\mathscr{RES}$s is increasing today. These sources represent energy derived from natural resources that have less environmental impact and are infinitely renewable. Unlike nuclear and fossil fuels, $\mathscr{RES}$s contribute significantly to the fight against climate change. Renewable energy sources, including geothermal, hydro, wind, and solar, reduce carbon emissions without endangering natural ecosystems.

Furthermore, $\mathscr{RES}$s are critical to a sustainable energy future. Because they are derived from inexhaustible natural resources, they provide long-term energy security and reduce dependence on energy imports by increasing energy independence. From an economic perspective, the $\mathscr{RE}$ sector is growing. $\mathscr{RE}$ projects create new jobs, contribute to a green economy, and support economic development.

In conclusion, $\mathscr{RES}$s represent the key to the global energy transition with their environmental, economic, and social benefits. They play a critical role in ensuring a sustainable life for future generations.

There is a significant amount of uncertainty because many $\mathscr{RES}$s are still in their infancy in developing nations. Effective choices must be made, and a suitable procedure for choosing the best sources is required. A crucial step in the $\mathscr{DM}$ process, particularly when developing decision models, is assessing the current criteria and choosing the best available resources. This research addresses the primary issue: "Once

the criteria to be considered in the selection of $\mathscr{RES}$ are determined, is it possible to propose a new $\mathscr{DM}$ model that will help $\mathscr{DMR}$s estimate their uncertainties to address the selection of $\mathscr{RES}$s?"

1.2. Research gap

Choosing a suitable technology is essential in selecting $\mathscr{RES}$s, which can be considered a classic $\mathscr{MCDM}$ problem.

$\mathscr{RES}$s take their place in our lives as alternative energies because they are resources that exist spontaneously and do not run out over time. In this situation, selecting the optimal management technology is complex and unresolved. Different sources and technologies can be selected in several ways. It is crucial to evaluate which of the options is the best. Fundamental factors, such as environmental, technical, economic, and social, should all be considered while evaluating each option. Choosing the most appropriate solution for such situations is a challenging $\mathscr{MCDM}$ problem with various qualitative and quantitative aspects. The suggested methodology tackles the selection of $\mathscr{RES}$s. In order to rate candidates, model the connected vagueness, and optimize their benefits, this study uses a $\mathscr{MD}$ method based on IVFFSs.

When applied to the selection of $\mathscr{RES}$s, the $\mathscr{MD}$ method has the potential to fill some gaps in the literature:

- It will address the lack of diversity in $\mathscr{DM}$ methods. The literature extensively uses techniques like TOPSIS, AHP, WASPAS, and COPRAS. However, since the $\mathscr{MD}$ method is less preferred, a study using this method will demonstrate the applicability of an alternative $\mathscr{MCDM}$ technique to the energy selection problem.
- By reflecting uncertainty and differences between criteria, the method maximizes the differences between criteria, bringing a unique perspective to the $\mathscr{DM}$ process. This allows for clearer identification of distinguishing differences between alternatives that might otherwise be overlooked in traditional methods.
- $\mathscr{RE}$ selection, in terms of group $\mathscr{DM}$ and $\mathscr{DMR}$ opinions, is generally a multi-actor issue (government, investors, environmentalists, academia). A $\mathscr{MD}$ approach can more objectively reflect the differences in criteria in group $\mathscr{DM}$ settings. This could address the lack of a more balanced integration of $\mathscr{DMR}$ opinions in the literature.
- Given regional or country-specific implementation gaps, standardized methods are often used in studies on developing countries like Türkiye or regional energy policies. An analysis using $\mathscr{MD}$ can reveal how country-specific criteria are weighted differently, providing a fresh perspective for policy decision support systems.
- A more balanced approach to sustainability by simultaneously balancing environmental, economic, social, and technical criteria may yield different results. This closes a gap in the literature on analyses that rely on classical scoring or unidimensional weightings.

1.3. Contribution

The study's noteworthy contributions are highlighted by the following points:

- Proposing a new $\mathscr{MD}$ method based on IVFFSs to solve the $\mathscr{MCDM}$ problems.
- Given the algorithm of the new method.
- Analysed $\mathscr{MCDM}$ problem of selecting $\mathscr{RES}$s with IVFF-$\mathscr{MD}$ method.
- Making robustness analysis.
- The suggested methodology will be verified and validated through comparative evaluations using various techniques.
- Traditional maximization-deviation methods (Wang, 1997; Wei, 2008) work with clear numbers or standard Intuitive Fuzzy Sets (IFS). This restricts the decision-maker's decision space. The proposed model is the first MD model to address uncertainty via lower and upper bounds and to use cubic elasticity ($u^3 + v^3 \leq 1$) with Interval-Valued Fermatean Fuzzy Sets (IVFFS).
- While classical maximization-deviation models only consider membership and non-membership values, the degree of hesitation is explicitly included in the IVFF distance function developed in this study. The developed Lagrangian optimization model has been theoretically reformulated to maximize the deviation of the hesitation intervals.

2. Literature Review

Zadeh's [4] fuzzy set (FS) notion is essential in the mathematical technique of fuzzy modeling, which describes uncertainty in human systems. However, this technique is insufficient to fully express human judgments. In response to this weakness, Atanassov [6] created the intuitionistic fuzzy set (IFS) theory. IFS is not designed to manage situations where the sum of MD and ND for some alternatives exceeds one ([7–9]). Yager [10, 11] developed Pythagorean fuzzy sets (PFSs) to get around this restriction by loosening it up so that the only condition at any evaluation of an option is that the total of the squares of MD and ND is less than one ([12–14]). Senapati and Yager ([15, 16]) developed the FFS theory in response to the limitations imposed by PFSs. In response to the limits imposed by IFSs and PFSs, Senapati and Yager ([15, 16]) introduced the FFS theory. In an FFS, the cubic total of membership and non-membership degrees must be less than or equal to one. In addition, FFS-related applications are depicted in [16–25].

Numerous studies have ranked RES using $\mathscr{MCDM}$ methodologies. These methods are instrumental when selecting the ideal RES, necessitating balancing several complex considerations. Kolagar et al. proposed a hybrid strategy that combines DEA and the fuzzy best-worst method to prioritize RES in Iran [26]. An integrated system comprising fuzzy-TOPSIS, AHP, and Slack-based DEA was created by Xu et al. [27] in order to rank and prioritize Pakistan's most sustainable and effective hydrogen generation techniques. The economic, technological, political, social, and environmental aspects of sustainability are all included in this approach. Jha et al. [28] focused on utilizing an Energy Index metric and a fuzzy AHP to rank $\mathscr{RE}$ options in India. This index was created by combining the scores of several solutions based on eleven environmental and techno-economic factors. Solangi et al. [29] evaluated several potential sites for solar power installations using fuzzy VIKOR and AHP algorithms. Fuzzy VIKOR was used to sort viable solutions after each criterion and sub-criterion

was weighed using AHP. Shah et al. [30] used a combination of fuzzy Delphi, fuzzy AHP, and environmental DEA approaches to investigate the viability of various RES for hydrogen production in Pakistan. Geothermal, biomass, wind, solar, micro-hydro, and municipal solid waste were the six $\mathscr{RES}$ choices that the researchers concentrated on. In a study by Longsheng et al. [31], the SWOT factors and strategies were completed by literature research. The twelve SWOT-derived strategies were then ranked using Grey-TOPSIS, utilizing the FAHP weights to offer a systematic technique to strategy assessment. The existing literature shows that the FAHP, FDEA techniques effectively select and rank RES. Kahraman et al. [32] introduced an $\mathscr{MCDM}$ methodology based on axiomatic design and AHP techniques to assist nations in selecting which $\mathscr{RES}$ to invest in. In [7], $\mathscr{RE}$ technologies for power production in Türkiye were evaluated using intuitionistic fuzzy TOPSIS. Lee and Chang presented a new $\mathscr{MCDM}$ method combining WSM, VIKOR, TOPSIS, and ELECTRE [1]. They utilized Shannon's entropy weighted technique to rank $\mathscr{RES}$s, assessing the importance of each aspect. Using a hybrid $\mathscr{DM}$ methodology that included the TOPSIS-I and BWM techniques and several criteria, the most significant alternatives for sustainable $\mathscr{RE}$ were identified in [33]. The model proposed by Öztürk et al. [34] to assist $\mathscr{DMR}$s in selecting $\mathscr{RES}$s comprises AHP and VIKOR. This model shows how the criteria affect Chicago's $\mathscr{RE}$ options' performance metrics and priority. The best $\mathscr{RE}$ options in Türkiye are evaluated in [8] using the intuitionistic fuzzy EDAS technique. Husain et al. [35] presented a new and trustworthy integrated approach that combines the entropy, CRITIC, PIV, MABAC, MARCOS, WASPAS, MOORA, EDAS, GRA, and TOPSIS methodologies to aid in $\mathscr{DM}$ in the field of sustainable energy. In order to evaluate $\mathscr{RES}$s in impoverished countries, Dehshiri et al. [12] suggested a decision framework that included BWM and Interval-Valued Pythagorean Fuzzy WASDPAS approaches. Luhaniwal et al. [36] investigate various $\mathscr{RES}$s in India, including solar, geothermal, hydro, biomass, wave, onshore, and offshore wind energy, using an integrated DEA and fuzzy AHP approach. Shamsipour et al. [37] evaluated five $\mathscr{RE}$ technologies in Isfahan: solar photovoltaic, biomass, wind, concentrated solar power, and geothermal energy. They did this by combining fuzzy DEMATEL-ANP and fuzzy MULTIMOORA algorithms. Wang et al. [38] established an $\mathscr{MCDM}$ to examine energy policies and investments in $\mathscr{RES}$s. First, a balanced scorecard technique examines the criteria using a correlation coefficient according to interval type-2 FSs. Then, using interval type-2 FSts, a FTOPSIS and FDEMATEL approach is used. The work of Abdalla et al. [39] addresses uncertainty with membership, non-membership, and hesitation degrees, as well as multiple parameter subsets (hypersoft). This work successfully models multidimensional and complex parametric environments. However, the computational complexity is very high, and it lacks a bias-maximization mechanism to objectively optimize the criterion weights. Tahir and Shadid [40] demonstrated predictive flexibility by integrating machine learning into their work. Of course, this method requires large datasets and cannot optimize weights as precisely as the maximization-deviation method for small-group expert decisions. Jin et al. [41] reflect the interaction between criteria and distance using interactive terms. In the study by Adak et al. [42], successful results are obtained in assignment problems using global distance measurements.

Wu and Chen [43] investigated $\mathscr{MCDM}$ problems with linguistic information using the $\mathscr{MD}$ method. Wei [9] examined the $\mathscr{MD}$ approach in an intuitionistic fuzzy setting. Liang, Zhang, and Liu [14] employed the $\mathscr{MD}$ approach to address $\mathscr{MCDM}$ problems and proposed aggregation operators under the interval-valued Pythagorean fuzzy environment. Using the $\mathscr{MD}$ approach, Sahin and Liu [44] developed two novel neutrosophic models and used them to solve $\mathscr{MCDM}$ problems. Selvachandran et al. [45], who used the $\mathscr{MD}$ approach for $\mathscr{MCDM}$, proposed the single-valued neutrosophic TOPSIS model. By utilizing neutrosophic information to $\mathscr{MD}$ approach, Xiong and Cheng [46] proposed a novel method for calculating the weights of the qualities. Pamucar et al. [47], who also used the $\mathscr{MD}$ approach to establish the attribute weights, constructed the LNN WASPAS model. Deebani et al. [48] developed a maximization bias model to evaluate the weights of criteria in the decision-making process using T-global fuzzy 2-tuple linguistic clusters. In their paper, Zhang and Xu [49] propose a possible degree-based D-S proof theory method to aid selection in a probabilistic linguistic environment. They then construct a two-objective programming model to determine attribute weights by maximizing bias and minimizing information uncertainty. Liu et al. [50] introduced a new maximizing-deviation strategy by using a novel loss function for objective feature weighting.

3. Preliminaries

3.1. Interval-valued Fermatean fuzzy sets

Definition 3.1. *[19] Let $SUB[0,1]$ be a closed subinterval of the unit interval. An IVFFS on $E \neq \emptyset$ is an expression given by $F = \{(k, [\zeta_{F_L}(k), \zeta_{F_U}(k)], [\eta_{F_L}(k), \eta_{F_U}(k)]) : k \in E\}$, where $\zeta_F(k), \eta_F(k) \in SUB[0,1]$ with $0 < \sup_k(\zeta_F(k))^3 + \sup_k(\eta_F(k))^3 \leq 1$.*

The equation $\theta_F = [\theta_{FL}, \theta_{FU}] = [(1-\zeta_{FU}^3 - \eta_{FU}^3)^{1/3}, (1-\zeta_{FL}^3 - \eta_{FL}^3)^{1/3}]$ is said to be a hesitation degree.

Definition 3.2. *[19] For IVFFSs $F = ([\zeta_{F_L}(a), \zeta_{F_U}(a)], [\eta_{F_L}(a), \eta_{F_U}(a)])$, $F_1 = ([\zeta_{F_{1L}}(a), \zeta_{F_{1U}}(a)], [\eta_{F_{1L}}(a), \eta_{F_{1U}}(a)])$,*
$F_2 = ([\zeta_{F_{2L}}(a), \zeta_{F_{2U}}(a)], [\eta_{F_{2L}}(a), \eta_{F_{2U}}(a)])$,

- $F_1 \cup F_2 = ([\max(\zeta_{F_{1L}}, \zeta_{F_{2L}}), \max(\zeta_{F_{1U}}, \zeta_{F_{2U}})], [\min(\eta_{F_{1L}}, \eta_{F_{2L}}), \min(\eta_{F_{1U}}, \eta_{F_{2U}})])$
- $F_1 \cap F_2 = ([\min(\zeta_{F_{1L}}, \zeta_{F_{2L}}), \min(\zeta_{F_{1U}}, \zeta_{F_{2U}})], [\max(\eta_{F_{1L}}, \eta_{F_{2L}}), \max(\eta_{F_{1U}}, \eta_{F_{2U}})])$
- $F^c = ([\eta_{F_L}, \eta_{F_U}], [\zeta_{F_L}, \zeta_{F_U}])$
- $F_1 \oplus F_2 = \left(\left[\sqrt[3]{(\zeta_{F_{1L}})^3 + (\zeta_{F_{2L}})^3 - (\zeta_{F_{1L}})^3.(\zeta_{F_{2L}})^3}, \right.\right.$
  $\left.\left. \sqrt[3]{(\zeta_{F_{1U}})^3 + (\zeta_{F_{2U}})^3 - (\zeta_{F_{1U}})^3.(\zeta_{F_{2U}})^3} \right], [\eta_{F_{1L}}\eta_{F_{2L}}, \eta_{F_{1U}}\eta_{F_{2U}}] \right)$
- $F_1 \otimes F_2 = \left([\zeta_{F_{1L}}\zeta_{F_{2L}}, \zeta_{F_{1U}}\zeta_{F_{2U}}], \left[\sqrt[3]{(\eta_{F_{1L}})^3 + (\eta_{F_{2L}})^3 - (\eta_{F_{1L}})^3.(\eta_{F_{2L}})^3}, \right.\right.$
  $\left.\left. \sqrt[3]{(\eta_{F_{1U}})^3 + (\eta_{F_{2U}})^3 - (\eta_{F_{1U}})^3.(\eta_{F_{2U}})^3} \right] \right)$

- $\lambda F = \left(\left[\sqrt[3]{1-\left(1-\zeta_{F_L}^3\right)^{\lambda}}, \sqrt[3]{1-\left(1-\zeta_{F_U}^3\right)^{\lambda}} \right], \left[\eta_{F_L}^{\lambda}, \eta_{F_U}^{\lambda} \right] \right)$
- $F^{\lambda} = \left(\left[\zeta_{F_L}^{\lambda}, \zeta_{F_U}^{\lambda} \right], \left[\sqrt[3]{1-\left(1-\eta_{F_L}^3\right)^{\lambda}}, \sqrt[3]{1-\left(1-\eta_{F_U}^3\right)^{\lambda}} \right] \right)$

Definition 3.3. *[51] For the IVFFS* $F = ([\zeta_{FL}(k), \zeta_{FU}(k)], [\eta_{FL}(k), \eta_{FU}(k)])$*, the equations*

$$\mathscr{SC}(F) = 1/2\left([(\zeta_{FL}(k))^3 + (\zeta_{FU}(k))^3] - [(\eta_{FL}(k))^3 + (\eta_{FU}(k))^3] \right)$$
$$\mathscr{AC}(F) = 1/2\left([(\zeta_{FL}(k))^3 + (\zeta_{FU}(k))^3] + [(\eta_{FL}(k))^3 + (\eta_{FU}(k))^3] \right)$$
$$\overline{\mathscr{SC}}(F) = \frac{(\mathscr{SC}(F)+1)}{2}. \tag{3.1}$$

are called score, accuracy, and normalized score functions, respectively.

It is note that $\mathscr{SC}(F) \in [-1,1]$, $\mathscr{AC}(F) \in [0,1]$, and $\overline{\mathscr{SC}}(F) \in [0,1]$.

IVFF weighted averaging(IVFFWA) and geometric(IVFFWG) operators are characterized by

$$IVFFWA(F_1,F_2,\cdots,F_n) = \left(\left[\sqrt[3]{\left(1-\prod_{i=1}^{n}\left(1-\zeta_{F_{iL}}^3\right)^{\omega_i} \right)}, \sqrt[3]{\left(1-\prod_{i=1}^{n}\left(1-\zeta_{F_{iU}}^3\right)^{\omega_i} \right)} \right], \left[\prod_{i=1}^{n}(\eta_{F_{iL}})^{\omega_i}, \prod_{i=1}^{n}(\eta_{F_{iU}})^{\omega_i} \right] \right), \tag{3.2}$$

$$IVFFWG(F_1,F_2,\cdots,F_n) = \left(\left[\prod_{i=1}^{n}(\zeta_{F_{iL}})^{\omega_i}, \prod_{i=1}^{n}(\zeta_{F_{iU}})^{\omega_i} \right], \left[\sqrt[3]{\left(1-\prod_{i=1}^{n}\left(1-\eta_{F_{iL}}^3\right)^{\omega_i} \right)}, \sqrt[3]{\left(1-\prod_{i=1}^{n}\left(1-\eta_{F_{iU}}^3\right)^{\omega_i} \right)} \right] \right), \tag{3.3}$$

where ω_k is given as the influence weight.

3.2. Linear Diophantine fuzzy sets

Linear Diophantine Fuzzy Sets (LDFS), first introduced to the literature by Riaz and Hashmi [52], are a highly powerful, flexible set theory that aims to overcome the rigid mathematical limitations of traditional fuzzy sets (IFS, PFS, FFS, etc.). In traditional Intuitive Fuzzy (IFS) sets, the sum of the membership (ζ) and non-membership (η) degrees is at most 1 ($\zeta+\eta \leq 1$). Pythagorean Fuzzy (PFS) sets have a sum of squares constraint ($\zeta^2+\eta^2 \leq 1$), and Fermatean Fuzzy (FFS) sets have a sum of cubes constraint ($\zeta^3+\eta^3 \leq 1$). However, in real-life scenarios, an expert might want to set the membership degree for a criterion to 0.9 and the non-membership degree to 0.8. In this case, since $\zeta^3+\eta^3 = 0.9^3+0.8^3 = 0.729+0.512 = 1.241 > 1$, even the Fermatean structure is insufficient.

LDFS resolves this bottleneck by including coefficients α and β, called "reference parameters" (or control parameters), into the system. The basic mathematical structure of LDFS is as follows:

$$\mathfrak{D} = \{[x, (\zeta(x), \eta(x)), (\alpha, \beta)] : x \in X\}$$

with the condition $\alpha\zeta(x)+\beta\eta(x) \leq 1$.

Here, α and $\beta \in [0,1]$ are the reference parameters and satisfy the condition $\alpha+\beta \leq 1$. Thanks to these parameters, the decision space can always be kept within a consistent boundary by adjusting the control coefficients, regardless of how large the degrees of membership and non-membership are. LDFS allows decision-makers the freedom to add their own physical or mental constraints as parameters to the system.

The relationship between Interval-Valued Fermatean Fuzzy Sets (IVFFS) and LDFS represents two different philosophical and mathematical approaches to dealing with uncertainty:

- *Boundary Expansion Method:* FFS/IVFFS expands the decision space along a non-linear curve by increasing the exponential degree (cubing). LDFS, on the other hand, maintains the linear constraint but uses exogenous weighting/reference parameters to stretch the space.
- *Interval Flexibility vs. Parametric Flexibility:* The IVFFS approach captures the internal fluctuation (ambiguity) in the data by providing values with lower and upper bounds (intervals) rather than a single number. LDFS, however, works with singular values but parameterizes exogenous factors.
- *Methodological Complementarity:* Both methods aim to eliminate the limitations of IFS and PFS. Comparing these two methods in the paper will rationally establish the "strong position" of proposed IVFF-MD model among modern fuzzy theories in the literature.

Another modern fuzzy framework developed in the literature to expand the flexibility of decision-makers is Linear Diophantine Fuzzy Sets (LDFS) [52]. Aiming to overcome the rigid mathematical limitations of traditional heuristic and Pythagorean fuzzy structures, LDFS operates under the constraint $\alpha\zeta+\beta\eta \leq 1$ by relating membership (ζ) and non-membership (η) degrees through linear control parameters (α,β). While LDFS provides flexibility using exogenous reference parameters, Interval Fermatean Fuzzy Sets (IVFFS), the focus of this study, combines exponential degree flexibility ($u^3+v^3 \leq 1$) with interval-valued lower and upper bounds. IVFFS allows decision-makers to model interval ambiguity in the data itself using cubic freedom, without needing to include additional parameters. In this respect, IVFFS offers a natural and robust infrastructure for data-driven variance-maximization models in complex energy selection scenarios.

4. Method

4.1. IVFF-$\mathscr{MD}$ method

The weights of the criteria are decided by the $\mathscr{MD}$ model. The decision can then be taken once the IVFFWA operator is shown to aggregate the provided decision information. Lastly, the suggested method's algorithm is presented.

Firstly, let's set up the $\mathscr{MCDM}$ problem in the IVFF environment:

- A discrete set of alternatives: $S = \{S_1, S_2, \cdots, S_m\}$.
- A finite set of criteria: $K = \{K_1, K_2, \cdots, K_n\}$.
- A set of $\mathscr{DMR}$s: $U = \{U_1, U_2, \cdots, U_g\}$.
- Let $\lambda = \{\lambda_1, \lambda_2, \cdots, \lambda_g\}$ show the influence weights of $\mathscr{DMR}$s ($0 \leq \lambda_k \leq 1$ and $\sum_{k=1}^{g} \lambda k = 1$).
- Let U^k: $\omega^k = (\omega_1^k, \omega_2^k, \cdots, \omega_n^k)^T$ indicate the weight vectors of criteria for the $\mathscr{DMR}$.

The k^{th} $\mathscr{DMR}$ expresses the j^{th} criterion of the i^{th} alternative in the problem with IVFFN F_{ij}^k.

Definition 4.1. *The IVFF decision matrix($\mathscr{DCSM}$) is defined by* $P^k = (F_{ij}^k)_{m\times n} = ([\zeta^L_{(F_{ij}^k)}, \zeta^U_{(F_{ij}^k)}], [\eta^L_{(F_{ij}^k)}, \eta^U_{(F_{ij}^k)}])_{m\times n}$, $k \in 1, 2, \cdots, g$ *if all entries of the matrix* P^k *are IVFFNs.*

Now, let us set up the $\mathscr{MD}$ model to determine the optimal weights.

The $\mathscr{MD}$ method, originally proposed by Wang [5], is used to determine the weights of criteria for solving $\mathscr{MCDM}$ problems with crisp (non-fuzzy) numbers. In this research, an optimization model for identifying the ideal criteria weights in an IVFF context is established using the main structure of the $\mathscr{MD}$ approach. First, we compute the deviations between each alternative and the others using the IVFF-distance metric.

The deviation value between the alternatives S_ξ and S_σ ($\xi \neq \sigma$) is defined as follows:

Definition 4.2. *The deviation value between the alternatives* S_ξ *and* S_σ ($\xi \neq \sigma$) *is defined as follows:*

$$D_{\xi\sigma j}^k = \omega_j^k DIST\left(F_{\xi j}^k, F_{\sigma j}^k\right) = \frac{1}{4}\omega_j^k \Bigg(\left|(\hat{m}^-_{F_{\xi j}}(k))^3 - (\hat{m}^-_{F_{\sigma j}}(k))^3\right| + \left|(\hat{m}^+_{F_{\xi j}}(k))^3 - (\hat{m}^+_{F_{\sigma j}}(k))^3\right|$$
$$+ \left|(\hat{n}^-_{F_{\xi j}}(k))^3 - (\hat{n}^-_{F_{\sigma j}}(k))^3\right| + \left|(\hat{n}^+_{F_{\xi j}}(k))^3 - (\hat{n}^+_{F_{\sigma j}}(k))^3\right| + \left|(\theta^-_{F_{\xi j}}(k))^3 - (\theta^-_{F_{\sigma j}}(k))^3\right| + \left|(\theta^+_{F_{\xi j}}(k))^3 - (\theta^+_{F_{\sigma j}}(k))^3\right| \Bigg).$$

where $\mathscr{DMR}$ U_k ($k = 1, 2, \cdots, g$) *and the criterion* K_j ($j = 1, 2, \cdots, n$).

Proposition 4.3. *Let* F_1 *and* F_2 *be two IVFFNs. The Interval Fermatean Fuzzy Distance Measurement function satisfies the basic metric conditions.*

Proof. Non-negativity: All components in the distance formula are in absolute value $|x|$, and the coefficient in front of it is $1/4 > 0$. Therefore, the condition $DIST(F_1, F_2) \geq 0$ is satisfied for every F_1, F_2.

Identity of Indiscernibles: $DIST(F_1, F_2) = 0$ is possible if and only if all expressions within absolute values are equal to zero. This requires that the lower and upper bounds of the intervals $(\hat{m}^-, \hat{m}^+, \hat{n}^-, \hat{n}^+, \theta^-, \theta^+)$ be exactly equal, i.e., $F_1 = F_2$.

Symmetry: Due to the absolute value property, the equality $|a^3 - b^3| = |b^3 - a^3|$ holds. Therefore, the condition $DIST(F_1, F_2) = DIST(F_2, F_1)$ is directly satisfied. □

Then, for the criterion K_j ($j = 1, 2, \cdots, n$) and the $\mathscr{DMR}$ U_k ($k = 1, 2, \cdots, g$), the deviation value between the alternative S_i ($i = 1, 2, \cdots, m$) and all the other alternatives can be calculated as:

$$D_{\xi j}^k = \sum_{\sigma=1}^{m} \omega_j^k DIST\left(F_{\xi j}^k, F_{\sigma j}^k\right).$$

Furthermore, the deviation value of all the alternatives to the other alternatives can be calculated as:

$$D_j^k = \sum_{\xi=1}^{m}\sum_{\sigma=1}^{m} \omega_j^k DIST\left(F_{\xi j}^k, F_{\sigma j}^k\right).$$

A criterion has a lesser significance in the prioritizing process for an $\mathscr{MCDM}$ problem if the criterion values of all alternatives under a criterion differ just a little. On the other hand, this criterion is more crucial in selecting the best option if there are discernible disparities in all choices' criterion values. In other words, while ranking the alternatives, a criterion should be given a lower weight if its values are similar across alternatives; if not, a larger weight should be given to the criterion that deviates from the norm, regardless of its importance. Specifically, most $\mathscr{DMR}$s will consider a criterion insignificant and give it zero weight if all alternatives receive the same score on that criterion.

In order to choose the weight vector $omega^k$ for the $\mathscr{DMR}$ U_k $(k=1,2,\cdots,g)$, we create an ideal model that optimizes all deviation values for every criterion as follows:

$$\begin{cases} \max D^k = \sum_{j=1}^{n}\sum_{\xi=1}^{m}\sum_{\sigma=1}^{m} \omega_j^k DIST\left(F_{\xi j}^k, F_{\sigma j}^k\right) \\ \text{s.t.} \quad \sum_{j=1}^{n}\left(\omega_j^k\right)^3 = 1, \\ \omega_j^k \geq 0, \quad j=1,2,\cdots,n. \end{cases} \tag{4.1}$$

The Lagrange function of the optimization Model (4.1) can be obtained as:

$$\mathfrak{L}(\omega^k,\lambda) = \sum_{j=1}^{n}\sum_{\xi=1}^{m}\sum_{\sigma=1}^{m} \omega_j^k DIST\left(F_{\xi j}^k, F_{\sigma j}^k\right) + \frac{\lambda}{3}\left(\sum_{k=1}^{n}(\omega_j^k)^3 - 1\right)$$

where The Lagrange multiplier variable is represented by the real number λ.

If we take the partial derivative for $\mathfrak{L}$,

$$\begin{aligned} \frac{\partial \mathfrak{L}}{\partial \omega_j^k} &= \sum_{\xi=1}^{m}\sum_{\sigma=1}^{m} DIST\left(F_{\xi j}^k, F_{\sigma j}^k\right) + \lambda.(\omega_j^k)^2 = 0, \\ \frac{\partial \mathfrak{L}}{\partial \lambda} &= \frac{1}{3}\left(\sum_{j=1}^{n}(\omega_j^k)^3 - 1\right) = 0. \end{aligned} \tag{4.2}$$

If $(\omega_j^k)^2$ in Equation (4.2) is left alone, then

$$(\omega_j^k)^2 = -\frac{1}{\lambda}\sum_{\xi=1}^{m}\sum_{\sigma=1}^{m} DIST\left(F_{\xi j}^k, F_{\sigma j}^k\right).$$

If the square root of both sides is taken, then

$$\omega_j^k = \sqrt{-\frac{1}{\lambda}}\sqrt{\sum_{\xi=1}^{m}\sum_{\sigma=1}^{m} DIST\left(F_{\xi j}^k, F_{\sigma j}^k\right)}.$$

Let's substitute the expression we found, ω_j^k, into the equation $\sum_{j=1}^{n}(\omega_j^k)^3 = 1$, which is the constraint of the problem:

$$\sum_{j=1}^{n}\left(\sqrt{-\frac{1}{\lambda}}\sqrt{\sum_{\xi=1}^{m}\sum_{\sigma=1}^{m} DIST\left(F_{\xi j}^k, F_{\sigma j}^k\right)}\right)^3 = 1$$

$$\left(\sqrt{-\frac{1}{\lambda}}\right)^{3/2}\sum_{j=1}^{n}\left(\sqrt{\sum_{\xi=1}^{m}\sum_{\sigma=1}^{m} DIST\left(F_{\xi j}^k, F_{\sigma j}^k\right)}\right)^{3/2} = 1.$$

If the parameter $\sqrt{-1/\lambda}$ is retrieved from here:

$$\sqrt{-1/\lambda} = \frac{1}{\left[\sum_{j=1}^{n}\left(\sqrt{\sum_{\xi=1}^{m}\sum_{\sigma=1}^{m} DIST\left(F_{\xi j}^k, F_{\sigma j}^k\right)}\right)^{3/2}\right]^{1/3}}.$$

When this value is substituted into the definition of ω_j^k, the final weight formula (Equation 12) is derived analytically. In the final stage, normalization is performed using Equation (13) to fully satisfy the constraint that the sum of the weights is 1 ($\sum_{j=1}^{n}\overline{\omega}_j^k = 1$).

Using (4.2),

$$\omega_j^k = \frac{\sum_{\xi=1}^{m}\sum_{\sigma=1}^{m} DIST\left(F_{\xi j}^k, F_{\sigma j}^k\right)}{\sqrt{\sum_{j=1}^{n}\left(\sum_{\xi=1}^{m}\sum_{\sigma=1}^{m} DIST\left(F_{\xi j}^k, F_{\sigma j}^k\right)\right)^2}}.$$

Finally, the optimal weight ω_j^k is normalized as:

$$\overline{\omega}_j^k = \frac{\omega_j^k}{\sum_{j=1}^{n}\omega_j^k}. \tag{4.3}$$

We can create a different programming model if the attribute weight information is entirely unknown:

$$\begin{cases} & \max D^k = \sum_{j=1}^{n} \sum_{\xi=1}^{m} \sum_{\sigma=1}^{m} \omega_j^k DIST\left(F_{\xi j}^k, F_{\sigma j}^k\right) \\ s.t. & \\ & \sum_{j=1}^{n} \omega_j^k = 1, \quad \omega_j^k \geq 0, \quad j = 1,2,\cdots,n. \end{cases} \tag{4.4}$$

Model (4.4) is solved to find the optimal solution for $\omega^k = (\omega_1^k, \omega_2^k, \cdots, \omega_n^k)^T$. We must ascertain the weights of the criteria for the group after acquiring weights of the criteria for each $\mathscr{DMR}$. Indicate the group's weight for the criterion K_j using ω_j^*. Then, to identify the ideal weights of criteria for the group, we further develop an optimal model that minimizes consistency as follows:

$$\begin{cases} & \min E(\omega^*) = \sum_{j=1}^{n} \sum_{k=1}^{g} \alpha_k |\omega_j^k - \omega_j^*| \\ s.t. & \\ & \sum_{j=1}^{n} \omega_j^* = 1, \quad \omega_j^* \geq 0, \quad j = 1,2,\cdots,n. \end{cases} \tag{4.5}$$

Model (4.5) solve and

$$\phi_j^k = \frac{1}{2}\left(\left|\omega_j^k - \omega_j^*\right| + \left(\omega_j^k - \omega_j^*\right)\right),$$
$$\varphi_j^k = \frac{1}{2}\left(\left|\omega_j^k - \omega_j^*\right| - \left(\omega_j^k - \omega_j^*\right)\right).$$

The following line programming model is then created from the ideal Model (4.5):

$$\begin{cases} & \min E(\omega^*) = \sum_{j=1}^{n} \sum_{k=1}^{g} \alpha_k (\phi_j^k + \varphi_j^k) \\ & \omega_j^k - \omega_j^* - \phi_j^k + \varphi_j^k = 0, \\ s.t. & \phi_j^k \geq 0, \\ & \varphi_j^k \geq 0, \\ & \phi_j^k \varphi_j^k = 0, \\ & \sum_{j=1}^{n} \omega_j^* = 1, \quad \omega_j^* \geq 0, \quad j = 1,2,\cdots,n. \end{cases} \tag{4.6}$$

Model (4.6) is solved to find the optimal solution for $\omega^k = (\omega_1^k, \omega_2^k, \cdots, \omega_n^k)^T$.

At this stage, the alternatives will be ranked.

Once the group's ideal weights for the criteria have been determined, we often need to combine the available data to identify the overall preference value of each choice before making a choice. The order of the alternatives will be established using the IFWA (Equation (3.2)) (or IFWG (Equation (3.3))) operator.

4.2. Algorithm

The algorithm and flow chart (Figure 4.1) of the $\mathscr{MD}$ model based on IVFF are:

Step 1: Create the IVFF-$\mathscr{DCSM}$.

Step 2: Solve Equation (4.3) or Model (4.4) to find the weights of the criterion for each $\mathscr{DMR}$.

Step 3: Solve Model (4.6) to determine the weights of the group's criterion.

Step 4: Determine the alternative's overall preference values. U_i.

Step 5: Compare the magnitude of each alternative's comprehensive preference values to get the best ranking order for the alternatives. Then, choose the best alternative.

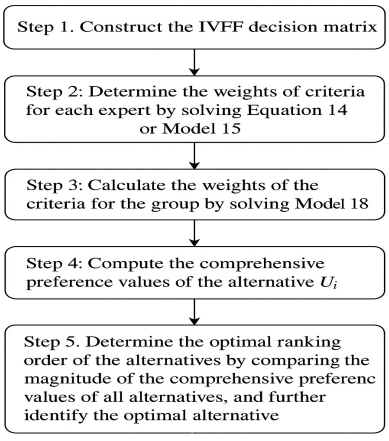


Figure 4.1: Flow chart of new method

4.3. Profiles of decision-makers and data collection process

In this study, a case study of renewable energy source selection was conducted to test the applicability and accuracy of the proposed IVFF-MD-based MCDM model. A broad pool of experts was used to ensure unbiased, scientifically sound decisions. Three decision-makers (DM1, DM2, DM3) were strategically selected to represent both academic depth and sectoral expertise.

The profiles, areas of expertise, years of sectoral experience, and weighting coefficients (λ_k) of the decision-makers are detailed in Table 4.1. The weights of the experts were determined using objective criteria, in accordance with the decision analytics literature, considering their education levels, total years of experience in renewable energy projects, and managerial competencies.

Decision Maker	Corporate Sector	Education Level	
DM_1	Academy/University	Doctorate(Ph.D.)	
DM_2	Private Sector / Energy Company	Master's Degree (M.Sc.)	
DM_3	Public / Environment and Urbanization	Bachelor's Degree (B.Sc.)	
	Area of Expertise and Focus	Industry Experience(Years)	Decision Weight (λ_k)
DM_1	Renewable Energy Policies and Sustainability Management	16 Years	0.35
DM_2	Solar and Wind Energy Investments, Project and Field Management	12 Years	0.35
DM_3	Environmental Impact Assessment (EIA) and Grid Integration Regulations	10 Years	0.30

Table 4.1: Demographic profiles, areas of expertise, and decision weights of decision makers

Data Collection Process:
To ensure the transparency and reproducibility of the study, the data collection process was carried out in three main stages:

- *Determination of Criteria and Alternatives:* Based on a review of the literature and global renewable energy standards (IRENA, IEA reports, etc.), 5 alternative sources and 10 evaluation criteria were identified. The suitability of these criteria for local and global scales was confirmed in the first focus group meeting with experts.
- *Obtaining Linguistic Assessments (Questionnaire/Interview):* Experts were provided with the Linguistic Scale and the corresponding Interval Fermatean Fuzzy Numbers (IVFFN) described in the article as guides for evaluating the alternatives according to the criteria. Data were collected through approximately 45-minute semi-structured interviews with each expert, followed by the completion of matrix forms.
- *Consistency and Clarification Check:* The collected expert matrices were checked for any information loss or mathematical inconsistencies (violation of the fermatean set constraint $u^3 + v^3 \leq 1$), and the experts' hesitation levels (θ) were functionally verified to generate the final input matrices.

4.4. Advantages and limitations of the proposed methodology

This study presents a novel multi-criteria decision-making (MCDM) framework that integrates Interval-Valued Fermatean Fuzzy Sets (IVFFS) with Deviation Maximization (DM) methods. While this developed methodology has significant advantages over existing approaches in the literature, it also has limitations in guiding future studies. The strengths and limitations of the method are detailed below:

Advantages:

- *Advanced Uncertainty Modeling and Decision Flexibility:* Traditional Intuitive Fuzzy (IFS) and Pythagorean Fuzzy (PFS) sets are subject to the mathematical constraints $u+v \leq 1$ and $u^2+v^2 \leq 1$, respectively. The IVFFS structure used in the proposed model, however, offers cubic flexibility ($u^3+v^3 \leq 1$), allowing experts to express their membership and non-membership judgments over a much wider range. Furthermore, defining values as interval-valued, with lower and upper bounds rather than a single net number, more realistically reflects the ambiguity and lack of information in human thought.
- *Objective and Fair Weight Optimization:* In traditional MCDM models, criterion weights often rely on subjective estimates or direct scoring by decision-makers, introducing human bias and errors into the process. The developed IVFF-MD model analytically maximizes the deviations between alternatives using the Lagrangian multiplier method, thereby determining weights in a completely data-driven and objective manner.
- *Consensus and Consistency in Group Decisions:* The developed linear programming-based optimization model is designed to minimize individual disagreements and inconsistencies in group decisions. In this way, conflicting judgments from different experts are filtered through a mathematical optimization process to achieve a rational consensus.

Limitations:

- *Growth of Matrix Sizes and Data Density:* The proposed model establishes interval-valued membership, non-membership, and hesitation matrices for each expert. As the number of decision-makers (k), alternatives (m), and criteria (n) increases, the number of IVFF distance matrix dimensions to be calculated grows geometrically, and the data collection process becomes more complex.
- *Computational Burden and Optimization Complexity:* For cases where criterion weight information is partially known, the proposed linear programming models (Models 14, 15, and 17) contain numerous absolute-value constraints. In large-scale industrial problems or multi-criteria big data applications, solving these models with standard Simplex or Inner Point algorithms may require high processing power and time (computational burden).
- *Qualitative Data Dependence:* The model is fundamentally grounded in experts' linguistic evaluations. If the expert pool is insufficient or comprises individuals unfamiliar with the subject matter, erroneous inputs in the initial matrices (based on the garbage-in, garbage-out principle) can negatively impact the accuracy of the optimization model.

Here is Figure 4.2, representing the methodological framework of proposed IVFF-MD model. It breaks down the process into four interconnected phases: Data Collection & Preparation, Objective Weight Determination, Group Decision Integration, and Evaluation & Ranking, clearly showing how the interval-valued Fermatean fuzzy sets and maximizing deviation method work together within the COPRAS algorithm.

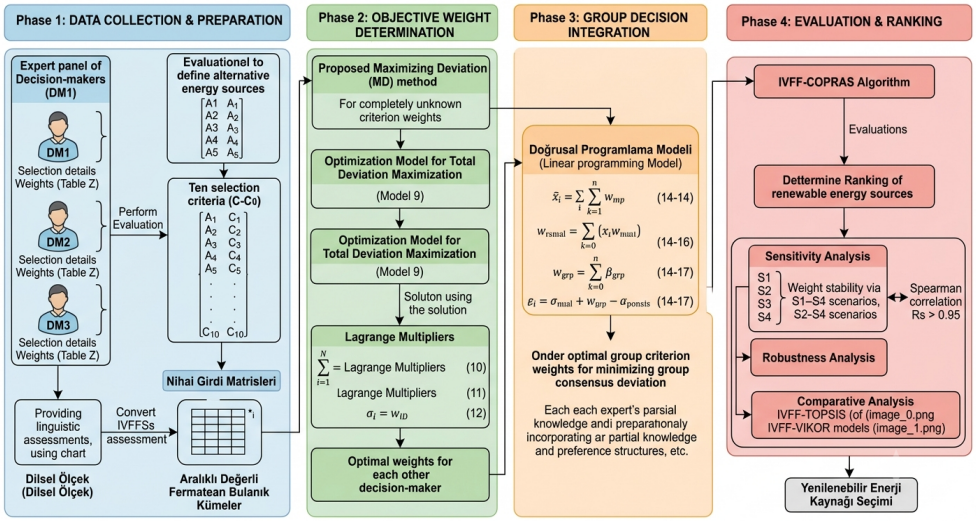


Figure 4.2: Methodological framework of the proposed IVFF-MD model

5. Application

5.1. Problem design

In addition to the efficient production and consumption of conventional energy sources and the reduction of their environmental impact, the idea of sustainable development—which has grown to be a topic of great concern for all societies worldwide—has highlighted the need to switch to clean and limitless energy sources. $\mathscr{RE}$ research has proliferated due to environmental degradation, global warming, and the growing energy demand primarily satisfied by fossil fuels. It is also predicted that fossil fuels will soon run out. $\mathscr{RE}$ is derived from the flow of energy that occurs naturally while processes continue. $\mathscr{RES}$s are resources like solar, water, wind, and waves that are exploited to generate other energy sources before they run out. $\mathscr{RES}$s can generate sustainable energy and are sourced from natural resources. The following are the primary categories of $\mathscr{RE}$ sources (Figure 5.1).

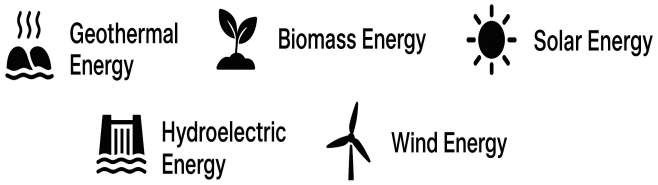


Figure 5.1: Renewable energy sources

Alternative S1: Geothermal Energy

Geothermal means ground heat. Water produced by natural processes—particularly precipitation—reaches the magma layer through fissures in the Earth's crust. The magma layer's heated water rises to the surface as steam and hot water. Turbines can turn the water and steam that reach the surface into energy. Geothermal energy is the thermal energy stored in the Earth's crust. This surface energy is transformed into electrical power by well-established power facilities. Additionally, it can be utilized in many patient-favored physical therapy facilities, tourist attractions, and central heating and cooling systems found in homes and workplaces.

Alternative S2: Bioenergy / Biomass Energy

This type of energy is an inexhaustible resource, readily available everywhere. It is considered a suitable and important energy source, particularly for rural areas, as it contributes to socio-economic development. Specially grown plants like corn and wheat, grasses, seaweed, marine algae, animal waste, fertilizer, industrial waste, and any organic waste (fruit and vegetable waste) left over from houses are biomass sources. The role of biomass in addressing the energy crisis is growing, despite the depletion of fossil fuels (coal, etc.) and the environmental harm they cause.

Alternative S3: Solar Energy

The sun is the solar system's energy source for all planets. It is an indispensable resource, especially for all living things on Earth. The practicality of their use, especially in the summer months, and the significant reductions they provide in electricity bills make solar panels a

leading $\mathscr{RES}$ today. Solar panels, commonly found on the roofs of homes in cities and villages, can heat water, meet a home's hot water needs, or supply hot water to a home's heating system to meet heating needs. Solar energy technologies collect sunlight to generate heat or electricity. Solar energy is utilized in light, heat, and electricity. Solar energy systems convert the collected energy directly into electricity and can be installed on building roofs, appliances, and cars. Concentrated solar power plants use mirrors and lens systems to reflect solar radiation onto a relatively small area and generate electricity or heat.

Alternative S4: Hydroelectric Energy

The basis of hydroelectric energy is to harness the energy of flowing water and convert it into electricity. Hydroelectric power plants are renewable and provide a clean energy source for nature. Because water flows at higher elevations are faster, these plants are more useful in these areas. Because hydroelectric power plants rely on the energy of flowing water, they are used to improve fishing, facilitate transportation, irrigate, and, most importantly, generate energy.

Alternative S5: Wind Energy

Solar energy is the source of wind energy. Wind is produced by the pressure differential that results from solar energy heating the land and the water at different rates. Wind turbines convert the kinetic energy of the wind into mechanical and electrical energy when positioned in windy areas. The present wind speed and duration determine how much energy the wind produces. Currently, 2% of the world's electrical needs are met by wind. Compared to other power production methods, wind turbine technologies have a negligible environmental impact.

Evaluating $\mathscr{RES}$s typically involves considering a range of factors and categories. This assessment covers many aspects, from energy production potential to environmental impacts. $\mathscr{RES}$s (solar, wind, hydroelectric, biomass, geothermal) can be analyzed from various perspectives, and each is evaluated under different criteria. Technical, environmental, social, and economic factors are all impacted differently by $\mathscr{RE}$ systems. The criteria details of these aspects can be introduced as follows:

1 **Economic aspects have three criteria:** Investment cost(K1), O&M(K2), Electric cost(K3);
2 **Technical aspects have three criteria:** Efficiency(K4), Capacity factor(K5), and technical maturity(K6);
3 **Environmental aspects have two criteria:** greenhouse gas (GHG) emission(K7), land use(K8);
4 **Social aspects have two criteria:** Job creation(K9), social acceptance(K10).

- **Investment Cost:** It covers the cost of the equipment and installation. Purchasing mechanical equipment, installing technology, building roads, connecting to the national web, hiring engineers, drilling, and other incidental construction activity are all examples of investment expenses [53]. The expenses and rewards of investments must be taken into account by the investors. The most popular economic criterion for assessing energy systems is investment cost.
- **O&M:** It includes money spent on energy, goods, and services for the operation of the energy system, as well as personnel wages. It is divided into two sections: (1) operation costs, which include salaries for staff and the money spent on energy, goods, and services for the operation of the energy system [53]; and (2) maintenance costs.
- **Electric Cost:** It alludes to how much different energy generation systems cost. Land, construction, operation, fuel, equipment, and interest charges are all included in the total cost of the electrical power-producing process. This is an important financial sign as well. The ratio of energy input to energy production is known as efficiency. The most popular technical criterion for assessing energy systems is this one. The amount of sound energy extracted from an energy source is known as efficiency. The efficiency coefficient, or the ratio of output to input energy, is one of the most popular efficiency measures.
- **Capacity Factor:** It displays the installed capacity divided by the annual total production. The ratio of electrical energy generated by a generating unit over a given period of time that might have been produced at continuous whole power operation during the same period is known as the power plant's capacity factor [54]. There are significant differences in the capacity factors of various power plant types. The weather impacts RE's capacity factor; for instance, hydropower plants' average electricity generating capacity is higher in the summer, which raises the capacity factor. While solar energy is influenced by sunlight and wind energy is influenced by wind speed, geothermal and biomass energy are operational nearly around the clock.
- **Technical Maturity:** Technology relates to how dependable the adopted technology is and how widely it is used nationwide. This criterion has to deal with the accepted technology's level of dependability and national adoption. A qualitative 5-point rating system is used in this study to evaluate the technology, with five denoting very high maturity (i.e., commercially mature technology with a strong market position) and 1 denoting very low maturity (i.e., only laboratory testing).
- **GHG Emission:** It refers to the greenhouse gas emissions created by the technology throughout its life cycle. One of the most popular metrics for assessing the stainability of $\mathscr{RES}$s is the quantity of greenhouse gas emissions from a particular $\mathscr{RE}$ system. Here, it is necessary to assess the life-cycle of greenhouse gas emissions from various renewable technologies. Emissions are expressed as g CO2eq/kWh, or equivalent emissions of CO2 per energy unit produced [58]. A life-cycle emissions assessment considers the energy production system's extraction, refining, processing, transportation, construction, operation and maintenance, and deconstruction phases.
- **Land Use:** The land area needed for the technology is defined by its land usage. Because the energy system directly impacts the environment and landscape, the quantity of land needed for each plant is a crucial factor in the evaluation. Varying energy systems may occupy varying amounts of land, even when the products are identical. Thus, land usage needs to be taken into account.
- **Job Creation:** The energy project is expected to generate potential job opportunities. An energy supply system might have a large workforce from construction to operation. Therefore, when developing RE, the inhabitants should be considered by evaluating the enhancement of their quality of life and creating jobs.
- **Social Acceptance:** It shows that the general public accepts $\mathscr{RE}$ technology. This criterion relates to the degree of public acceptance of RE, which is crucial in determining how RE technologies are implemented and reaching energy policy goals. It is crucial because public opinion and pressure groups can significantly impact how long an energy project takes to finish. It is important to remember that social approval cannot be measured directly. A qualitative scale, with one denoting strong resistance and five denoting strong support, is used in this study to quantify social acceptance.

Linguistic Terms	ζ_L	ζ_U	η_L	η_U
Certainly High Importance(CH)	0.95	1	0	0
Very High Importance(VH)	0.8	0.9	0.1	0.2
High Importance(H)	0.7	0.8	0.2	0.3
Slightly More Importance(SM)	0.6	0.65	0.35	0.4
Equally Importance(E)	0.5	0.5	0.5	0.5
Slightly Less Importance(SL)	0.35	0.4	0.6	0.65
Low Importance(L)	0.2	0.3	0.7	0.8
Very Low Importance(VL)	0.1	0.2	0.8	0.9
Certainly Low Importance(CL)	0	0	0.95	1

Table 5.1: Scale values according to IVFF

5.2. Computations

For this study, four $\mathscr{DMR}$s were interviewed to assess criteria and options associated with the RES selection dilemma. The first $\mathscr{DMR}$ has 29 years of experience and is an Electrical and Electronics Engineering professor. The second $\mathscr{DMR}$ is an engineer who has worked for the Ministry of Energy and Natural Resources of the Republic of Türkiye for 20 years at the General Directorate of Energy Affairs. A worldwide bank employs the third $\mathscr{DMR}$, an electrical engineer with 16 years of experience, as an Energy Efficiency Specialist. The fourth $\mathscr{DMR}$ is an engineer who has worked for a private corporation in the energy industry for 11 years. Assume that the criteria weights are entirely unknown and that $\mathscr{DMR}$s' weight vector is $\lambda = (0.33, 0.28, 0.22, 0.17)$. It is expected that IVPFNs represent the assessment values of alternatives regarding criteria provided by the $\mathscr{DMR}$s, as shown in the IVFF group-$\mathscr{DCSM}$ provided in Table 5.2.

		U1						U2			
Criteria	S1	S2	S3	S4	S5	Criteria	S1	S2	S3	A4	S5
K1	CH	SM	L	H	VH	K1	VH	SM	SL	VH	CH
K2	SM	H	L	CH	CH	K2	E	H	VL	VH	CH
K3	CH	SM	SL	H	H	K3	CH	E	L	H	SM
K4	SM	H	CH	SM	E	K4	H	H	VH	SM	E
K5	L	SM	E	VH	CH	K5	VL	E	E	CH	VH
K6	CH	VH	CH	H	SM	K6	VH	VH	VH	H	H
K7	CH	VL	VL	SL	H	K7	CH	L	VL	L	H
K8	SM	H	CH	H	SL	K8	SM	VH	CH	H	E
K9	CH	CL	L	VL	SL	K9	CH	VL	VL	CL	SL
K10	VH	VH	H	SM	H	K10	VH	CH	VH	SM	H
		U3						U4			
Criteria	S1	S2	S3	S4	S5	Criteria	S1	S2	S3	S4	S5
K1	CH	H	SL	H	VH	K1	CH	SM	VL	H	SM
K2	L	E	SM	H	SL	K2	E	H	SL	H	VH
K3	VH	SM	VL	SM	E	K3	CH	L	VL	E	SM
K4	E	SM	H	VH	E	K4	SM	H	VH	H	SM
K5	CL	SL	SL	H	H	K5	VL	SM	SL	VH	CH
K6	H	H	VH	SM	E	K6	CH	VH	VH	H	SM
K7	VH	VL	CL	SL	H	K7	CH	SL	L	SL	VH
K8	SL	H	VH	SM	L	K8	E	H	CH	E	VL
K9	VH	CL	CL	VL	SL	K9	CH	CL	VL	VL	E
K10	H	VH	VH	E	SM	K10	VH	CH	SM	SL4	E

Table 5.2: IVFF group decision matrix

Equation (4.3) is used to determine the criteria weights for each $\mathscr{DMR}$.

$$\begin{aligned}
\omega^1 &= (0.214, 0.091, 0.067, 0.025, 0.125, 0.206, 0.14, 0.027, 0.045, 0.06)^T \\
\omega^2 &= (0.307, 0.045, 0.033, 0.157, 0.052, 0.188, 0.096, 0.067, 0.023, 0.032)^T \\
\omega^3 &= (0.153, 0.102, 0.041, 0.100, 0.029, 0.079, 0.108, 0.036, 0.012, 0.016)^T \\
\omega^4 &= (0.225, 0.059, 0.107, 0.018, 0.091, 0.167, 0.211, 0.055, 0.042, 0.025)^T
\end{aligned}$$

To determine the weights of the group's criterion, a linear programming model will be constructed (Model (4.6)).

$$\begin{aligned}\min E(\omega^*) &= 0.33\times(\phi_1^1+\varphi_1^1+\cdots+\phi_{10}^1+\varphi_{10}^1)\\ &+ 0.28\times(\phi_1^2+\varphi_1^2+\cdots+\phi_{10}^2+\varphi_{10}^2)\\ &+ 0.22\times(\phi_1^3+\varphi_1^3+\cdots+\phi_{10}^3+\varphi_{10}^3)\\ &+ 0.17\times(\phi_1^4+\varphi_1^4+\cdots+\phi_{10}^4+\varphi_{10}^4),\end{aligned}$$

$$\begin{aligned}s.t.\quad & 0.000-\omega_1^*-\phi_1^1+\varphi_1^1=0;\\ & 0.000-\omega_2^*-\phi_2^1+\varphi_2^1=0;\\ & 0.000-\omega_3^*-\phi_3^1+\varphi_3^1=0;\\ & \vdots\ \ \vdots\ \ \vdots\ \ \vdots\\ & 0.000-\omega_1^*-\phi_1^2+\varphi_1^2=0;\\ & 0.000-\omega_2^*-\phi_2^2+\varphi_2^2=0;\\ & \vdots\ \ \vdots\ \ \vdots\ \ \vdots\\ & 0.000-\omega_1^*-\phi_1^3+\varphi_1^3=0;\\ & 0.000-\omega_2^*-\phi_2^3+\varphi_2^3=0;\\ & \vdots\ \ \vdots\ \ \vdots\ \ \vdots\\ & 0.000-\omega_1^*-\phi_1^4+\varphi_1^4=0;\\ & 0.000-\omega_2^*-\phi_2^4+\varphi_2^4=0;\\ & \vdots\ \ \vdots\ \ \vdots\ \ \vdots\\ & 0.000-\omega_{10}^*-\phi_{10}^4+\varphi_{10}^4=0\\ & \phi_j^k\geq 0,\\ & \varphi_j^k\geq 0,\\ & \phi_j^k\varphi_j^k=0,\quad j=1,2,\cdots,10,\quad k=1,2,3,4\\ & \omega_1^*+\cdots+\omega_{10}^*=1\\ & \omega_j^*>0\quad j=1,2,\cdots,10.\end{aligned}\tag{5.1}$$

When model (5.1) is solved, then

$$\omega^*=(0.221,0.07,0.14,0.06,0.074,0.19,0.14,0.042,0.03,0.033)^T.$$

In the meantime, we combine all of the individual $\mathscr{DCSM}$s into the collective $\mathscr{DCSM}$ using Equation (3.2). The outcomes are indicated in Table 5.3.

	S1	S2	S3	S4	S5
K1	([0.52, 0.00], [0.00, 0.00])	([0.67, 0.74], [0.23, 0.30])	([0.34, 0.34], [0.85, 0.90])	([0.63, 0.72], [0.33, 0.45])	([0.52, 0.00], [0.00, 0.00])
K2	([0.43, 0.46], [0.66, 0.71])	([0.70, 0.80], [0.18, 0.28])	([0.41, 0.40], [0.80, 0.84])	([0.56, 0.00], [0.00, 0.00])	([0.60, 0.00], [0.00, 0.00])
K3	([0.54, 0.00], [0.00, 0.00])	([0.56, 0.60], [0.38, 0.42])	([0.34, 0.34], [0.94, 0.95])	([0.49, 0.55], [0.60, 0.66])	([0.73, 0.77], [0.20, 0.26])
K4	([0.43, 0.46], [0.00, 0.00])	([0.60, 0.67], [0.40, 0.50])	([0.68, 0.00], [0.00, 0.00])	([0.34, 0.37], [0.90, 0.91])	([0.31, 0.31], [0.96, 0.97])
K5	([0.31, 0.31], [0.90, 0.95])	([0.50, 0.52], [0.60, 0.63])	([0.34, 0.34], [0.94, 0.95])	([0.68, 0.00], [0.00, 0.00])	([0.54, 0.00], [0.00, 0.00])
K6	([0.81, 0.00], [0.00, 0.00])	([0.68, 0.81], [0.27, 0.40])	([0.66, 0.00], [0.00, 0.00])	([0.61 0.70], [0.37, 0.47])	([0.40, 0.46], [0.79, 0.83])
K7	([0.84, 0.00], [0.00, 0.00])	([0.34, 0.34], [0.82, 0.87])	([0.31, 0.31], [0.94, 0.95])	([0.34, 0.34], [0.67, 0.72])	([0.40, 0.46], [0.79, 0.83])
K8	([0.34, 0.34], [0.91, 0.93])	([0.37, 0.45], [0.83, 0.88])	([0.60, 0.00], [0.00, 0.00])	([0.40, 0.46], [0.79, 0.83])	([0.34, 0.34], [0.90, 0.92])
K9	([0.73, 0.00], [0.00, 0.00])	([0.21, 0.21], [0.96, 1.00])	([0.31, 0.31], [0.96, 0.97])	([0.31, 0.31], [0.96, 0.97])	([0.31, 0.31], [0.94, 0.95])
K10	([0.51, 0.63], [0.60, 0.70])	([0.65, 0.00], [0.00, 0.00])	([0.31, 0.40], [0.88, 0.91])	([0.34, 0.34], [0.94, 0.96])	([0.63, 0.72], [0.33, 0.45])

Table 5.3: Aggregated $\mathscr{DCSM}$

In order to acquire the comprehensive preference values of options as displayed in Table 5.4, we lastly use Equation (3.3) to aggregate the collective decision data in Table 5.3. Equation (3.1) calculates the scores of each choice's comprehensive preference values. We can determine the ranking of each alternative based on these score values, as indicated in Table 5.4.

According to Table 5.4, $S_4 > S_5 > S_3 > S_2 > S_1$, making S_4—biomass energy—the best option. The suggested approach can assist the $\mathscr{DMR}$ in choosing $\mathscr{RESS}$s and successfully handle the $\mathscr{RESS}$s selection problem. Furthermore, other MCGDM problems with partial weight information under IVFF contexts can also be solved using the suggested approach.

Alternative	Aggregated Preference Values	Scores	Ranking
S1	([0.54, 0.58], [0.00, 0.00])	0.59	5
S2	([0.93, 0.00], [0.00, 0.47])	0.68	4
S3	([0.91, 0.92], [0.90, 0.00])	0.70	3
S4	([0.85, 0.87], [0.36, 0.00])	0.81	1
S5	([0.85, 0.88], [0.68, 0.00])	0.75	2

Table 5.4: The aggregated preference values, scores, and ranking of alternatives

6. Discussion

The previous section ranked $\mathscr{RES}$s. This ranking resembles the actual energy combination of many countries today (hydro remains dominant, wind and solar are rapidly rising, and biomass and geothermal are more niche sources). This assessment demonstrates a logical ranking regarding current capacity, feasibility, and policy priorities.

To evaluate such a ranking, it is necessary to look at two dimensions: Managerial(technical) and strategic(political).

From a managerial perspective, the assessment can be as follows: Hydroelectric energy contributes to grid stability with its high capacity and ease of energy storage, and has a long lifespan. According to the results, hydroelectric energy's first-place ranking indicates its existing robust infrastructure and high production capacity. Disadvantages of hydroelectric energy include its environmental impact and the risk of drought. Advantages of wind energy include its low operating costs and near-zero carbon emissions. Its second-place ranking in the current study demonstrates its acceptance as a strategic investment area, particularly in high-potential regions.. Disadvantages of wind energy include intermittent generation, noise, and location dependency. Solar energy is easy to install, modular, and has rapidly decreasing costs. The third-place ranking indicates that, despite its rapid growth, solar energy has not yet been able to provide a base load. Disadvantages of solar energy include the problem of nighttime generation, namely intermittent generation, and the need for storage. Its integration with waste management and continuous production is a strength of biomass energy. Logistical challenges associated with its raw materials and the emission generation it generates, despite being carbon neutral, are disadvantages of biomass energy. Considering its operational challenges, its fourth-place ranking in the study makes sense. Geothermal energy provides continuous, uninterrupted energy and is low in carbon. Its limited widespread applicability explains the fifth finding in the study. Disadvantages of geothermal energy include its limited local potential, high investment costs, and environmental risks.

From a strategic perspective, the evaluation can be made as follows: This ranking may reflect the responding $\mathscr{DMR}$s' country conditions or the priorities of their respective institutions. Turning to domestic resources, such as hydroelectric and wind energy, is consistent with reducing fossil fuel imports. This demonstrates the prioritization of energy security. Since solar energy ranked third in these results, it can be considered a $\mathscr{RES}$ that should be supported regarding climate policies. Biomass and geothermal energy, on the other hand, may indicate that it should be limited to local projects.

6.1. Robustness analysis

Something is solid, strong, and well-made when said to be robust. An analytical technique must yield the same result every time and everywhere it is applied, whether in the pharmaceutical, engineering, commercial, economic, or industrial sectors. The idea of method robustness was created in order to achieve this. The robustness of a technique indicates its dependability under normal operating conditions and quantifies its capacity to tolerate minor, deliberate alterations in method parameters.

One factor at a time or an experimental design assesses robustness. Since only one factor is altered and the others remain constant in the one factor at a time approach, the impact of altering one factor can be observed. Although the data is considerably easier to analyze, this strategy can take much longer than the experimental design approach, where the elements are explored simultaneously.

The COPRAS method can simultaneously evaluate both beneficial and detrimental criteria. The $\mathscr{DM}$ process is transparent, and what is calculated and how is clearly defined at each step. It has a simple and understandable structure, providing a clear ranking of alternatives, thus enabling $\mathscr{DMR}$s to make the right decision. Therefore, it is used in areas such as comparing $\mathscr{RES}$s and projects, evaluating environmental projects, product and process optimizations, and identifying different transportation systems.

The following algorithm steps of the IVFF-COPRAS method will be used for Robustness Analysis.

IVFF-COPRAS Decision Steps:

Step 1: The construction of the individual IVFF-$\mathscr{DCSM}$.

Step 2: The IVFF-weighted averaging operator is used to create the IVFF-$\mathscr{DCSM}$.

Step 3: Equation (6.1) is used to acquire the IVFF maximizing indices for the benefit criterion, while Equation (6.2) is used to compute the IVFF minimizing indices for the cost criterion.

$$a_i = \left(\left[\sqrt[3]{1-\prod_{j=1}^{l}\left(1-\zeta_{ijL}^3\right)^{\omega_j}}, \sqrt[3]{1-\prod_{j=1}^{l}\left(1-\zeta_{ijU}^3\right)^{\omega_j}} \right], \left[\prod_{j=1}^{l}\eta_{ijL}^{\omega_j}, \prod_{j=1}^{l}\eta_{ijU}^{\omega_j} \right] \right) \tag{6.1}$$

$$b_i = \left(\left[\sqrt[3]{1-\prod_{j=l+1}^{n}\left(1-\zeta_{ijL}^3\right)^{\omega_j}}, \sqrt[3]{1-\prod_{j=l+1}^{n}\left(1-\zeta_{ijU}^3\right)^{\omega_j}} \right], \left[\prod_{j=l+1}^{n}\eta_{ijL}^{\omega_j}, \prod_{j=l+1}^{n}\eta_{ijU}^{\omega_j} \right] \right) \tag{6.2}$$

where $j = 1, 2, \cdots, l$ shows benefit criteria and $j = l+1, \cdots, n$ denotes cost criteria.

Step 4: Equation (6.3) is used to calculate the relative degrees:

$$\xi_i = SC(a_i) + \frac{\sum_{i=1}^{m} SC(b_i)}{SC(b_i)\sum_{i=1}^{m} \frac{1}{SC(b_i)}} \tag{6.3}$$

where $i = 1, 2, \cdots, m$.

Step 5: Equation (6.4) is used to assess the utility degree of options:

$$U_i = \frac{\xi_i}{\xi_{max}} \times 100. \tag{6.4}$$

Step 6: The option with the highest utility degree is the best one.

Commonly, COPRAS uses criteria weights and alternative normalization to calculate each alternative's benefit rating for beneficial criteria and loss rating for non-beneficial criteria, then generates the final ranking. However, in real life, robustness analysis is performed to determine how small changes in input data can alter the ranking. This tests the decision model's reliability and the results' sensitivity.

Robustness analysis using COPRAS is performed as follows: First, calculations are performed using the COPRAS algorithm. Then, scenario changes are defined in the parameters. This way, the criterion weights are adjusted up or down by a certain percentage. Measurement errors or uncertainties are introduced. Alternatives are added and removed. Thus, COPRAS is recalculated based on the newly generated scenarios. COPRAS is repeated for each variation. The method is considered robust if two alternatives remain the same in most scenarios. The decision is considered fragile if even small changes significantly alter the ranking.

We will analyze the study's robustness using IVFF-COPRAS [55]. The IVFF-COPRAS results were identical to those obtained using the $\mathscr{MD}$ method. In order to test the solution obtained using the IVFF-COPRAS algorithm, each alternative was first removed from the issue separately. The ranking of the available options according to cost and benefit criteria is shown in Table 6.1. The table shows that the IVFF-COPRAS solution has no rank reversal problem.

Alternatives	Ranking 1	Ranking 2	Ranking 3	Ranking 4
S_1	-	-	-	-
S_2	4	-	-	-
S_3	3	2	-	-
S_4	1	1	1	-
S_5	2	3	2	2

Table 6.1: Robustness analysis

6.2. Sensitivity and stability analysis

In this study, a comprehensive sensitivity analysis was conducted to assess the stability of the proposed IVFF-MD (Interval Fermatean Fuzzy Deviation Maximization) model under small changes in experts' subjective evaluations or potential noise in the input data

Since the proposed model is based on an objective weighting mechanism, the Interval Fermatean Fuzzy Values (IVFFN) in the initial decision matrix used as input can directly affect stability. Accordingly, four different scenarios (S1, S2, S3, S4) were created by adding random variations (perturbations) to the lower and upper limits of the membership (ζ) and non-membership (η) degrees of the expert evaluations in the original decision matrix:

Scenario 1 (H_1): The membership degrees (ζ^- and ζ^+) of IVFF values in all expert evaluation matrices have been increased by 5%, and the non-membership degrees (η^- and η^+) have been decreased by 5% (normalized while preserving Fermatean cluster constraints)

Scenario 2 (H_2): Membership degrees were decreased by 5%, and non-membership degrees were increased by 5%.

Scenario 3 (H_3): A small amount of randomly distributed noise ranging from $[-0.05, +0.05]$ was added to the values in all matrices.

Scenario 4 (H_4): To assess the magnitude of data fluctuations, the random noise ratio was increased to the range $[-0.10, +0.10]$ (10% change).

The proposed IVFF-MD model was rerun for these 4 different scenarios, and the new criterion weights (ω_j) were calculated. The final ranking of the alternatives was recalculated using the COPRAS method with the new weights. The effect of these subtle changes in the input data on the criterion weights is presented in Table 6.2.

Table 6.2 shows that intentional changes of 5% to 10% to the input matrices and the addition of random noise lead to very small, negligible fluctuations in the objective criterion weights generated by the IVFF-MD model. The relative positions of the criterion with the highest importance, C_3, and the criterion with the lowest importance, C_{10}, as well as the overall importance hierarchy among all criteria (in all S1, S2, S3, and S4 scenarios), are completely preserved.

The alternative rankings obtained by integrating these new weight sets into the COPRAS ranking algorithm are presented in Table 6.3 and shown in Figure 6.1.

The results in Table 6.3 clearly demonstrate that the developed methodology is highly stable. The best alternative (A_2) and the second best alternative (A_1) maintained their positions and stability even when the input data was skewed by 10% (S4). Only in Scenario 4, which contains extreme noise, was a local swap observed between alternatives A_3 and A_5, which have very close performance scores.

	Original Weights	H_1	H_2	H_3	H_4
K_1	0.1245	0.1239	0.1251	0.1240	0.1232
K_2	0.0982	0.0985	0.0978	0.0989	0.0994
K_3	0.1510	0.1502	0.1515	0.1512	0.1498
K_4	0.0874	0.0870	0.0879	0.0868	0.0881
K_5	0.1136	0.1141	0.1130	0.1132	0.1145
K_6	0.0761	0.0765	0.0758	0.0766	0.0755
K_7	0.1324	0.1319	0.1330	0.1321	0.1332
K_8	0.0652	0.0650	0.0655	0.0659	0.0646
K_9	0.0918	0.0922	0.0912	0.0911	0.0926
K_{10}	0.0598	0.0607	0.0592	0.0602	0.0591

Table 6.2: Changes in criterion weights according to different sensitivity scenarios

	Original Ranking	H_1	H_2	H_3	H_4
A_1	2	2	2	2	2
A_2	1	1	1	1	1
A_3	4	4	4	4	5
A_4	3	3	3	3	3
A_5	5	5	5	5	4

Table 6.3: Ranking results of alternatives according to scenarios

To statistically assess the high agreement between scenarios, Spearman's Rank Correlation Coefficient (r_s) was calculated between the original ranking and the scenario rankings. The correlation between the original ranking and S1, S2, and S3 was $r_s = 1.000$ (perfect agreement); the correlation with the 10% noisy S4 scenario was $r_s = 0.900$. The extremely high average correlation coefficient of 0.975 demonstrates that the proposed IVFF-MD-based MCDM model is highly robust, insensitive, and stable to uncertainties and small deviations in the input data.

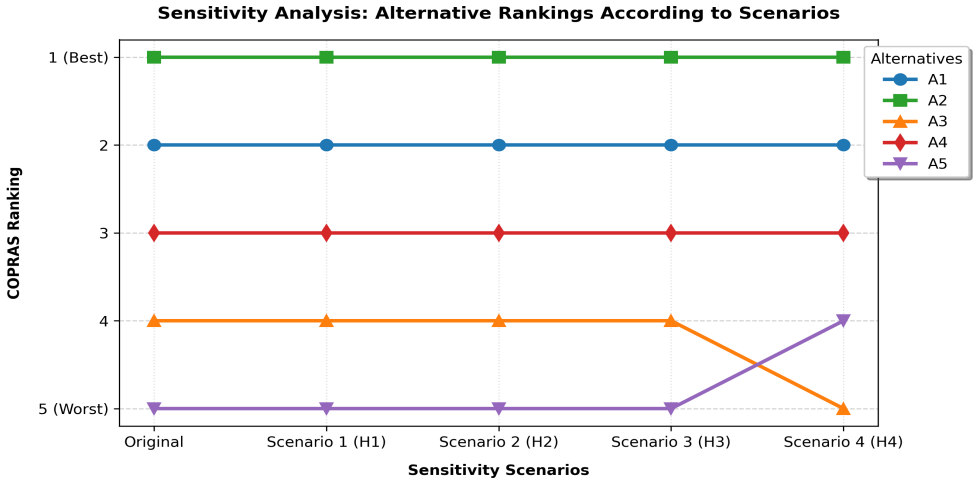


Figure 6.1: Sensitivity analysis

6.3. Comparative analysis

First, the results of two studies ([56, 57]) with RES selection will be presented for the comparative analysis. Then, the ordering will be performed using the $\mathscr{MD}$ method based on intuitionistic fuzzy and Pythagorean fuzzy sets ([9], [14]).

Method	Ranking
PF-MDM [14]	$S_4 > S_1 > S_2 > S_5 > S_3$
IF-MDM [9]	$S_4 > S_2 > S_5 > S_1 > S_3$
BOCR - AHP [56]	$S_4 > S_3 > S_5 > S_1 > S_2$
AHP-TOPSIS [57]	$S_4 > S_5 > S_2 > S_3 > nuclear$
Proposed Method	$S_4 > S_5 > S_3 > S_2 > S_1$

Table 6.4: Comparative analysis

6.4. Implications

Choosing $\mathscr{RES}$s is not just a technical matter but has significant managerial and policy implications. These impacts can vary depending on which source (solar, wind, hydro, biomass, geothermal, etc.) is chosen in the $\mathscr{DM}$ process.

Managerial implications: This proposed method and the ranking of $\mathscr{RES}$s provide clear information for investment strategies and risk management. When choosing renewable resources, energy companies must consider capital intensity, payback period, and technological risks. For example, solar panels may offer shorter-term profitability, while geothermal investments have longer-term and higher initial costs. This ranking increases operational efficiency and simplifies technology selection. Managers must also determine infrastructure optimization, maintenance strategies, and resource selection. For example, wind turbines are maintenance-intensive, while solar panels require less maintenance. Diversifying the portfolio provides a competitive advantage. By investing in different renewable resources, companies can diversify their energy portfolio. This diversity provides a more robust position against market fluctuations, improves financial performance, and creates attractiveness for investors. Choosing the right resource increases investor confidence and facilitates raising funds within sustainability criteria (environmental, social, and governance - ESG). This brings the concept of corporate sustainability to life and positively impacts the image of countries/institutions. A country's or company's choice of renewable resources directly impacts its brand image and stakeholder trust. For example, a shift toward low-carbon resources like solar and wind strengthens perceptions of environmental responsibility.

Policy implications: This proposed method and ranking of $\mathscr{RES}$s are essential to countries' energy security and, consequently, their independence. Thus, resource selection can reduce a country's dependence on energy imports. For example, Türkiye's solar and wind potential investment can reduce fossil fuel imports and the current account deficit. It also offers rich opportunities for regional development and employment policies. Policymakers can support regional employment and local development through renewable resource selection. For example, wind turbine factories or solar panel assembly facilities can stimulate the regional economy. This can be beneficial for countries to formulate climate policies in line with international policies and fulfill their international obligations. Fulfilling international climate commitments, such as the Paris Agreement and the Green Deal, determines resource selection. Choosing low-carbon resources contributes to greenhouse gas emission reduction targets. Properly using a country's resources can facilitate incentive mechanisms, making regulatory processes easier. This is because the state can implement incentives (feed-in tariffs, tax deductions, investment credits) to prioritize specific resources. This allows internal and external investors to influence their preferences directly. Considering these rankings will play a decisive role in infrastructure network planning. Policymakers will develop policies for energy storage, smart grids, and a balanced energy mix based on the source selection. Selecting $\mathscr{RE}$ systems within the framework of environmentally sound policies will facilitate social acceptance and ensure public support. As is well known, while hydroelectricity may face environmental and social objections in some regions, solar projects generally enjoy higher social acceptance.

Managerial and policy implications of $\mathscr{RES}$s ranked and analyzed for robustness using the $\mathscr{MCDM}$ technique are shown in Figure 6.2.

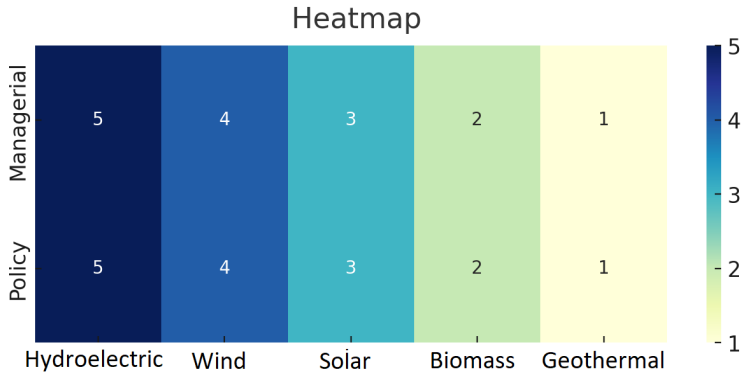


Figure 6.2: Heatmap

7. Conclusion

Since IVFFS is a generalization of IVIFS and IVPFS, it can represent more ambiguous data, suggesting that it may be more suited to managing real-world $\mathscr{DM}$ applications. The environment's complexity and unpredictability mean that the weights of $\mathscr{DMR}$s and qualities are never fully understood or known. The $\mathscr{MD}$ approach is suggested to get over this restriction and tackle such $\mathscr{MCDM}$ issues. In this research, we explore the $\mathscr{MCDM}$ problems using IVFFSs by combining the IVFFS with the traditional $\mathscr{MD}$ method. We build two new $\mathscr{DM}$ models based on the conventional $\mathscr{MD}$ technique and the fundamental ideas of IVFFSs. Additionally, we have used the new models we suggested to tackle the $\mathscr{MCDM}$ problems using IVFF data.

In order to assess the choice of $\mathscr{RES}$s, an example is provided at the end, confirming the accuracy and scientific validity of the established model. The benefits of our proposed methods include expanding the breadth of assessment information and resolving $\mathscr{MCDM}$ difficulties with incomplete attribute weights. Though it is challenging to get relevant $\mathscr{DM}$ data because there are not enough $\mathscr{DMR}$s with an architectural background and fuzzy theory, the recently described models can produce more accurate $\mathscr{DM}$ results.

The rankings from this study will provide significant guidance on administrative investment priorities, R&D budgets, and infrastructure planning. It will also guide the selection of resources used to determine incentives, feed-in tariffs, local employment programs, and environmental regulations.

Future Research Directions:

Considering the success and limitations of the methodological framework presented in this study, the following strategic directions and areas for development are suggested for future research:

Expansion with Different Fuzzy Frameworks: The proposed Deviation Maximization (MD)- based optimization model is grounded in Interval-Valued Fermatean Fuzzy Sets (IVFFS). In future studies, this weighting mechanism can be adapted to more recent fuzzy theories, such as Linear Diophantine Fuzzy Sets (LDFS), Spherical Fuzzy Sets, or Type-2 Fuzzy Sets, which manage membership degrees more flexibly through exogenous control parameters, thereby deepening comparative analyses.

Adaptation to Large-Scale and Dynamic Decision Problems: To alleviate the computational complexity of the developed linear programming models, optimization processes can be integrated with meta-heuristic algorithms (Genetic Algorithms, Particle Swarm Optimization, etc.) in future research. Thus, big data-based industrial decision problems involving hundreds of criteria or alternatives can be solved in much shorter time frames.

Diversification of Application Areas: This study focuses on selecting renewable energy sources. The proposed unbiased and objective weighting model can be applied to various strategic and operational MCDM problems, such as green supply chain management, smart city location selection, sustainable waste management, and risk analysis in the healthcare sector, and its robustness can be tested across these fields.

Software Integration and Decision Support Systems: To enable decision-makers to use the method in practice without directly encountering mathematical equations and optimization constraints, a web-based or open-source (R, Python libraries, etc.) user-friendly Decision Support System (DSS) interface can be developed that runs the proposed IVFF-MD-COPRAS algorithm in the background.

Abbreviations and Symbols

Abbreviation	**Description**
MCDM	Multi-Criteria Decision-Making
IFS	Intuitionistic Fuzzy Set
PFS	Pythagorean Fuzzy Set
FFS	Fermatean Fuzzy Set
IVFFS	Interval-Valued Fermatean Fuzzy Set
IVFFN	Interval-Valued Fermatean Fuzzy Number
MD	Maximizing Deviation
IVFF-MD	Interval-Valued Fermatean Fuzzy Maximizing Deviation
COPRAS	Complex Proportional Assessment
TOPSIS	Technique for Order of Preference by Similarity to Ideal Solution
DM	Decision-Maker
LDFS	Linear Diophantine Fuzzy Set
Symbols	**Description**
X	The universe of discourse
x	An element belonging to the universe of discourse X
$\zeta_F(x)$	Membership degree of the element x in a fuzzy framework
$\eta_F(x)$	Non-membership degree of the element x in a fuzzy framework
$\theta_F(x)$	Hesitation degree of the element x in a fuzzy framework
$[\zeta_{FL}, \zeta_{FU}]$	Interval-valued membership bounds (lower and upper)
$[\eta_{FL}, \eta_{FU}]$	Interval-valued non-membership bounds (lower and upper)
$[\theta_{FL}, \theta_{FU}]$	Interval-valued hesitation bounds (lower and upper)
$DIST(F_1, F_2)$	Distance measure between two interval-valued Fermatean fuzzy numbers
ω_j	Weight of the j-th criterion
ω_j^k	Weight of the j-th criterion assigned by the k-th decision-maker
λ_k	Weight/importance coefficient of the k-th decision-maker
$\mathfrak{L}$	Lagrange function used for weight optimization models
λ	Lagrange multiplier parameter
C_j	The j-th selection/evaluation criterion ($j = 1, 2, \ldots, n$)
A_i	The i-th alternative energy source ($i = 1, 2, \ldots, m$)
r_s	Spearman's rank correlation coefficient

Abbreviations and Symbols

Article Information

Artificial Intelligence Statement: The preparation of this article involved the use of certain artificial intelligence-based tools for language and writing support. Grammarly EDU was used for English grammar and phrasing corrections. ChatGPT was employed to emphasize the results more clearly in the abstract. In addition, ChatGPT was used to revise the section concerning Linear Diophantine fuzzy sets in accordance with the reviewers' suggestions. Furthermore, ChatGPT was consulted regarding whether this topic should be addressed in the Conclusion section, and it was decided not to include any additional explanation on the subject in that section. All content and suggestions generated by artificial intelligence tools were reviewed by the authors, and necessary revisions were made. The final manuscript was prepared under the full responsibility of the authors.

Conflict of Interest Disclosure: No potential conflict of interest was declared by the author.

Plagiarism Statement: This article was scanned by the plagiarism program.

References

[1] H. C. Lee, C. T. Chang, *Comparative analysis of MCDM methods for ranking renewable energy sources in Taiwan*, Renew. Sustain. Energy Rev., **92** (2018), 883-896. https://doi.org/10.1016/j.rser.2018.05.007

[2] REN21, *Renewables 2025 Global Status Report*, (2025). https://www.ren21.net/gsr-2025/

[3] International Energy Agency, *Global Energy Review 2025*, (2025). https://www.iea.org/reports/global-energy-review-2025

[4] L. A. Zadeh, *Fuzzy sets*, Inform. and Control, **8**(3) (1965), 338-353. https://doi.org/10.1016/S0019-9958(65)90241-X

[5] Y. M. Wang, *Using the method of maximizing deviation to make decision for multiindices*, J. Syst. Eng. Electron., **8**(3) (1997), 21-26.

[6] K. Atanassov, *Intuitionistic fuzzy sets*, Fuzzy Sets Syst., **20**(1) (1986), 87-96. https://doi.org/10.1016/S0165-0114(86)80034-3

[7] F. Boran, K. Boran, T. Menlik, *The evaluation of renewable energy technologies for electricity generation in Turkey using intuitionistic fuzzy TOPSIS*, Energy Sources Part B, **7**(1) (2012), 81-90. https://doi.org/10.1080/15567240903047483

[8] C. Dumrul, F. Bilgili, F. Zarali, et al., *The evaluation of renewable energy alternatives in Turkey using intuitionistic-fuzzy EDAS methodology*, Environ. Sci. Pollut. Res., **31**(10) (2024), 15503-15524. https://doi.org/10.1007/s11356-023-31816-7

[9] G. W. Wei, *Maximizing deviation method for multiple attribute decision making in an intuitionistic fuzzy setting*, Knowl.-Based Syst., **21**(8) (2008), 833-836. https://doi.org/10.1016/j.knosys.2008.03.038

[10] R. R. Yager, *Pythagorean fuzzy subsets*, Proc. 2013 Joint IFSA World Congr. NAFIPS Annu. Meet., Edmonton, Canada, (2013), 57-61. https://doi.org/10.1109/IFSA-NAFIPS.2013.6608375

[11] R. R. Yager, *Pythagorean membership grades in multicriteria decision-making*, IEEE Trans. Fuzzy Syst., **22**(4) (2014), 958-965. https://doi.org/10.1109/TFUZZ.2013.2278989

[12] S. J. Hosseini Dehshiri, M. Amiri, A. Mostafaeipour, et al., *Evaluation of renewable energy projects based on sustainability goals using a hybrid Pythagorean fuzzy-based decision approach*, Energy, **297** (2024), Article ID 131272. https://doi.org/10.1016/j.energy.2024.131272

[13] M. Kirişci, İ. Demir, N. Şimşek, et al., *The novel VIKOR methods for generalized Pythagorean fuzzy soft sets and its application to children of early childhood in COVID-19 quarantine*, Neural Comput. Appl., **34**(3) (2022), 1877-1903. https://doi.org/10.1007/s00521-021-06427-3

[14] W. Liang, X. Zhang, M. Liu, *The maximizing deviation method based on an interval-valued Pythagorean fuzzy weighted aggregating operator for multiple criteria group decision analysis*, Discrete Dyn. Nat. Soc., **2015** (2015), Article ID 746572. https://doi.org/10.1155/2015/746572

[15] T. Senapati, R. R. Yager, *Fermatean fuzzy sets*, J. Ambient Intell. Humaniz. Comput., **11** (2020), 663-674. https://doi.org/10.1007/s12652-019-01377-0

[16] T. Senapati, R. R. Yager, *Some new operations over Fermatean fuzzy numbers and application of Fermatean fuzzy WPM in multiple criteria decision making*, Informatica, **30**(2) (2019), 391-412. https://doi.org/10.15388/Informatica.2019.211

[17] H. Garg, G. Shahzadi, M. Akram, *Decision-making analysis based on Fermatean fuzzy Yager aggregation operators with application in COVID-19 testing facility*, Math. Probl. Eng., **2020** (2020), Article ID 7279027. https://doi.org/10.1155/2020/7279027

[18] N. Alkan, C. Kahraman, *Prioritization of supply chain digital transformation strategies using multi-expert Fermatean fuzzy analytic hierarchy process*, Informatica, **34**(1) (2023), 1-33. https://doi.org/10.15388/22-INFOR493

[19] S. Jeevaraj, *Ordering of interval-valued Fermatean fuzzy sets and its applications*, Expert Syst. Appl., **185** (2021), Article ID 115613. https://doi.org/10.1016/j.eswa.2021.115613

[20] M. Kirişci, *Data analysis for panoramic X-ray selection: Fermatean fuzzy type correlation coefficients approach*, Eng. Appl. Artif. Intell., **126** (2023), Article ID 106824. https://doi.org/10.1016/j.engappai.2023.106824

[21] M. Kirişci, *Correlation coefficients of Fermatean fuzzy sets with a medical application*, J. Math. Sci. Model., **5**(1) (2022), 16-23. https://doi.org/10.33187/jmsm.1039613

[22] M. Kirişci, N. Şimşek, *A novel kernel principal component analysis with application disaster preparedness of hospital: Interval-valued Fermatean fuzzy set approach*, J. Supercomput., **79** (2023), 19848-19878. https://doi.org/10.1007/s11227-023-05395-w

[23] D. Liu, Y. Liu, X. Chen, *Fermatean fuzzy linguistic set and its application in multicriteria decision-making*, Int. J. Intell. Syst., **34**(5) (2019), 878-894. https://doi.org/10.1002/int.22079

[24] T. Senapati, R. R. Yager, *Fermatean fuzzy weighted averaging/geometric operators and its application in multi-criteria decision-making methods*, Eng. Appl. Artif. Intell., **85** (2019), 112-121. https://doi.org/10.1016/j.engappai.2019.05.012

[25] N. Şimşek, M. Kirişci, *Incomplete Fermatean fuzzy preference relations and group decision-making*, Topol. Algebra Appl., **11**(1) (2023), Article ID 20220125. https://doi.org/10.1515/taa-2022-0125

[26] M. Kolagar, S. M. H. Hosseini, R. Felegari, et al., *Policy-making for renewable energy sources in search of sustainable development: A hybrid DEA-FBWM approach*, Environ. Syst. Decis., **40**(4) (2020), 485-509. https://doi.org/10.1007/s10669-019-09747-x

[27] L. Xu, Y. Wang, S. A. A. Shah, et al., *Economic viability and environmental efficiency analysis of hydrogen production processes for the decarbonization of energy systems*, Processes, **7**(8) (2019), Article ID 494. https://doi.org/10.3390/pr7080494

[28] S. K. Jha, H. Puppala, *Prospects of renewable energy sources in India: Prioritization of alternative sources in terms of energy index*, Energy, **127** (2017), 116-127. https://doi.org/10.1016/j.energy.2017.03.110

[29] Y. A. Solangi, S. A. A. Shah, H. Zameer, et al., *Assessing the solar PV power project site selection in Pakistan: Based on AHP-fuzzy VIKOR approach*, Environ. Sci. Pollut. Res., **26**(29) (2019), 30286-30302. https://doi.org/10.1007/s11356-019-06172-0

[30] S. A. A. Shah, *Feasibility study of renewable energy sources for developing the hydrogen economy in Pakistan*, Int. J. Hydrogen Energy, **45**(32) (2020), 15841-15854. https://doi.org/10.1016/j.ijhydene.2019.09.153

[31] C. Longsheng, S. A. A. Shah, Y. A. Solangi, et al., *An integrated SWOT-multi-criteria analysis of implementing sustainable waste-to-energy in Pakistan*, Renew. Energy, **195** (2022), 1438-1453. https://doi.org/10.1016/j.renene.2022.06.112

[32] C. Kahraman, İ. Kaya, S. Cebi, *A comparative analysis for multiattribute selection among renewable energy alternatives using fuzzy axiomatic design and fuzzy analytic hierarchy process*, Energy, **34**(10) (2009), 1603-1616. https://doi.org/10.1016/j.energy.2009.07.008

[33] A. Alshamrani, P. Majumder, A. Das, et al., *An integrated BWM-TOPSIS-I approach to determine the ranking of alternatives and application of sustainability analysis of renewable energy*, Axioms, **12**(2) (2023), Article ID 159. https://doi.org/10.3390/axioms12020159

[34] B. Ozturk, X. Chen, G. Budak, *Ranking renewable energy alternatives for Chicago by integrated analytic hierarchy process and VIseKriterijumska Optimizacija I Kompromisno Resenje*, Int. J. Environ. Sci. Technol., **21** (2024), 5411-5420. https://doi.org/10.1007/s13762-023-05374-x

[35] A. M. Husain, M. M. Hasan, Z. A. Khan, et al., *A robust decision-making approach for the selection of an optimal renewable energy source in India*, Energy Convers. Manage., **301** (2024), Article ID 117989. https://doi.org/10.1016/j.enconman.2023.117989

[36] J. Luhaniwal, S. Agarwal, T. Mathur, *An integrated DEA-fuzzy AHP method for prioritization of renewable energy sources in India*, Sci. Rep., **15**(1) (2025), Article ID 838. https://doi.org/10.1038/s41598-024-84891-2

[37] R. Shamsipour, A. Nohegar, A. H. Ehsani, et al., *A comprehensive assessing of renewable energy sources ranking by fuzzy DANP and fuzzy MULTIMOORA (case study Isfahan Province, Iran)*, Int. J. Environ. Res., **19** (2025), Article ID 137. https://doi.org/10.1007/s41742-025-00763-1

[38] S. Wang, W. Li, H. Dincer, et al., *Recognitive approach to the energy policies and investments in renewable energy resources via the fuzzy hybrid models*, Energies, **12**(23) (2019), Article ID 4536. https://doi.org/10.3390/en12234536

[39] M. E. M. Abdalla, A. Uzair, A. Ishtiaq, et al., *Algebraic structures and practical implications of interval-valued Fermatean neutrosophic super HyperSoft sets in healthcare*, Spectrum Oper. Res., **2**(1) (2025), 240-259. https://doi.org/10.31181/sor21202523

[40] M. Tahir, M. I. Shahid, *An intelligent Industry 5.0 logistics decision system: Circular supply chain management with Fermatean neutrosophic hypersoft sets and machine learning*, J. Contemp. Decis. Sci., **2**(1) (2026), 260-286. https://doi.org/10.67334/cds21202618

[41] J. Jin, X. Yang, H. Du, et al., *A novel interval-valued intuitionistic fuzzy distance measure incorporating min/max interaction terms*, J. Contemp. Decis. Sci., **2**(1) (2026), 84-96. https://doi.org/10.67334/cds21202610

[42] A. Adak, D. Pamucar, W. Ali, *Solving Pythagorean fuzzy assignment problems in management: A framework based on spherical distance measures*, Manag. Sci. Adv., **3**(1) (2026), 84-95. https://doi.org/10.31181/msa31202636

[43] Z. Wu, Y. Chen, *The maximizing deviation method for group multiple attribute decision making under a linguistic environment*, Fuzzy Sets Syst., **158**(14) (2007), 1608-1617. https://doi.org/10.1016/j.fss.2007.01.013

[44] R. Şahin, P. Liu, *Maximizing deviation method for neutrosophic multiple attribute decision making with incomplete weight information*, Neural Comput. Appl., **27** (2016), 2017-2029. https://doi.org/10.1007/s00521-015-1995-8

[45] G. Selvachandran, S. G. Quek, F. Smarandache, et al., *An extended technique for order preference by similarity to an ideal solution (TOPSIS) with maximizing deviation method based on integrated weight measure for single-valued neutrosophic sets*, Symmetry, **10**(7) (2018), Article ID 236. https://doi.org/10.3390/sym10070236

[46] W. Xiong, J. Cheng, *A novel method for determining the attribute weights in the multiple attribute decision-making with neutrosophic information through maximizing the generalized single-valued neutrosophic deviation*, Information, **9**(6) (2018), Article ID 137. https://doi.org/10.3390/info9060137

[47] D. Pamucar, S. Sremac, Ž. Stević, et al., *New multi-criteria LNN WASPAS model for evaluating the work of advisors in the transport of hazardous goods*, Neural Comput. Appl., **31** (2019), 5045-5068. https://doi.org/10.1007/s00521-018-03997-7

[48] W. Deebani, M. Ibrar, Z. Shah, et al., *An integrated T-spherical fuzzy 2-tuple linguistic WASPAS framework with Hamy mean aggregation for wildlife conservation planning*, J. Appl. Math., **2026**(1) (2026), Article ID 2428239. https://doi.org/10.1155/jama/2428239

[49] Y. Zhang, G. Xu, *A possible degree-based D-S evidence theory method for ranking new energy vehicles based on online customer reviews and probabilistic linguistic term sets*, Mathematics, **13**(4) (2025), Article ID 583. https://doi.org/10.3390/math13040583

[50] Z. Liu, D. Wang, M. Deveci, et al., *Interval-valued Pythagorean fuzzy distance-based extended inferior ratio method for multiattribute decision-making: Application to green supplier selection in manufacturing industry*, Appl. Soft Comput., **185** (2025), Article ID 113935. https://doi.org/10.1016/j.asoc.2025.113935

[51] P. Rani, A. R. Mishra, *Interval-valued Fermatean fuzzy sets with multi-criteria weighted aggregated sum product assessment-based decision analysis framework*, Neural Comput. Appl., **34**(10) (2022), 8051-8067. https://doi.org/10.1007/s00521-021-06782-1

[52] M. Riaz, M. R. Hashmi, *Linear Diophantine fuzzy set and its applications towards multi-attribute decision-making problems*, J. Intell. Fuzzy Syst., **37**(4) (2019), 5417-5439. https://doi.org/10.3233/JIFS-190550

[53] J. J. Wang, Y. Y. Jing, C. F. Zhang, et al., *Review on multi-criteria decision analysis aid in sustainable energy decision-making*, Renew. Sustain. Energy Rev., **13**(9) (2009), 2263-2278. https://doi.org/10.1016/j.rser.2009.06.021

[54] E. W. Stein, *A comprehensive multi-criteria model to rank electric energy production technologies*, Renew. Sustain. Energy Rev., **22** (2013), 640-654. https://doi.org/10.1016/j.rser.2013.02.001

[55] A. R. Mishra, P. Liu, P. Rani, *COPRAS method based on interval-valued hesitant Fermatean fuzzy sets and its application in selecting desalination technology*, Appl. Soft Comput., **119** (2022), Article ID 108570. https://doi.org/10.1016/j.asoc.2022.108570

[56] M. Kabak, M. Dağdeviren, *Prioritization of renewable energy sources for Turkey by using a hybrid MCDM methodology*, Energy Convers. Manage., **79** (2014), 25-33. https://doi.org/10.1016/j.enconman.2013.11.036

[57] J. Ren, B. K. Sovacool, *Prioritizing low-carbon energy sources to enhance China's energy security*, Energy Convers. Manage., **92** (2015), 129-136. https://doi.org/10.1016/j.enconman.2014.12.044