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BENCHMARKING FUZZY-BASED MCDM APPROACHES IN RENEWABLE ENERGY SOURCES SELECTION: A NEW INTERVAL-VALUED NEUTROSOPHIC FUZZY DEMATEL-ANP-TOPSIS FRAMEWORK

Yakup ÇELİKBİLEK*

*Assoc. Prof. Dr., Istanbul University, Faculty of Science, Department of Computer Science, yakup.celikbilek@istanbul.edu.tr, ORCID ID: 0000-0003-0585-1085

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ABSTRACT

Assessing renewable energy resources requires robust multi-criteria decision-making tools capable of handling uncertainty, vagueness, and the complex interactions among sustainability-related criteria. This study provides a comprehensive comparison of several widely used fuzzy-based multi-criteria decision-making methods applied to renewable energy source evaluation, including Fuzzy DEMATEL, Fuzzy AHP, Fuzzy ANP, Fuzzy TOPSIS, Fuzzy VIKOR, Fuzzy COPRAS, Fuzzy ELECTRE, etc., and also spherical, intuitionistic or neutrosophic fuzzy variants reported in the literature. By applying each method to the same dataset, the analysis highlights the similarities, divergences, and sensitivity patterns that emerge across different fuzzy modelling perspectives. Building on these comparative insights, the study introduces a novel interval-valued neutrosophic fuzzy hybrid decision-making framework integrating DEMATEL, ANP, and TOPSIS. In the proposed model, interval-valued neutrosophic fuzzy DEMATEL is employed to capture causal relationships among criteria and determine influence weights, while interval-valued neutrosophic fuzzy ANP models interdependencies within the decision network. Finally, interval-valued neutrosophic fuzzy TOPSIS is used to generate a robust and discriminative ranking of renewable energy source alternatives. The results demonstrate that the hybrid interval-valued neutrosophic framework offers enhanced consistency, stronger representation of expert hesitation, and improved prioritization stability compared with conventional fuzzy MCDM methods. Overall, this study advances the methodological landscape of renewable energy source decision-making by both benchmarking existing fuzzy techniques and proposing an innovative interval-valued neutrosophic hybrid approach that can support more reliable and sustainable energy planning.

Keywords: Renewable Energy Sources, TOPSIS, ANP, MCDM, interval-valued neutrosophic sets.
JEL Classification: C44, P28, Q29

YENİLENEBİLİR ENERJİ KAYNAKLARININ SEÇİMİNDE BULANIK TABANLI ÇKKV YAKLAŞIMLARININ KARŞILAŞTIRILMASI: YENİ BİR ARALIK DEĞERLİ NÖTROSOFİK BULANIK DEMATEL-ANP-TOPSIS ÇERÇEVESİ

ÖZET

Yenilenebilir enerji kaynaklarının değerlendirilmesi; belirsizlik, muğlaklık ve sürdürülebilirlikle ilişkili kriterler arasındaki karmaşık etkileşimleri ele alabilen sağlam çok kriterli karar verme araçlarını gerektirmektedir. Bu çalışma, yenilenebilir enerji kaynağı değerlendirmesinde uygulanan ve yaygın olarak kullanılan çeşitli bulanık tabanlı çok kriterli karar verme yöntemlerinin kapsamlı bir karşılaştırmasını sunmaktadır. Bu yöntemler arasında Bulanık DEMATEL, Bulanık AHP, Bulanık ANP, Bulanık TOPSIS, Bulanık VIKOR, Bulanık COPRAS, Bulanık ELECTRE gibi yaklaşımlar ile literatürde rapor edilen küresel, sezgisel veya nötrosofik bulanık varyantlar yer almaktadır. Her bir yöntemin aynı veri seti üzerinde uygulanmasıyla gerçekleştirilen analiz, farklı bulanık modelleme bakış açıları arasında ortaya çıkan benzerlikleri, ayrışmaları ve duyarlılık örüntülerini ortaya koymaktadır. Bu karşılaştırmalı bulgular üzerine inşa edilen çalışmada, DEMATEL, ANP ve TOPSIS yöntemlerini bütünleştiren yeni bir aralık değerli nötrosofik bulanık hibrit karar verme çerçevesi önerilmektedir. Önerilen modelde, kriterler arasındaki nedensel ilişkileri yakalamak ve etki ağırlıklarını belirlemek amacıyla aralık

değerli nötrosofik bulanık DEMATEL kullanılmaktadır. Karar ağındaki karşılıklı bağımlılıkların modellenmesi için aralık değerli nötrosofik bulanık ANP uygulanmaktadır. Son aşamada ise yenilenebilir enerji kaynağı alternatiflerinin sağlam ve ayırt edici bir sıralamasını elde etmek amacıyla aralık değerli nötrosofik bulanık TOPSIS yöntemi kullanılmaktadır. Elde edilen sonuçlar, hibrit aralık değerli nötrosofik çerçevenin, geleneksel bulanık ÇKKV yöntemlerine kıyasla daha yüksek tutarlılık, uzman tereddüdünün daha güçlü bir temsili ve önceliklendirme kararlılığında iyileşme sunduğunu göstermektedir. Genel olarak bu çalışma, mevcut bulanık teknikleri karşılaştırmalı olarak değerlendirmesinin yanı sıra, daha güvenilir ve sürdürülebilir enerji planlamasını destekleyebilecek yenilikçi bir aralık değerli nötrosofik hibrit yaklaşım önererek yenilenebilir enerji kaynağı karar verme alanındaki metodolojik literatüre katkı sağlamaktadır.
Anahtar Kelimler: Yenilenebilir Enerji Kaynakları, TOPSIS, ANP, ÇKKV, Aralık Değerli Nötrosofik Setler.
JEL Sınıflandırması: C44, P28, Q29

1. INTRODUCTION

The accelerating transition toward low-carbon energy systems has intensified global interest in renewable energy sources as viable alternatives to conventional fossil-based technologies. Governments, energy planners, and policymakers are increasingly required to evaluate a diverse range of renewable options-such as solar, wind, biomass, geothermal, and hydropower-each presenting unique technological characteristics, investment requirements, operational constraints, and environmental implications. Selecting the most appropriate renewable energy source is, therefore, not merely a technical decision but a strategic and multidimensional process that must account for sustainability targets, regional resource availability, socio-economic conditions, and long-term policy objectives. This complexity underscores the importance of systematic decision-making frameworks capable of integrating heterogeneous information and accommodating uncertain expert judgments.

Renewable energy planning naturally involves multiple, often conflicting criteria, including cost competitiveness, energy efficiency, environmental performance, social acceptance, technological maturity, and infrastructural compatibility. These criteria are interdependent and context-specific, making the selection task highly sensitive to both subjective assessments and contextual uncertainties. Traditional decision-making approaches, based on crisp numerical evaluations, typically assume well-defined preferences and deterministic conditions-assumptions that rarely hold in real-world energy evaluation processes. Experts frequently rely on linguistic expressions such as “high potential”, “moderate risk”, or “low cost-effectiveness”, which inherently contain vagueness and imprecision. This situational ambiguity necessitates analytical approaches capable of reflecting human cognitive uncertainty more accurately.

In this context, fuzzy set theory and its extensions have been widely adopted for multi-criteria energy decision-making due to their ability to model ambiguity, subjective opinions, and incomplete information. Over the past two decades, numerous fuzzy-based Multi-Criteria Decision Making (MCDM) methods -such as Fuzzy AHP, Fuzzy ANP, Fuzzy TOPSIS, Fuzzy VIKOR, Fuzzy DEMATEL, and their advanced variants including interval-valued, intuitionistic, spherical fuzzy forms, etc.- have been applied to renewable energy planning. Each method offers distinct modelling capabilities: hierarchical weighting in Fuzzy AHP, network-based dependency representation in Fuzzy ANP, distance-based ranking in Fuzzy TOPSIS, compromise-based evaluation in Fuzzy VIKOR, and causal influence analysis in Fuzzy DEMATEL. Although these approaches have contributed substantially to the literature, there remains limited comparative evidence regarding how they differ when applied to a common dataset, and how their outputs converge or diverge under identical decision conditions.

A further limitation in the existing literature is the lack of hybrid decision-making models that simultaneously integrate causal relationship analysis, interdependent weighting mechanisms, and robust ranking procedures within a unified fuzzy framework. Neutrosophic fuzzy sets, introduced to more comprehensively represent expert hesitation via truth-membership, indeterminacy-membership and falsity-membership degrees, offer an advanced mathematical foundation for modelling uncertainty. However, neutrosophic fuzzy hybrid models combining DEMATEL, ANP, and TOPSIS remain underexplored especially for renewable energy planning. Such an integrated structure has the potential to enhance decision consistency by capturing cause-effect structures, modelling criteria interdependencies, and strengthening alternative ranking robustness based on neutrosophic evaluations.

Motivated by these gaps, this study first conducts a comprehensive benchmarking analysis of widely used fuzzy-based MCDM methods applied to RES selection. By evaluating multiple prominent fuzzy methods on a common dataset, the study generates comparative insights into methodological performance, ranking sensitivity, and decision stability across different fuzzy approaches. Building on these insights, the study introduces a novel hybrid Interval-Valued Neutrosophic Fuzzy DEMATEL–ANP–TOPSIS framework designed to address key limitations of existing approaches. The proposed model leverages interval-valued neutrosophic fuzzy DEMATEL for rigorous causal mapping, interval-valued neutrosophic fuzzy ANP for deriving interdependent criteria weights, and interval-valued neutrosophic fuzzy TOPSIS for generating a transparent, distance-based ranking of renewable energy source alternatives. The framework aims to improve modelling granularity and reduce ambiguity in expert evaluations while providing a more analytically grounded decision structure.

The main contributions of this paper are threefold. First, it presents one of the most systematic benchmarking studies comparing major fuzzy-based MCDM methods for renewable energy source selection using identical criteria and alternatives. Second, it proposes a novel hybrid interval-valued neutrosophic fuzzy decision-making model that integrates causal, relational, and ranking components. Third, it validates the proposed model and demonstrates its analytical advantages through comparative analyses, sensitivity evaluations, and methodological robustness tests.

The remainder of this paper is structured as follows. Section 2 provides a detailed literature review on renewable energy sources (RES) decision-making and fuzzy Multi-Criteria Decision Making (MCDM) approaches. Section 3 describes the methodological framework, datasets, and computational procedures used in both the benchmarking and hybrid model. Section 4 reports the outcomes of the proposed interval-valued neutrosophic hybrid framework. Section 5 offers visualization, comparison and interpretation of the results. Finally, Section 6 concludes the study with discussions and conclusions including key insights and future research directions.

2. LITERATURE REVIEW AND RENEWABLE ENERGY SOURCE DECISION-MAKING APPROACHES

The evaluation of renewable energy sources (RES) has increasingly relied on fuzzy multi-criteria decision-making (MCDM) methods, which have become some of the most preferred and frequently applied analytical tools in contemporary energy planning research. This growing prominence is largely attributed to their ability to incorporate linguistic judgments, capture the internal vagueness of expert assessments, and minimize the influence of personal bias in complex decision environments. Traditional crisp evaluation techniques often fall short when dealing with uncertain, imprecise, or subjective information—conditions that are inherent to RES assessment due to fluctuating resource availability, technological variability, and socio-economic considerations. In contrast, fuzzy MCDM approaches, such as fuzzy AHP, fuzzy VIKOR, fuzzy TOPSIS, and their advanced extensions, provide more detailed and representative judgements of expert opinions by allowing degrees of membership rather than rigid classifications. As a result, these methods enhance the robustness, transparency, and reliability of decision-making processes, making them indispensable in studies aiming to prioritize RES alternatives, optimize energy portfolios, and support sustainable policy development. Given the reasons outlined above, the following literature review with different RES decision-making approaches is given below under various thematic categories to provide a clearer and more systematic examination of existing studies in literature.

Conventional multi-criteria decision-making (MCDM) approaches have long served as foundational analytical tools for evaluating RES, especially in contexts where decision parameters are clearly defined, structured, and predominantly quantitative. Methods such as AHP (Analytical Hierarchy Process) (Saaty, 1977; Saaty, 1980), ANP (Analytical Network Process) (Saaty, 1996), TOPSIS (Technique of Order Preference Similarity to the Ideal Solution) (Hwang and Yoon, 1981), VIKOR (Vise Kriterijumska Optimizacija I Kompromisno Resenje) (Opricovic, 1998), ELECTREE (Elimination Et Choix Traduisant la REaite) (Roy, 1968) and PROMETHEE (Preference Ranking Organization Method for Enrichment Evaluations) (Brans, 1982; Brans and Vincke, 1982) allow decision makers to systematically compare alternatives based on a predefined hierarchy of criteria, compute relative weights, and derive preference rankings through transparent mathematical formulations. In RES planning, these conventional methods offer advantages such as ease of implementation, conceptual clarity, and straightforward interpretability, making them suitable for early-stage feasibility studies and data-rich contexts. However, their reliance on exact numerical inputs and rigid preference structures often limits their applicability when expert opinions, environmental risks, and socio-economic factors exhibit uncertainty or imprecision. Despite this limitation, conventional MCDM techniques remain widely utilized as a baseline or benchmarking tool due to their methodological robustness and longstanding acceptance in decision sciences.

Fuzzy and advanced fuzzy MCDM approaches have emerged as indispensable tools in RES evaluation, driven by the inherent uncertainty, linguistic vagueness, and subjective judgments embedded in energy planning processes. Techniques such as Fuzzy AHP (M2: Çelikbilek and Tüysüz, 2015; Wang et al., 2020; Taylan et al., 2020; Tarife et al., 2023), Fuzzy TOPSIS (Taylan et al., 2020; Alghassab, 2022), Fuzzy VIKOR (M3: Çelikbilek and Tüysüz, 2015; Taylan et al., 2020; Abdul et al., 2024), Fuzzy ELECTRE (M5: Çelikbilek, 2023; Shanthi and Basavaraju, 2024; Mao et al., 2024; Kang et al., 2024), Fuzzy COPRAS (M6: Çelikbilek, 2025a; Guan et al., 2023; Yilmaz, 2023), and their extensions—including grey (M1: M4: Çelikbilek and Tüysüz, 2016; Badi et al., 2023, Debnath et al., 2024), intuitionistic fuzzy (Ilbahar et al., 2022; Bilgili et al., 2022; Gupta et al., 2023; Tripathi et al., 2023; Joshi et al., 2023; Ke et al., 2023; Anjum et al., 2025), hesitant fuzzy (Acar et al., 2018; Alghassab, 2022; Krishankumar et al., 2022; Narayanamoorthy et al., 2023; Sahu et al., 2023; Zhang et al., 2023), spherical fuzzy (Kutlu Gündoğdu and Kahraman, 2020; Nguyen et al., 2022; Alkan, 2023; Ghoushchi et al., 2023; Abdul and Wenqi, 2024; Alballa et al., 2024), interval type-2 fuzzy (Hendiani and Walther, 2023; Karamoozian et al., 2023; Sağbaş et al., 2023; Li et al., 2025; Zhang et al., 2025), and neutrosophic frameworks (M7: M8: Çelikbilek, 2025b; Atassi and Yang, 2022; Ali, 2023; Masoomi et al., 2023; Abbas et al., 2025; Mishra et al., 2025) —enable decision makers to incorporate degrees of membership rather than rigid numerical assignments. This flexibility provides a more refined representation of expert assessments and better captures ambiguity related to climate conditions, technological performance, socio-political constraints, and environmental impacts. As renewable energy systems often involve complex, interdependent factors with limited empirical data, fuzzy-based methods offer enhanced realism and improve the credibility of rankings and prioritizations. Consequently, they have become some of the most prevalent analytical approaches in contemporary RES decision-making literature. For these reasons, and considering that Çelikbilek's studies offer valuable reference points within this research domain, his work will be examined in a comparative manner, and the associated dataset will be employed in the application phase of the present study. The method codes of the studies and the related methods in these studies are mentioned with Mlabeled symbols to be used in the comparison part briefly with these symbols. Together with all these considerations, and for the purpose of providing background information and evaluating the existing literature, the following section also examines other RES approaches.

Hybrid and integrated decision-making approaches combine the strengths of multiple methods, some of which listed above, to overcome the limitations of any single technique, resulting in more comprehensive and robust evaluation frameworks for renewable energy planning. Examples include AHP-TOPSIS, DEMATEL-ANP, BWM-VIKOR, SWARA-COPRAS, and entropy-weighted fuzzy systems. Hybrid models facilitate the integration of diverse analytical functions such as determining objective and subjective weights, analyzing causal relationships among criteria, and deriving multi-dimensional rankings under uncertainty. In RES contexts -where technical, economic, environmental, and social factors interact in complex ways- integrated approaches provide a more holistic perspective by triangulating insights from different methodologies. This combination not only strengthens the sensitivity and stability of results but also enhances decision transparency by cross-validating findings across multiple analytical layers (Doost et al., 2024). As a result, hybrid MCDM frameworks have gained considerable momentum in studies aiming to identify optimal RES alternatives, evaluate sustainability trade-offs, and support regional or national energy policy formulation.

Optimization and AI-based decision approaches represent a rapidly expanding domain in RES analysis, driven by the growing need for predictive accuracy (Unsal et al., 2024), dynamic modelling (Srinivasan et al., 2023; Yousef et al., 2023; Ukoba et al., 2024), and automated decision-making (Ukoba et al., 2024; Sriram et al., 2025). Methods such as genetic algorithms (GA), particle swarm optimization (PSO), multi-objective evolutionary algorithms, neural networks, reinforcement learning, and other machine learning–enhanced models enable researchers to optimize energy system configurations (Bagherian et al., 2021; Gribis et al., 2023), predict resource availability (Alkabbani et al., 2021), and analyze large-scale datasets with high complexity (Li and Wu, 2025). These techniques are especially valuable for tasks such as optimizing hybrid energy systems, forecasting solar and wind outputs, designing storage strategies, and addressing multi-objective trade-offs between cost, emissions, and reliability. In contrast to traditional MCDM methods that rely heavily on expert judgment, AI-based approaches leverage iterative learning and data-driven patterns to generate decision recommendations. Their ability to handle high-dimensional datasets, capture nonlinear interactions, and adapt to changing system conditions positions them as crucial tools for developing the resilient and intelligent energy systems envisioned in modern sustainability agendas.

Scenario-based and uncertainty-driven decision approaches play a critical role in renewable energy planning by addressing variability in future conditions such as climate fluctuations (Ramadan et al., 2021; Moradi et al., 2025; Nuriyev and Nuriyev, 2025), market prices (Sharma et al., 2017; Song et al., 2021; Khademi and Rezaei, 2022), policy shifts (Kaya et al., 2018; Nuriyev et al., 2023; Nuriyev and Nuriyev, 2025), and technological advancements (Kalbar et al., 2012; Parvaned and Hammad, 2024; Mizrak and Şahin, 2025). Techniques including Monte Carlo simulation, stochastic programming, robustness analysis, and scenario-based sensitivity modelling enable decision makers to evaluate how renewable energy alternatives perform under different possible futures. These methods acknowledge that energy planning is inherently uncertain and that deterministic rankings may not hold when external conditions change. By incorporating probabilistic distributions, risk profiles, and scenario narratives, uncertainty-based models provide deeper insights into the resilience and stability of renewable options. This allows planners to identify strategies that remain viable across a broad spectrum of conditions rather than relying on a single, static evaluation. Such approaches are increasingly important for long-term investment planning, national energy roadmaps, and climate-adaptive renewable energy deployment.

Sustainability-oriented decision frameworks integrate environmental, economic, social, and technical dimensions into renewable energy evaluation to ensure that decisions align with broader sustainability goals. Approaches such as life cycle assessment (LCA)-MCDM combinations (Siksnelyte-Butkiene et al., 2020; Das and De, 2023), triple bottom line–based frameworks (Saiprasad et al., 2019; Sepehr et al., 2020; Ecer, 2021; Lerman et al., 2021; Liao, 2023; Ragazou et al., 2024), and ESG-oriented evaluation methods (Xu and Zhao, 2024; Kara et al., 2025; Sklavos et al., 2025) account for the multifaceted consequences of RES deployment. These frameworks enable researchers to assess impacts such as greenhouse gas reductions, resource consumption, social acceptance, job creation, ecosystem disturbance, and long-term economic viability. By emphasizing the interconnectedness of sustainability dimensions, these models provide a more balanced and ethically grounded basis for selecting RES alternatives. In practice, sustainability-oriented frameworks help policymakers, investors, and planners prioritize energy technologies that offer the greatest societal value while minimizing negative trade-offs. As global energy transitions accelerate, such comprehensive frameworks are becoming increasingly essential for guiding responsible and future-proof energy strategies.

Despite the substantial body of research employing various conventional, fuzzy, hybrid, and AI-enhanced decision-making approaches for renewable energy source selection, several critical gaps continue to limit the methodological maturity and comparative reliability of existing studies. A recurring issue within the literature is the lack of systematic benchmarking across different fuzzy-based MCDM frameworks, particularly under conditions of uncertainty where linguistic evaluations, interdependent criteria, and nonlinear decision structures dominate. Many studies rely on single-model analyses without cross-validating results through alternative fuzzy environments or integrated causal weighting mechanisms, which raises concerns regarding methodological robustness and generalizability. Furthermore, the majority of existing works do not sufficiently address the propagation of uncertainty across sequential decision layers such as causal analysis, criteria weighting, and alternative ranking. This creates a clear need for more comprehensive frameworks capable of linking interrelationships among criteria with advanced fuzzy representations that capture both indeterminacy and interval-valued ambiguity. In this context, comparative benchmarking becomes essential to identify methodological strengths, limitations, and performance differences across fuzzy MCDM families. Accordingly, the present research contributes to filling this gap by proposing a novel Interval-Valued Neutrosophic Fuzzy DEMATEL-ANP-TOPSIS framework, designed to enhance the reliability of renewable energy source evaluation by integrating causal dependence analysis, neutrosophic uncertainty modeling, and multi-stage ranking. By systematically comparing this framework with established approaches in the literature, the study aims to generate clearer methodological insights and provide a stronger benchmarking foundation for future renewable energy decision-making research.

3. METHODOLOGY

In this section, detailed methodology of the study is given under three sub-sections as Dataset and Evaluation Criteria, Overview of Compared Fuzzy-Based MCDM Methods and The Proposed Integrated Neutrosophic Fuzzy DEMATEL-ANP-TOPSIS Framework. In the first sub-section, details of the evaluation criteria and the dataset used for the comparison and the application of the new Integrated Neutrosophic Fuzzy Framework are explained. Then, in the second sub-section, overview of compared fuzzy-based MCDM methods are listed and interpreted. Finally, the application of the proposed integrated neutrosophic fuzzy framework with the dataset is comprehensively analyzed and reviewed.

3.1. Dataset and Evaluation Criteria

There are various studies evaluating Renewable Energy Sources (RES) by using different criteria sets in the literature. Çelikbilek and Tüysüz (2015) evaluated RES under 11 criteria set. RES alternatives are evaluated by applying not only fuzzy MCDM methods (Çelikbilek and Tüysüz, 2015; Çelikbilek, 2023; Çelikbilek, 2025a; Çelikbilek, 2025b) but also grey MCDM methods (Çelikbilek and Tüysüz, 2016; Çelikbilek, 2016) with the listed criteria set by the authors. Due to the diversity of the applications and the results, this study used the same criteria and data set from the thesis of Çelikbilek (2016) in order to compare methodologies while applying the proposed integrated neutrosophic fuzzy DEMATEL–ANP–TOPSIS framework. The criteria set used for the evaluation of RES in the studies are given below in Table 1 (Çelikbilek, 2016; Çelikbilek, 2025).

Table 1. The Criteria Set used for the Evaluation of RES.

Symbol	Criterion
C1	Accessibility and Sustainability
C2	Efficiency/Effectiveness
C3	Diversity of Usage Areas
C4	Storability
C5	Transmission Efficiency
C6	Initial Investment Cost
C7	Simplicity of the Facility
C8	Technology Requirements
C9	Maintenance Requirements
C10	Accident Risk and Effects
C11	Harms to Nature and Human

3.2. Overview of Compared Fuzzy-Based MCDM Methods

The results obtained from the studies and methodological approaches detailed in the previous sections are comprehensively listed in Table 2. This table consolidates the comparative findings of the eight previously discussed methods, providing both the criteria set rankings used for the evaluation of RES alternatives and the final rankings of RES alternatives themselves. To enrich this comparative perspective, the results derived from This Study (TS) have also been incorporated into the table for the graphics in Section 5, where these combined outcomes will be further examined through visual representations, enabling a more intuitive assessment of similarities, divergences, and methodological differences across the nine different approaches. This integrative comparison not only highlights the robustness of the proposed IVN-based framework but also situates its results within the broader context of established decision-making techniques in the renewable energy literature.

Table 2. Comparison of the Fuzzy-Based MCDM evaluations of RES.

Symbol	**Ranking in the Related Methods**							
Criteria	**M1**	**M2**	**M3**	**M4**	**M5**	**M6**	**M7**	**M8**
C1	10	9	9	10	9	9	9	9
C2	6	4	4	6	4	4	10	10
C3	9	11	11	9	11	11	11	11

C4	5	3	3	5	3	3	3	3
C5	7	5	5	7	5	5	6	6
C6	8	7	7	8	7	7	5	5
C7	4	6	6	4	6	6	8	8
C8	2	1	1	2	1	1	1	1
C9	11	10	10	11	10	10	4	4
C10	1	2	2	1	2	2	2	2
C11	3	8	8	3	8	8	7	7
RES	**M1**	**M2**	**M3**	**M4**	**M5**	**M6**	**M7**	**M8**
A1	1	1	1	1	1	2	1	1
A2	2	2	2	2	3	3	2	3
A3	3	3	4	3	2	1	4	2
A4	5	4	5	5	5	5	5	5
A5	4	5	3	4	4	4	3	4

3.3. The Proposed Integrated Interval-Valued Neutrosophic Fuzzy DEMATEL–ANP–TOPSIS Framework

The proposed integrated interval-valued neutrosophic (IVN) Fuzzy DEMATEL–ANP–TOPSIS Framework is given in this section in detail. The proposed approach has three main parts. In the first part, the relationship among the criteria set is examined by applying IVN DEMATEL (Decision making trial and evaluation laboratory). Then, in the second part, the weights and the priority vectors of the decision matrix are obtained by applying the IVN ANP. Finally, in the third part, the evaluation and ranking of the RES alternatives are calculated by applying the proposed IVN TOPSIS approach. To understand the details of the proposed approach, checking the basic information about the IVN sets and their operations can be better. The studies of Zhang et al. (2016), Karaşan and Kahraman (2018), Kahraman et al. (2019) and Deveci and Torkayesh (2021) can be checked for the details of IVN sets and their operations.

3.3.1. The Interval-Valued Neutrosophic DEMATEL

Decision Making Trial and Evaluation Laboratory (DEMATEL) method, originally proposed by Gabus et al. (1972), aims to identify the causal interrelationships within a set of criteria. It origins from graph theory and the method enables the determination of both the direction and intensity of influences among criteria. Moreover, it provides a quantitative assessment of how strongly each criterion affects or is affected by others, thereby offering a comprehensive understanding of the structural dependencies within the system. There are various applications of DEMATEL with neutrosophic sets in different energy-related problems (E.g. Abdel-Basset et al., 2024; Çelikbilek, 2025b; Edalatpanah, 2025; Pakdel et al., 2025).

The calculation procedures of IVN DEMATEL approach are given step by step below.

Step 1: The Problem, the Criteria Set, and Linguistic Scales: First of all, the problem is clearly defined in detail including alternative set, criteria set. Subsequently, the relevant set of criteria associated with the problem is identified. A linguistic scale accompanied by IVN number representations is then established, not only to facilitate expert evaluations but also to support subsequent computational procedures. The linguistic assessment scale adopted for the IVN-DEMATEL analysis in this study, along with its corresponding IVN representations, is presented in Table 3.

Table 3. Linguistic Evaluation Scale and Equivalent Neutrosophic Numbers for DEMATEL.

Linguistic Term	Crisp Score	Neutrosophic Sets
No Influence (NO)	0	$\langle[0.05,0.10],[0.70,0.80],[0.85,0.90]\rangle$
Very Low Influence (VL)	1	$\langle[0.20,0.30],[0.50,0.60],[0.60,0.70]\rangle$
Low Influence (L)	2	$\langle[0.40,0.50],[0.30,0.40],[0.35,0.45]\rangle$
High Influence (H)	3	$\langle[0.70,0.80],[0.10,0.20],[0.05,0.15]\rangle$
Very High Influence (VH)	4	$\langle[0.85,0.90],[0.05,0.10],[0.05,0.10]\rangle$

In the DEMATEL framework, each criterion is assumed to have no influence on itself; therefore, the main diagonal of the direct-relation matrix is excluded from expert evaluations. In traditional DEMATEL, the main diagonal is directly set to zero. To ensure consistency with the neutrosophic DEMATEL formulation, rather than assigning $\langle[0.05,0.10],[0.70,0.80],[0.85,0.90]\rangle$, the vector $\langle[0,0],[1,1],[1,1]\rangle$ is used for diagonal entries to explicitly represent the state of absolute no influence.

Step 2: Combining the IVN Relation Matrices: The pairwise comparison matrices constructed from the criteria set is evaluated by the decision makers to determine the relational structure among the criteria. It is important to mention that pairwise comparisons in DEMATEL differ from those in AHP and ANP. In AHP or ANP, only the upper (or lower) triangular of the main diagonal of the matrix is assessed. In contrast, DEMATEL requires evaluations on both sides of the main diagonal, since the influence between two criteria is not necessarily mutual. That is, while criterion A may influence criterion B, criterion B may exert no influence—or a different level of influence—on criterion A.

Step 3: Combining All IVN Direct Relation Matrices: Let $\tilde{R}_d = \left[\langle \tilde{r}_{ij}\rangle\right]_{n\times n}$ denote the direct relation matrix provided by decision maker $d \in D$, and let $\tilde{S} = \left[\langle \tilde{s}_{ij}\rangle = \langle \left[T^L_{S_{ij}}, T^U_{S_{ij}}\right], \left[I^L_{S_{ij}}, I^U_{S_{ij}}\right], \left[F^L_{S_{ij}}, F^U_{S_{ij}}\right]\rangle\right]_{n\times n}$ represent the aggregated direct-relation matrix. The individual direct relation matrices obtained from all decision makers are combined by taking their average, as specified in Eq. (1).

$$\tilde{S} = \frac{\sum_{i=1}^{D} \tilde{R}_i}{D} \tag{1}$$

Step 4: Deneutrosophicating the IVN Direct Relation Matrix: Let $S = \left[s_{ij}\right]_{n\times n}$ denote the crisp direct-relation matrix. The neutrosophic direct-relation matrix of the criteria set is converted into its crisp form through a deneutrosophication process applying the Eq. (2) (Bolturk and Kahraman, 2018) as the score function. This conversion provides crisp values that allow the identification and interpretation of the relational structure among the criteria.

$$s_{ij} = \frac{T^L_{s_{ij}} + T^U_{s_{ij}}}{2} + \left(1 - \frac{I^L_{s_{ij}} + I^U_{s_{ij}}}{2}\right)\left(I^U_{s_{ij}}\right) - \left(\frac{F^L_{s_{ij}} + F^U_{s_{ij}}}{2}\right)\left(1 - F^U_{s_{ij}}\right) \tag{2}$$

Step 5: Normalizing the Direct Relation Matrix: Eq. (3) is used for the normalization of the direct relation matrix S.

$$s_{ij} = \frac{s_{ij}}{\max\left[\max_j\left(\sum_{i=1}^{n} s_{ij}\right), \max_i\left(\sum_{j=1}^{n} s_{ij}\right)\right]} \tag{3}$$

Step 6: Calculating of the Total Relation Matrix: Eq. (4) is used for the calculation of the total relation matrix of criteria set. In the equation, $T = \left[t_{ij}\right]_{n\times n}$ is the total relation matrix and I is identity matrix.

$$T = S(I - S)^{-1} \tag{4}$$

Step 7: Determining the Relation Among Criteria: To identify whether each criterion predominantly influences others or is primarily influenced by them, the column sums $C =$

$[c_i]_{n\times 1}$ and row sums $R = [r_j]_{1\times n}$ are computed for all criteria. After obtaining the C and R vectors, their sum and difference are calculated. If $(c_i - r_i) > 0$, Criterion i is interpreted as a cause, meaning it exerts a dominant influence on other criteria. Conversely, if $(c_i - r_i) < 0$, Criterion i is considered an effect, indicating that it is predominantly influenced by the other criteria.

$$c_i = \sum_{j=1}^{n} t_{ij} \tag{5}$$

$$r_j = \sum_{i=1}^{n} t_{ij} \tag{6}$$

Step 8: Constructing the Network Structure: To construct the network structure, a threshold value must first be specified by the decision makers. If an element $t_{ij} \in T_{n\times n}$ is greater than or equal to this threshold, it is considered to represent a meaningful relationship, including its direction, between Criterion i and Criterion j. In cases where the decision makers are unable to set an appropriate threshold, it may be determined by computing the average value of the total relation matrix. Additionally, the threshold can be adjusted upward or downward depending on the desired sensitivity level in capturing the strength of the relationships.

3.3.2. The Interval-Valued Neutrosophic ANP

The Analytic Network Process (ANP), introduced by Saaty (1996), is a generalization of AHP designed to solve MCDM problems that involve interdependencies and feedback among criteria. The IVN ANP (IVN-ANP) follows the same fundamental solution framework as the classical ANP but embeds IVN numbers throughout the computational procedures. This incorporation of IVN representations is particularly useful in group decision making process that includes subjective judgments and high uncertainty, as it helps to mitigate individual bias and the inherent vagueness of linguistic assessments. The IVN-ANP procedure employed in this study is adapted from the study of Bolturk and Kahraman (2018) and is outlined step-by-step below.

Computational steps of the grey based ANP applied in this study are given below.

Step 1: The Problem, the Criteria Set, and Linguistic Scales: Similarly, as DEMATEL, first of all, the problem is clearly defined in detail including alternative set, criteria set. Subsequently, the relevant set of criteria associated with the problem is identified. A linguistic scale accompanied by IVN number representations is then established, not only to facilitate expert evaluations but also to support subsequent computational procedures. The linguistic assessment scale adopted for the IVN-ANP analysis in this study, along with its corresponding IVN representations, is presented in Table 4 (Bolturk and Kahraman, 2018). Pairwise comparisons in the ANP method are conducted similarly to those in AHP. However, unlike AHP, ANP involves pairwise comparisons not only among criteria but also among sub-criteria and alternatives that may exert mutual influence on one another. This consideration of interdependencies distinguishes ANP from AHP. The pairwise comparison judgments are organized into matrices structured as illustrated below. Additionally, unlike AHP, not all criteria in ANP are compared with each other. Criteria that are found to have no relationship based on DEMATEL network analysis are excluded from the pairwise comparison process.

Table 4. Linguistic Scales and their IVN Number Representations.

Linguistic Term	Neutrosophic Sets
Equally Important	$\langle[0.50,0.50],[0.50,0.50],[0.50,0.50]\rangle$
Weakly More Important	$\langle[0.50,0.60],[0.35,0.45],[0.40,0.50]\rangle$
Moderately Important	$\langle[0.55,0.65],[0.30,0.40],[0.35,0.45]\rangle$
Moderately More Important	$\langle[0.60,0.70],[0.25,0.35],[0.30,0.40]\rangle$
Strongly Important	$\langle[0.65,0.75],[0.20,0.30],[0.25,0.35]\rangle$

Strongly More Important	$\langle[0.70,0.80],[0.15,0.25],[0.20,0.30]\rangle$
Very Strongly Important	$\langle[0.75,0.85],[0.10,0.20],[0.15,0.25]\rangle$
Very Strongly More Important	$\langle[0.80,0.90],[0.05,0.10],[0.10,0.20]\rangle$
Extremely Important	$\langle[0.90,0.95],[0.00,0.05],[0.05,0.15]\rangle$
Extremely High Important	$\langle[0.95,1.00],[0.00,0.00],[0.00,0.10]\rangle$
Absolutely More Important	$\langle[1.00,1.00],[0.00,0.00],[0.00,0.00]\rangle$

The pairwise comparisons are obtained from the decision makers like the matrix given below. A_{IVN}^{d} is the pairwise comparison matrix of Decision Maker $d \in D$ and $\langle a_{ij}^{d}\rangle = \langle\left[T_{a_{ij}}^{L}, T_{a_{ij}}^{U}\right], \left[I_{a_{ij}}^{L}, I_{a_{ij}}^{U}\right], \left[F_{a_{ij}}^{L}, F_{a_{ij}}^{U}\right]\rangle$, where $i, j \in [1, n]$.

$$A_{IVN}^{d} = \begin{bmatrix} \langle a_{11}^{d}\rangle & \langle a_{12}^{d}\rangle & \cdots & \langle a_{1n}^{d}\rangle \\ \langle a_{21}^{d}\rangle & \langle a_{22}^{d}\rangle & \cdots & a_{2n}^{d} \\ \vdots & \vdots & \ddots & \vdots \\ \langle a_{n1}^{d}\rangle & \langle a_{n2}^{d}\rangle & \cdots & a_{nn}^{d} \end{bmatrix} \tag{7}$$

Step 2: Combining all IVN Pairwise Comparisons: Eq. (8) given below is applied to combine all the pairwise comparisons obtained by the decision makers. Aggregated pairwise comparison matrix is shown as $A_{IVN} = \left[\langle a_{ij}\rangle\right]_{n\times n}$.

$$\langle a_{ij}\rangle = \sqrt[D]{\prod_{i=1}^{D}\langle a_{ij}^{d}\rangle} \tag{8}$$

Step 3: Deneutrosophicating the IVN Pairwise Comparison Matrix: The IVN pairwise comparison matrix is deneutrosophicated by applying Eq. (2) given in the previous sub-section.

Step 4: Calculating the Priority Vectors: For each criterion column, pairwise comparison matrices are conducted using the AHP method among the criteria that influence it as explained in the previous steps, resulting in priority vectors. The dimensions of these priority vectors are not fixed; rather, they vary depending on the number of criteria affecting each individual criterion. Once the priority vectors are computed, they are placed into a vector of size n (the total number of criteria), with the values assigned to the positions representing the influencing criteria, while the remaining positions -corresponding to non-influencing criteria- are assigned a value of zero.

Step 5: Generating the Supermatrix: All the priority vectors computed up to this stage are combined to form the weighted supermatrix $W = \left[a_{ij}\right]_{n\times n}$. The dimension of this supermatrix is $n \times n$. In cases where both sub-criteria and main criteria exist, this process is carried out in two steps: first, the sub-criteria matrices are constructed, and then these sub-criteria matrices are aggregated to form the overall main supermatrix.

Step 6: Calculating the limit supermatrix and the global weights: Prior to obtaining the limit supermatrix, it is necessary to ensure that the supermatrix is normalized, column stochastic. This involves normalizing each column by dividing every element by the total sum of that column. Following this normalization step, the columns sum to one. The limit supermatrix is then determined by applying Eq. (9) to the normalized supermatrix. In the limit supermatrix, all column vectors become identical. By normalizing this limit supermatrix, the global weights of all elements are derived, with the total sum of these global weights equal to one.

$$\lim_{k\to\infty} W^k \tag{9}$$

3.3.3. The Interval-Valued Neutrosophic TOPSIS

IVN TOPSIS is an advanced decision-making method designed to handle uncertainty, indeterminacy, and inconsistency more effectively than traditional approaches. Building on the classical TOPSIS framework (Hwang and Yoon, 1981), IVN TOPSIS incorporates IVN sets to represent and process information that is vague, incomplete, or contradictory. This enhanced capability allows decision makers to capture the inherent ambiguity of real-world problems more realistically.

The IVN theory extends fuzzy and intuitionistic fuzzy sets by introducing three membership degrees: truth, indeterminacy, and falsity, each expressed as intervals rather than precise values. This detailed representation supports a richer characterization of uncertainty, which is particularly useful in complex decision making environments where information is often imprecise or partially unknown. By integrating IVN sets with the TOPSIS ranking procedure, the method calculates the relative closeness of each alternative to the positive ideal and negative ideal solutions, taking into account the IVN uncertainty.

The classical TOPSIS method and its variants are applied to various problems in literature such as engineering design (Mendez et al., 2020; Chede et al., 2021; Wang et al., 2022; Hameed et al., 2022), supplier selection (Sureeyatanapas et al., 2018; Jain et al., 2018; Rouyendegh et al., 2020; Hajiaghaei-Keshteli et al., 2023), medical diagnosis (Akram et al., 2020; Zulqarnain et al., 2020; Naeem et al., 2021; Demirtaş and Dalkılıç, 2023; Masmali et al., 2024), risk assessment (Gul eet al., 2021; Koulinas et al., 2021; Awodi et al., 2023; Dang et al., 2024; Yu and Liu, 2025; Tang et al., 2025), etc. However, IVN TOPSIS theory and applications have not been constructed and applied yet to many different problems and fields by incorporating flexibility and robustness. Compared to classical TOPSIS and other variants, IVN TOPSIS offers improved handling of ambiguous data and better supports decision makers in scenarios with incomplete or inconsistent information. Because of this, following IVN TOPSIS framework is derived from the studies of Karaşan et al. (2019) and Sharma et al. (2019) for the evaluation of RES alternatives and their comparison.

Step 1: The Problem, the Criteria Set, the Alternatives and Creating the IVN Decision Matrix: The first step of TOPSIS method is also the same as the other methods. The decision problem is clearly and comprehensively defined, including the alternatives set and the evaluation criteria set. Following this, the relevant criteria related to the problem are identified. To accurately capture expert judgments under uncertainty, a linguistic scale based IVN numbers is established. This scale not only facilitates expert assessments by allowing expression of truth, indeterminacy, and falsity degrees with interval values but also supports the mathematical computations required in the IVN TOPSIS methodology. The priority vectors obtained in the previous sub-sections are combined to construct the IVN decision matrix as $A = \left[\langle \tilde{a}_{ij} \rangle\right]_{m\times n}$. Here, m is the number of RES alternatives and n is the number of criteria for the evaluation of these alternatives.

Step 2: Normalizing the IVN Decision Matrix: After constructing the decision matrix, the next step typically involves its normalization. However, when working with IVN numbers, there is a crucial consideration. If the decision matrix is derived through the IVN-AHP process in the initial step, it inherently represents a normalized IVN decision matrix. Consequently, this normalization step can be omitted.

$$\langle \tilde{a}_{ij} \rangle = \frac{\langle \tilde{a}_{ij} \rangle}{\left(\sum_{i=1}^{m} \langle \tilde{a}_{ij} \rangle^2\right)^{1/2}} \tag{10}$$

Step 3: Weighting the Normalized IVN Decision Matrix: Let $W = \left[w_j\right]$ represent the weight vector corresponding to the criteria set. To incorporate the relative importance of each criterion into the decision-making process, the weighted normalized IVN decision matrix, denoted as $WA = \left[\langle \widetilde{wa}_{ij} \rangle\right]_{m\times n}$, is computed. This matrix is obtained by applying the weighting procedure defined in Eq. (11), where each element of the normalized IVN decision matrix is multiplied by the respective criterion weight from W. The resulting matrix effectively combines both the normalized decision values and their corresponding weights, providing a comprehensive representation of the weighted assessments across all alternatives and criteria.

$$\langle \widetilde{wa}_{ij} \rangle = w_j \langle \tilde{a}_{ij} \rangle \tag{11}$$

Step 4: Determining the Positive and Negative Ideal Solutions: In this step, a Positive ideal solution (PIS) (A^+), and Negative ideal solution (NIS) (A^-) are derived from the values within the decision matrix corresponding to the problem. These solutions represent hypothetical alternatives that do not exist in the original problem but are constructed based on the best and the worst possible values for each criterion. According to the TOPSIS methodology, alternatives are evaluated based on their distances to these ideal and negative ideal solutions. Eq. (12) below illustrate the calculation assuming all criteria are beneficial (positive). For criteria that are considered non-beneficial (negative), the conditions are applied in the opposite manner as in Eq. (13); that is, the ideal solution for a negative criterion corresponds to its minimum value rather than the maximum value for the truth-membership (T) and maximum value rather than the minimum. Value for the indeterminacy-membership (I) and the falsity-membership (F).

$$A^+ = \langle \widetilde{wa}_j{}^+ \rangle = \langle \left[\max_i T^L_{\widetilde{wa}_{ij}}, \max_i T^U_{\widetilde{wa}_{ij}}\right], \left[\min_i I^L_{\widetilde{wa}_{ij}}, \min_i I^U_{\widetilde{wa}_{ij}}\right], \left[\min_i F^L_{\widetilde{wa}_{ij}}, \min_i F^U_{\widetilde{wa}_{ij}}\right] \rangle \tag{12}$$

$$A^- = \langle \widetilde{wa}_j{}^- \rangle = \langle \left[\min_i T^L_{\widetilde{wa}_{ij}}, \min_i T^U_{\widetilde{wa}_{ij}}\right], \left[\max_i I^L_{\widetilde{wa}_{ij}}, \max_i I^U_{\widetilde{wa}_{ij}}\right], \left[\max_i F^L_{\widetilde{wa}_{ij}}, \max_i F^U_{\widetilde{wa}_{ij}}\right] \rangle \tag{13}$$

Step 5: Calculating the Distances Among the Alternative and PIS/NIS: This step involves calculating the distances of each alternative to PIS and NIS. In the TOPSIS method, which employs Euclidean distance as the distance measure, d_i^+ denotes the distance of the *i-th* alternative from PIS, while d_i^- represents its distance from NIS. In IVN TOPSIS, these Euclidean distance calculation procedures are conducted by using IVN numbers as done in the previous sub-sections. The distances explained here are computed following the formulations provided in Eqs. (14-15).

$$d_i^+ = \sum_{j=1}^{n} d\left(\langle \widetilde{wa}_{ij} \rangle, \langle \widetilde{wa}_j{}^+ \rangle\right) \tag{14}$$

$$d_i^- = \sum_{j=1}^{n} d\left(\langle \widetilde{wa}_{ij} \rangle, \langle \widetilde{wa}_j{}^- \rangle\right) \tag{15}$$

Step 6: Calculating the Relative Closeness: The method proceeds from the principle that the most preferable alternative is the one that is farthest from NIS and simultaneously closest to the PIS. Based on this rationale, the relative closeness values of the alternatives to the ideal solution (A^+) are computed for the final evaluation, as shown below in Eq. (16). These relative closeness coefficients enable the ranking of alternatives by integrating both distance measures within a single performance indicator as RC_i.

$$RC_i = \frac{d_i^-}{d_i^+ + d_i^-} \tag{16}$$

Step 7: Deneutrosophicating the IVN Relative Closeness Values: The IVN relative closeness values are deneutrosophicated by applying Eq. (2) given in the previous sub-section.

Step 8: Ranking of the Alternatives: Since the relative closeness value for each alternative is calculated with respect to its distance from NIS, the alternative with the highest RC_i value is identified as the most desirable alternative. To evaluate the remaining alternatives, all RC_i values are ranked in descending order. The alternative with the smallest RC_i value is considered the least preferable, as it lies closest to the negative ideal solution and thus represents the poorest performance among the available alternatives.

4. Results: The Proposed Neutrosophic Fuzzy Hybrid Framework

In this section, the proposed integrated IVN Fuzzy DEMATEL–ANP–TOPSIS framework is applied to the evaluation of renewable energy sources (RES). Five key RES alternatives are considered: Solar Energy (SE), Wind Energy (WE), Hydroelectric Energy (HE), Geothermal Energy (GE), and Biomass Energy (BE). These alternatives were selected because they represent the most widely recognized and practically implemented renewable energy technologies across different regions. SE relies on converting sunlight into electricity through photovoltaic or thermal systems, making it highly suitable for areas with strong solar irradiation. WE utilizes the kinetic energy of moving air masses to produce power, offering strong potential especially in coastal or open-field locations. HE generates electricity from the potential and kinetic energy of flowing water, typically through dams or run-of-river systems, and is known for its stability and high capacity factors. GE exploits the Earth's internal heat, providing a consistent and low-emission energy source particularly effective in geothermal-rich zones. Lastly, BE converts organic matter into usable energy forms, allowing waste materials to be valorized within sustainable energy cycles.

All evaluations and pairwise comparisons were conducted by 11 experts who are actively involved in renewable energy-related research or professional practice. To enhance objectivity, the expert panel was formed by selecting individuals from various engineering disciplines, ensuring that multiple technical perspectives are represented. This interdisciplinary structure not only minimizes subjective evaluations but also enriches the analytical depth by bringing together expertise from electrical, mechanical, environmental, and energy engineering backgrounds.

A total of 11 criteria used in the evaluation, presented in Table 1, were taken from (Çelikbilek, 2016; Çelikbilek, 2025). These criteria encompass economic, environmental, operational, and technological aspects to provide a balanced and comprehensive assessment of RES alternatives. For the details of criteria set and data set, the mentioned study can be checked.

4.1. Determining Relationships

Based on the linguistic evaluations provided by 11 domain experts, the DEMATEL questionnaires were combined by applying Eq. (1). This computational step enabled the transformation of individual expert judgments into a unified decision structure, ensuring consistency and reducing subjectivity across the assessment process. Accordingly, the resulting Combined IVN Direct Relation Matrix of RES criteria set was obtained. The finalized matrix, which reflects the integrated IVN evaluations of causal interrelationships among the criteria, is presented in Table 5 below.

Table 5. Combined IVN Direct Relation Matrix of RES Criteria Set.

	C1	C2	C3	C4	C5	C6
C1	<[0.000,0.000],[1.000, 1.000],[1.000,1.000]>	<[0.681,0.754],[0.145, 0.218],[0.154,0.227]>	<[0.545,0.627],[0.231, 0.318],[0.259,0.340]>	<[0.568,0.645],[0.231, 0.318],[0.250,0.327]>	<[0.559,0.645],[0.218, 0.309],[0.231,0.318]>	<[0.495,0.590],[0.263, 0.363],[0.277,0.372]>
C2	<[0.595,0.663],[0.222, 0.300],[0.250,0.318]>	<[0.000,0.000],[1.000, 1.000],[1.000,1.000]>	<[0.645,0.736],[0.145, 0.236],[0.131,0.222]>	<[0.536,0.627],[0.240, 0.336],[0.250,0.340]>	<[0.513,0.600],[0.254, 0.345],[0.281,0.368]>	<[0.477,0.572],[0.281, 0.381],[0.300,0.395]>
C3	<[0.359,0.436],[0.400, 0.490],[0.472,0.550]>	<[0.454,0.545],[0.295, 0.390],[0.331,0.422]>	<[0.000,0.000],[1.000, 1.000],[1.000,1.000]>	<[0.490,0.572],[0.286, 0.372],[0.327,0.409]>	<[0.563,0.636],[0.245, 0.327],[0.272,0.345]>	<[0.568,0.654],[0.218, 0.309],[0.227,0.313]>
C4	<[0.613,0.690],[0.186, 0.263],[0.209,0.286]>	<[0.686,0.772],[0.122, 0.209],[0.104,0.190]>	<[0.609,0.681],[0.209, 0.290],[0.222,0.295]>	<[0.000,0.000],[1.000, 1.000],[1.000,1.000]>	<[0.640,0.727],[0.159, 0.245],[0.154,0.240]>	<[0.600,0.690],[0.181, 0.272],[0.181,0.272]>
C5	<[0.577,0.654],[0.227, 0.309],[0.250,0.327]>	<[0.650,0.727],[0.168, 0.245],[0.177,0.254]>	<[0.609,0.690],[0.195, 0.281],[0.200,0.281]>	<[0.568,0.654],[0.213, 0.300],[0.231,0.318]>	<[0.000,0.000],[1.000, 1.000],[1.000,1.000]>	<[0.627,0.718],[0.163, 0.254],[0.154,0.245]>
C6	<[0.481,0.572],[0.277, 0.372],[0.304,0.395]>	<[0.581,0.663],[0.213, 0.300],[0.227,0.309]>	<[0.550,0.618],[0.259, 0.336],[0.300,0.368]>	<[0.381,0.463],[0.368, 0.463],[0.427,0.509]>	<[0.531,0.609],[0.268, 0.354],[0.295,0.372]>	<[0.000,0.000],[1.000, 1.000],[1.000,1.000]>
C7	<[0.450,0.536],[0.309, 0.400],[0.354,0.440]>	<[0.431,0.527],[0.295, 0.390],[0.340,0.436]>	<[0.390,0.481],[0.350, 0.445],[0.404,0.495]>	<[0.290,0.363],[0.459, 0.554],[0.545,0.618]>	<[0.413,0.500],[0.345, 0.436],[0.400,0.486]>	<[0.709,0.790],[0.118, 0.200],[0.100,0.181]>
C8	<[0.536,0.636],[0.227, 0.327],[0.227,0.327]>	<[0.686,0.772],[0.122, 0.209],[0.104,0.190]>	<[0.659,0.754],[0.131, 0.227],[0.104,0.200]>	<[0.454,0.545],[0.300, 0.400],[0.327,0.418]>	<[0.509,0.590],[0.268, 0.354],[0.304,0.386]>	<[0.822,0.881],[0.059, 0.118],[0.050,0.109]>
C9	<[0.504,0.600],[0.245, 0.345],[0.259,0.354]>	<[0.463,0.563],[0.281, 0.381],[0.304,0.404]>	<[0.500,0.590],[0.259, 0.354],[0.281,0.372]>	<[0.404,0.500],[0.336, 0.436],[0.377,0.472]>	<[0.381,0.472],[0.350, 0.445],[0.409,0.500]>	<[0.590,0.681],[0.181, 0.272],[0.186,0.277]>
C10	<[0.400,0.490],[0.336, 0.436],[0.381,0.472]>	<[0.404,0.481],[0.363, 0.454],[0.422,0.500]>	<[0.554,0.636],[0.231, 0.318],[0.254,0.336]>	<[0.431,0.518],[0.313, 0.409],[0.359,0.445]>	<[0.400,0.490],[0.331, 0.427],[0.386,0.477]>	<[0.568,0.654],[0.218, 0.309],[0.227,0.313]>

C11	<[0.290,0.363],[0.459, 0.554],[0.545,0.618]>	<[0.272,0.363],[0.445, 0.545],[0.527,0.618]>	<[0.427,0.509],[0.327, 0.418],[0.381,0.463]>	<[0.368,0.454],[0.372, 0.472],[0.427,0.513]>	<[0.368,0.454],[0.372, 0.472],[0.427,0.513]>	<[0.490,0.563],[0.300, 0.381],[0.350,0.422]>

	C7	**C8**	**C9**	**C10**	**C11**
C1	<[0.404,0.500],[0.336, 0.436],[0.377,0.472]>	<[0.577,0.672],[0.204, 0.300],[0.200,0.295]>	<[0.454,0.545],[0.295, 0.390],[0.331,0.422]>	<[0.263,0.354],[0.445, 0.545],[0.531,0.622]>	<[0.259,0.345],[0.463, 0.563],[0.550,0.636]>
C2	<[0.336,0.427],[0.390, 0.490],[0.454,0.545]>	<[0.568,0.663],[0.204, 0.300],[0.204,0.300]>	<[0.363,0.445],[0.386, 0.481],[0.450,0.531]>	<[0.231,0.309],[0.500, 0.600],[0.595,0.672]>	<[0.213,0.300],[0.500, 0.600],[0.600,0.686]>
C3	<[0.440,0.527],[0.313, 0.409],[0.354,0.440]>	<[0.495,0.581],[0.272, 0.363],[0.304,0.390]>	<[0.354,0.445],[0.372, 0.472],[0.431,0.522]>	<[0.350,0.436],[0.390, 0.490],[0.450,0.536]>	<[0.381,0.472],[0.354, 0.454],[0.404,0.495]>
C4	<[0.540,0.636],[0.222, 0.318],[0.231,0.327]>	<[0.572,0.663],[0.200, 0.290],[0.209,0.300]>	<[0.522,0.618],[0.240, 0.336],[0.254,0.350]>	<[0.386,0.481],[0.336, 0.436],[0.386,0.481]>	<[0.295,0.390],[0.409, 0.509],[0.486,0.581]>
C5	<[0.436,0.527],[0.313, 0.409],[0.354,0.445]>	<[0.654,0.736],[0.154, 0.236],[0.154,0.236]>	<[0.345,0.445],[0.372, 0.472],[0.431,0.531]>	<[0.300,0.372],[0.454, 0.545],[0.545,0.618]>	<[0.322,0.400],[0.422, 0.518],[0.500,0.577]>
C6	<[0.709,0.781],[0.131, 0.209],[0.122,0.195]>	<[0.668,0.745],[0.150, 0.227],[0.154,0.231]>	<[0.500,0.590],[0.259, 0.354],[0.281,0.372]>	<[0.572,0.663],[0.200, 0.290],[0.209,0.300]>	<[0.404,0.472],[0.377, 0.463],[0.445,0.513]>
C7	<[0.000,0.000],[1.000, 1.000],[1.000,1.000]>	<[0.722,0.800],[0.113, 0.190],[0.100,0.177]>	<[0.654,0.736],[0.159, 0.245],[0.150,0.231]>	<[0.654,0.727],[0.168, 0.245],[0.177,0.250]>	<[0.413,0.500],[0.331, 0.427],[0.381,0.468]>
C8	<[0.754,0.836],[0.081, 0.163],[0.050,0.131]>	<[0.000,0.000],[1.000, 1.000],[1.000,1.000]>	<[0.654,0.745],[0.145, 0.236],[0.127,0.218]>	<[0.500,0.590],[0.259, 0.354],[0.281,0.372]>	<[0.445,0.545],[0.281, 0.381],[0.313,0.413]>
C9	<[0.654,0.745],[0.145, 0.236],[0.127,0.218]>	<[0.700,0.790],[0.109, 0.200],[0.077,0.168]>	<[0.000,0.000],[1.000, 1.000],[1.000,1.000]>	<[0.618,0.709],[0.163, 0.254],[0.159,0.250]>	<[0.454,0.545],[0.295, 0.390],[0.331,0.422]>
C10	<[0.563,0.636],[0.245, 0.327],[0.272,0.345]>	<[0.595,0.672],[0.209, 0.290],[0.227,0.304]>	<[0.668,0.745],[0.154, 0.236],[0.150,0.227]>	<[0.000,0.000],[1.000, 1.000],[1.000,1.000]>	<[0.704,0.763],[0.154, 0.218],[0.172,0.231]>
C11	<[0.518,0.609],[0.240, 0.336],[0.259,0.350]>	<[0.581,0.663],[0.218, 0.309],[0.222,0.304]>	<[0.490,0.572],[0.286, 0.372],[0.327,0.409]>	<[0.690,0.754],[0.159, 0.227],[0.172,0.236]>	<[0.000,0.000],[1.000, 1.000],[1.000,1.000]>

Following this procedure, the matrix given in Table 5 was deneutrosophicated by applying Eq. (2–3), resulting in the matrix shown in Table 6. Subsequently, Eq. (3–4) was applied to this deneutrosophicated matrix to reveal the final causal relationships among the criteria set, resulting the Total Relation Matrix of the RES Criteria Set, which is given in Table 7.

To determine the presence or absence of causal influence among criteria set, a threshold value is calculated by taking the arithmetic mean of all elements in the total relation matrix. Cells with values exceeding this threshold indicate the existence of a significant causal relationship between the corresponding pair of criteria. The threshold value can be adjusted upward or downward, depending on expert opinion or depending on whether a more restrictive or more inclusive set of criterion relationships is desired.

In this study, the threshold was determined to be 0.543. All cells exceeding this value are highlighted in bold. These bold-marked entries indicate that the criterion represented in the row exerts an influence on the criterion represented in the corresponding column. For instance, criterion C1 has an influence on criteria C6 and C8. Conversely, when examining the influences acting upon C1, only criterion C8 exceeds the threshold and therefore demonstrates an impact on C1.

Moreover, for columns in which no value exceeds the threshold value, the highest value in that column is selected to ensure that the ANP computations yield a valid result and that no criterion is inadvertently excluded from the analysis. In this study, since no value above 0.543 was identified in the columns corresponding to criteria C4 and C11, the highest entries -0.530 in the C4 column (located in the C8 row) and 0.483 in the C11 column (also located in the C8 row)- were selected. This implies that criterion C8 exerts influence on both C4 and C11. Because no other criterion exhibits a significant effect in these columns, a value of 1 will be assigned to these specific cells in the ANP matrix, while all other cells in the same columns will be assigned a value of 0.

Table 6. Combined Deneutrosophicated Direct Relation Matrix RES Criteria Set.

	C1	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**	**C8**	**C9**	**C10**	**C11**
C1	0.000	0.749	0.619	0.643	0.642	0.589	0.496	0.675	0.539	0.367	0.361
C2	0.657	0.000	0.744	0.626	0.593	0.570	0.429	0.664	0.447	0.333	0.325
C3	0.440	0.539	0.000	0.564	0.631	0.653	0.523	0.575	0.445	0.439	0.471
C4	0.680	0.784	0.681	0.000	0.730	0.691	0.633	0.660	0.613	0.477	0.395

C5	0.648	0.722	0.692	0.647	0.000	0.723	0.521	0.736	0.443	0.387	0.408
C6	0.567	0.660	0.609	0.464	0.605	0.000	0.791	0.743	0.586	0.660	0.474
C7	0.529	0.517	0.478	0.379	0.495	0.803	0.000	0.809	0.745	0.725	0.496
C8	0.636	0.784	0.771	0.543	0.582	0.889	0.860	0.000	0.756	0.586	0.537
C9	0.598	0.558	0.586	0.496	0.468	0.680	0.756	0.812	0.000	0.712	0.539
C10	0.488	0.481	0.630	0.513	0.485	0.653	0.631	0.667	0.751	0.000	0.756
C11	0.379	0.375	0.504	0.455	0.455	0.556	0.605	0.667	0.564	0.750	0.000

Table 7. Total Relation Matrix RES Criteria Set.

	C1	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**	**C8**	**C9**	**C10**	**C11**
C1	0.404	0.539	0.531	0.467	0.492	**0.559**	0.511	**0.579**	0.490	0.437	0.391
C2	0.471	0.421	0.524	0.447	0.467	0.534	0.482	**0.554**	0.459	0.414	0.370
C3	0.437	0.484	0.420	0.431	0.463	0.536	0.486	0.536	**0.543**	0.422	0.384
C4	0.535	**0.589**	**0.585**	0.423	**0.545**	**0.623**	**0.574**	**0.630**	0.452	0.492	0.432
C5	0.505	**0.553**	**0.557**	0.482	0.424	**0.595**	0.532	**0.606**	0.495	0.455	0.411
C6	0.510	**0.561**	**0.564**	0.474	0.517	0.520	**0.583**	**0.627**	0.531	0.506	0.434
C7	0.495	0.533	0.537	0.454	0.494	**0.612**	0.472	**0.624**	0.541	0.506	0.430
C8	**0.567**	**0.629**	**0.637**	**0.530**	**0.565**	**0.692**	**0.645**	**0.591**	**0.602**	**0.544**	**0.483**
C9	0.517	**0.553**	**0.565**	0.481	0.505	**0.614**	**0.584**	**0.640**	0.459	0.517	0.447
C10	0.492	0.530	**0.557**	0.472	0.495	**0.596**	**0.556**	**0.609**	**0.543**	0.415	0.464
C11	0.431	0.466	0.490	0.420	0.444	0.529	0.501	**0.551**	0.473	0.466	0.326

4.2. Calculating the Weights

For the calculation of the criteria weights, the inter-criteria relationships obtained through the IVN-DEMATEL procedure and given in Table 7 are utilized. For each criterion, a pairwise comparison is conducted among the criteria that exert influence on it, and the degree of this influence is assessed using the linguistic evaluations given in Table 4. This comparison process is performed separately for every criterion in order to construct the corresponding comparison matrices.

Subsequently, the operations described in Section 3.3.2 are applied to each comparison matrix, generating the respective priority vectors. These vectors are then placed column by column into the ANP supermatrix, but only in the cells representing the intersections of criteria that share a causal relationship according to the IVN-DEMATEL results. For intersections between criteria that do not exhibit a relationship, an IVN value of the form $< [0.000,0.000], [1.000,1.000], [1.000,1.000] >$ is assigned to the corresponding cells, ensuring that unrelated criteria do not contribute to the weighting structure.

Finally, the IVN supermatrix obtained through the previous steps is deneutrosophicated and its limit is computed. This limiting process gives the Global Weights, which are reported in the final column of the matrix in Table 8. These global weights represent the overall importance of each criterion within the decision-making framework and serve as the criteria weights to be used in subsequent evaluation stages. Each value in the last column corresponds to the importance of the criterion located in the same row, thus providing the final priority structure necessary for the multi-criteria assessment.

Table 8. IVN Supermatrix and Global Weights of RES Criteria Set.

	C1	**C2**	**C3**	**C4**	**C5**	**C6**
C1	<[0.000,0.000],[1.000, 1.000],[1.000,1.000]>	<[0.000,0.000],[1.000, 1.000],[1.000,1.000]>	<[0.000,0.000],[1.000, 1.000],[1.000,1.000]>	<[0.000,0.000],[1.000, 1.000],[1.000,1.000]>	<[0.000,0.000],[1.000, 1.000],[1.000,1.000]>	<[0.247,0.253],[0.032, 0.026],[0.028,0.023]>
C2	<[0.000,0.000],[1.000, 1.000],[1.000,1.000]>	<[0.000,0.000],[1.000, 1.000],[1.000,1.000]>	<[0.000,0.000],[1.000, 1.000],[1.000,1.000]>	<[0.000,0.000],[1.000, 1.000],[1.000,1.000]>	<[0.000,0.000],[1.000, 1.000],[1.000,1.000]>	<[0.000,0.000],[1.000, 1.000],[1.000,1.000]>
C3	<[0.000,0.000],[1.000, 1.000],[1.000,1.000]>	<[0.000,0.000],[1.000, 1.000],[1.000,1.000]>	<[0.000,0.000],[1.000, 1.000],[1.000,1.000]>	<[0.000,0.000],[1.000, 1.000],[1.000,1.000]>	<[0.000,0.000],[1.000, 1.000],[1.000,1.000]>	<[0.000,0.000],[1.000, 1.000],[1.000,1.000]>
C4	<[0.000,0.000],[1.000, 1.000],[1.000,1.000]>	<[0.393,0.413],[0.050, 0.041],[0.045,0.038]>	<[0.350,0.341],[0.025, 0.022],[0.024,0.022]>	<[0.000,0.000],[1.000, 1.000],[1.000,1.000]>	<[0.468,0.475],[0.546, 0.534],[0.540,0.531]>	<[0.119,0.117],[0.140, 0.144],[0.145,0.150]>

C5	<[0.000,0.000],[1.000,1.000],[1.000,1.000]>	<[0.234,0.224],[0.130,0.133],[0.133,0.136]>	<[0.157,0.152],[0.135,0.146],[0.149,0.161]>	<[0.000,0.000],[1.000,1.000],[1.000,1.000]>	<[0.000,0.000],[1.000,1.000],[1.000,1.000]>	<[0.111,0.114],[0.154,0.156],[0.156,0.157]>
C6	<[0.000,0.000],[1.000,1.000],[1.000,1.000]>	<[0.164,0.158],[0.238,0.264],[0.258,0.282]>	<[0.150,0.148],[0.151,0.160],[0.161,0.170]>	<[0.000,0.000],[1.000,1.000],[1.000,1.000]>	<[0.000,0.000],[1.000,1.000],[1.000,1.000]>	<[0.000,0.000],[1.000,1.000],[1.000,1.000]>
C7	<[0.000,0.000],[1.000,1.000],[1.000,1.000]>	<[0.000,0.000],[1.000,1.000],[1.000,1.000]>	<[0.000,0.000],[1.000,1.000],[1.000,1.000]>	<[0.000,0.000],[1.000,1.000],[1.000,1.000]>	<[0.000,0.000],[1.000,1.000],[1.000,1.000]>	<[0.157,0.145],[0.095,0.103],[0.102,0.108]>
C8	<[1.000,1.000],[0.000,0.000],[0.000,0.000]>	<[0.150,0.146],[0.151,0.148],[0.152,0.150]>	<[0.124,0.125],[0.225,0.218],[0.218,0.209]>	<[1.000,1.000],[0.000,0.000],[0.000,0.000]>	<[0.532.0.525].[0.454.0.466].[0.460.0.469]>	<[0.124,0.122],[0.141,0.145],[0.145,0.148]>
C9	<[0.000,0.000],[1.000,1.000],[1.000,1.000]>	<[0.058,0.059],[0.431,0.413],[0.411,0.394]>	<[0.090,0.101],[0.276,0.261],[0.257,0.245]>	<[0.000,0.000],[1.000,1.000],[1.000,1.000]>	<[0.000,0.000],[1.000,1.000],[1.000,1.000]>	<[0.106,0.114],[0.249,0.237],[0.235,0.225]>
C10	<[0.000,0.000],[1.000,1.000],[1.000,1.000]>	<[0.000,0.000],[1.000,1.000],[1.000,1.000]>	<[0.129,0.133],[0.189,0.193],[0.191,0.193]>	<[0.000,0.000],[1.000,1.000],[1.000,1.000]>	<[0.000,0.000],[1.000,1.000],[1.000,1.000]>	<[0.135,0.135],[0.189,0.189],[0.189,0.188]>
C11	<[0.000,0.000],[1.000,1.000],[1.000,1.000]>	<[0.000,0.000],[1.000,1.000],[1.000,1.000]>	<[0.000,0.000],[1.000,1.000],[1.000,1.000]>	<[0.000,0.000],[1.000,1.000],[1.000,1.000]>	<[0.000,0.000],[1.000,1.000],[1.000,1.000]>	<[0.000,0.000],[1.000,1.000],[1.000,1.000]>

	C7	C8	C9	C10	C11	Global Weights
C1	<[0.000,0.000],[1.000,1.000],[1.000,1.000]>	<[0.212,0.232],[0.028,0.021],[0.023,0.018]>	<[0.000,0.000],[1.000,1.000],[1.000,1.000]>	<[0.000,0.000],[1.000,1.000],[1.000,1.000]>	<[0.000,0.000],[1.000,1.000],[1.000,1.000]>	**0.0696**
C2	<[0.000,0.000],[1.000,1.000],[1.000,1.000]>	<[0.213,0.200],[0.025,0.025],[0.025,0.025]>	<[0.000,0.000],[1.000,1.000],[1.000,1.000]>	<[0.000,0.000],[1.000,1.000],[1.000,1.000]>	<[0.000,0.000],[1.000,1.000],[1.000,1.000]>	**0.0575**
C3	<[0.000,0.000],[1.000,1.000],[1.000,1.000]>	<[0.000,0.000],[1.000,1.000],[1.000,1.000]>	<[0.261,0.246],[0.350,0.353],[0.362,0.365]>	<[0.000,0.000],[1.000,1.000],[1.000,1.000]>	<[0.000,0.000],[1.000,1.000],[1.000,1.000]>	**0.0143**
C4	<[0.378,0.387],[0.048,0.040],[0.044,0.037]>	<[0.142,0.134],[0.042,0.041],[0.042,0.041]>	<[0.000,0.000],[1.000,1.000],[1.000,1.000]>	<[0.000,0.000],[1.000,1.000],[1.000,1.000]>	<[0.000,0.000],[1.000,1.000],[1.000,1.000]>	**0.1260**
C5	<[0.000,0.000],[1.000,1.000],[1.000,1.000]>	<[0.097,0.092],[0.108,0.118],[0.118,0.127]>	<[0.000,0.000],[1.000,1.000],[1.000,1.000]>	<[0.000,0.000],[1.000,1.000],[1.000,1.000]>	<[0.000,0.000],[1.000,1.000],[1.000,1.000]>	**0.0648**
C6	<[0.083,0.078],[0.262,0.266],[0.273,0.280]>	<[0.043,0.044],[0.167,0.168],[0.170,0.171]>	<[0.000,0.000],[1.000,1.000],[1.000,1.000]>	<[0.000,0.000],[1.000,1.000],[1.000,1.000]>	<[0.000,0.000],[1.000,1.000],[1.000,1.000]>	**0.0530**
C7	<[0.000,0.000],[1.000,1.000],[1.000,1.000]>	<[0.093,0.089],[0.086,0.094],[0.093,0.099]>	<[0.000,0.000],[1.000,1.000],[1.000,1.000]>	<[0.000,0.000],[1.000,1.000],[1.000,1.000]>	<[0.000,0.000],[1.000,1.000],[1.000,1.000]>	**0.0527**
C8	<[0.227,0.212],[0.154,0.159],[0.160,0.162]>	<[0.000,0.000],[1.000,1.000],[1.000,1.000]>	<[0.419,0.421],[0.355,0.374],[0.362,0.376]>	<[1.000,1.000],[0.000,0.000],[0.000,0.000]>	<[1.000,1.000],[0.000,0.000],[0.000,0.000]>	**0.3969**
C9	<[0.141,0.152],[0.343,0.342],[0.332,0.331]>	<[0.066,0.069],[0.192,0.189],[0.187,0.184]>	<[0.000,0.000],[1.000,1.000],[1.000,1.000]>	<[0.000,0.000],[1.000,1.000],[1.000,1.000]>	<[0.000,0.000],[1.000,1.000],[1.000,1.000]>	**0.0524**
C10	<[0.171,0.171],[0.194,0.192],[0.192,0.189]>	<[0.074,0.075],[0.134,0.136],[0.135,0.137]>	<[0.320,0.333],[0.295,0.273],[0.276,0.259]>	<[0.000,0.000],[1.000,1.000],[1.000,1.000]>	<[0.000,0.000],[1.000,1.000],[1.000,1.000]>	**0.0801**
C11	<[0.000,0.000],[1.000,1.000],[1.000,1.000]>	<[0.061,0.065],[0.218,0.208],[0.207,0.198]>	<[0.000,0.000],[1.000,1.000],[1.000,1.000]>	<[0.000,0.000],[1.000,1.000],[1.000,1.000]>	<[0.000,0.000],[1.000,1.000],[1.000,1.000]>	**0.0327**

4.3. Evaluating the RES Alternatives

After identifying the interrelationships among the criteria through IVN-DEMATEL method and obtaining the criteria weights via the IVN-ANP procedure, the evaluation and ranking of RES alternatives using the IVN-TOPSIS approach are carried out in this section. Based on these previous steps, an IVN decision matrix is constructed to represent the performance of each RES alternative with respect to the evaluation criteria.

The IVN Decision Matrix of RES Evaluations are given in detail in Table 9. This decision matrix not only forms the basis for the following IVN-TOPSIS computation but also enables a direct interpretation of how each RES alternative performs under each criterion. By examining the values across the matrix, researchers and decision-makers can identify which RES alternative exhibits superior characteristics for a particular criterion and can therefore conduct a criterion-focused comparative assessment.

For instance, under criterion C5 (Transmission Efficiency), the Hydroelectric Energy alternative displays values that are significantly higher than those of the other RES alternatives. If this criterion carries substantial importance within the decision, it becomes highly reasonable that Hydroelectric Energy would emerge as the top-ranked alternative in the final IVN-TOPSIS results. Similar interpretive evaluations can be performed for the other criteria and RES alternatives, enabling a more detailed understanding of how each criterion influences the overall ranking.

Table 9. IVN Decision Matrix of RES Evaluations.

	C1	C2	C3	C4	C5	C6
SE	<[0.096,0.107],[0.218,0.236],[0.236,0.255]>	<[0.228,0.235],[0.144,0.148],[0.149,0.152]>	<[0.193,0.212],[0.096,0.101],[0.106,0.112]>	<[0.112,0.115],[0.242,0.253],[0.250,0.260]>	<[0.112,0.115],[0.287,0.296],[0.294,0.301]>	<[0.327,0.333],[0.141,0.159],[0.155,0.173]>
WE	<[0.068,0.069],[0.449,0.452],[0.442,0.442]>	<[0.115,0.119],[0.357,0.360],[0.356,0.360]>	<[0.248,0.261],[0.240,0.242],[0.235,0.235]>	<[0.095,0.096],[0.311,0.324],[0.302,0.313]>	<[0.064,0.066],[0.343,0.351],[0.335,0.343]>	<[0.349,0.357],[0.058,0.058],[0.060,0.061]>
HE	<[0.278,0.283],[0.076,0.080],[0.076,0.079]>	<[0.288,0.299],[0.073,0.074],[0.076,0.078]>	<[0.256,0.265],[0.106,0.109],[0.113,0.117]>	<[0.443,0.443],[0.029,0.032],[0.029,0.032]>	<[0.471,0.472],[0.027,0.029],[0.027,0.029]>	<[0.140,0.145],[0.189,0.197],[0.197,0.203]>
GE	<[0.439,0.459],[0.040,0.047],[0.037,0.043]>	<[0.286,0.288],[0.058,0.064],[0.056,0.062]>	<[0.134,0.152],[0.344,0.355],[0.329,0.339]>	<[0.147,0.155],[0.291,0.293],[0.289,0.289]>	<[0.147,0.154],[0.217,0.218],[0.216,0.216]>	<[0.083,0.094],[0.396,0.411],[0.375,0.390]>
BE	<[0.098,0.103],[0.196,0.205],[0.190,0.200]>	<[0.070,0.072],[0.361,0.362],[0.354,0.357]>	<[0.137,0.142],[0.203,0.204],[0.206,0.208]>	<[0.195,0.199],[0.110,0.114],[0.116,0.120]>	<[0.199,0.200],[0.114,0.117],[0.117,0.121]>	<[0.084,0.088],[0.191,0.202],[0.189,0.198]>

	C7	C8	C9	C10	C11
SE	<[0.114,0.116],[0.274, 0.284],[0.261,0.273]>	<[0.248,0.255],[0.128, 0.137],[0.137,0.145]>	<[0.165,0.169],[0.192, 0.194],[0.196,0.197]>	<[0.243,0.254],[0.126, 0.131],[0.132,0.136]>	<[0.208,0.211],[0.176, 0.179],[0.178,0.179]>
WE	<[0.278,0.285],[0.159, 0.180],[0.176,0.195]>	<[0.247,0.252],[0.173, 0.185],[0.183,0.193]>	<[0.223,0.227],[0.195, 0.197],[0.197,0.197]>	<[0.214,0.218],[0.181, 0.191],[0.187,0.195]>	<[0.258,0.259],[0.170, 0.183],[0.180,0.192]>
HE	<[0.255,0.262],[0.136, 0.147],[0.149,0.161]>	<[0.150,0.151],[0.182, 0.188],[0.183,0.186]>	<[0.184,0.192],[0.226, 0.228],[0.224,0.225]>	<[0.149,0.151],[0.221, 0.222],[0.220,0.221]>	<[0.235,0.236],[0.108, 0.115],[0.103,0.109]>
GE	<[0.180,0.191],[0.211, 0.226],[0.201,0.213]>	<[0.173,0.184],[0.275, 0.289],[0.262,0.274]>	<[0.169,0.181],[0.254, 0.262],[0.245,0.252]>	<[0.171,0.179],[0.258, 0.274],[0.244,0.258]>	<[0.136,0.140],[0.311, 0.318],[0.303,0.310]>
BE	<[0.158,0.160],[0.188, 0.195],[0.182,0.189]>	<[0.170,0.171],[0.221, 0.222],[0.217,0.221]>	<[0.240,0.251],[0.122, 0.129],[0.130,0.137]>	<[0.210,0.212],[0.197, 0.199],[0.203,0.206]>	<[0.157,0.160],[0.220, 0.221],[0.223,0.224]>

After applying Eqs. (10–11) using the decision matrix given in Table 9, the resulting matrix is further processed through Eqs. (12–13) to determine the values of A^{+} and A^{+}. These values correspond to the Positive Ideal Solution (PIS) and the Negative Ideal Solution (NIS), respectively. In the following stage of the IVN-TOPSIS calculations, these ideal solution values serve as reference benchmarks. The distance of each RES alternative from the PIS and the NIS is computed to assess their relative closeness to the optimal solution, meaning how far an alternative is from NIS. This step is essential for generating the final performance scores and ranking the alternatives in a systematic and analytically rigorous manner.

Table 10. IVN PIS and IVN NIS values of RES Evaluations.

	A^{+}	A^{-}
C1	<[0.0542,0.0566],[0.0049,0.0058],[0.0046,0.0053]>	<[0.0083,0.0085],[0.0560,0.0564],[0.0553,0.0553]>
C2	<[0.0333,0.0345],[0.0061,0.0068],[0.0059,0.0066]>	<[0.0081,0.0083],[0.0384,0.0385],[0.0380,0.0384]>
C3	<[0.0076,0.0079],[0.0027,0.0028],[0.0030,0.0032]>	<[0.0040,0.0042],[0.0098,0.0101],[0.0096,0.0099]>
C4	<[0.1050,0.1050],[0.0070,0.0077],[0.0071,0.0078]>	<[0.0225,0.0227],[0.0755,0.0787],[0.0739,0.0766]>
C5	<[0.0553,0.0554],[0.0033,0.0035],[0.0033,0.0036]>	<[0.0075,0.0077],[0.0425,0.0435],[0.0417,0.0427]>
C6	<[0.0352,0.0360],[0.0058,0.0058],[0.0061,0.0062]>	<[0.0083,0.0088],[0.0398,0.0413],[0.0385,0.0400]>
C7	<[0.0308,0.0316],[0.0151,0.0163],[0.0167,0.0181]>	<[0.0126,0.0128],[0.0305,0.0316],[0.0293,0.0307]>
C8	<[0.2125,0.2185],[0.1080,0.1156],[0.1167,0.1236]>	<[0.1285,0.1294],[0.2321,0.2439],[0.2233,0.2335]>
C9	<[0.0272,0.0285],[0.0138,0.0146],[0.0148,0.0156]>	<[0.0187,0.0192],[0.0287,0.0296],[0.0279,0.0287]>
C10	<[0.0422,0.0442],[0.0216,0.0224],[0.0228,0.0235]>	<[0.0259,0.0262],[0.0443,0.0470],[0.0422,0.0446]>
C11	<[0.0183,0.0183],[0.0073,0.0078],[0.0070,0.0074]>	<[0.0096,0.0099],[0.0212,0.0217],[0.0207,0.0212]>

Table 11, titled Relative Closeness, Results, and Ranking of RES, listed the final outcomes of the evaluation process in a detailed manner. The second and third columns of the table report the d_i^{+} and d_i^{-} values, which represent the distances of each alternative to PIS and NIS, respectively. These distances were computed using Eqs. (14–15). Following, the values in these two columns were incorporated into Eq. (16) to obtain the Relative Closeness (RC_i) values, which are given in the fourth column. By ranking the RC_i values in descending order, RES alternatives are ordered from the most preferable to the least preferable alternatives. Furthermore, to determine the preference percentages of RES alternatives, the best RES alternative is first assigned a value of 100%. The remaining alternatives are then scaled proportionally using their respective RC_i values, yielding the percentage values given in the fifth column. The final rankings of all RES alternatives are listed in the last column.

According to the proposed Interval-Valued Neutrosophic Fuzzy DEMATEL-ANP-TOPSIS Framework, the most preferable RES alternative is Solar Energy. This is followed by Wind Energy as the second-best RES alternative, while Biomass Energy emerges as the least preferable RES alternative within the evaluated RES set under evaluated criteria set.

Table 11. Relative Closeness, Results and Ranking of RES.

	d_i^{+}	d_i^{-}	RC_i	%	Ranking
SE	0.0102	0.0446	0.8132	100	1
WE	0.0132	0.0445	0.7707	95	2

HE	0.0100	0.0288	0.7427	91	3
GE	0.0185	0.0324	0.6368	78	4
BE	0.0147	0.0222	0.6013	74	5

5. Visualization and Interpretation of the Results of RES Evaluations

Figure 1 and Figure 2 given below present a comparative overview of the nine different results; eight obtained from the methods detailed in Section 2, Section 3.1, and Section 3.2, and one derived from This Study (TS). While Figure 1 illustrates the ranking results of the criteria set of RES alternatives, Figure 2 displays the ranking results of RES alternatives under each methodological approach. Together, these figures provide a holistic perspective on how different methodological configurations influence both criterion prioritization and alternative selection, thereby offering a richer basis for cross-method consistency analysis.

A closer examination of the comparative rankings in Figure 1 reveals that the most influential criterion across nearly all methods is C8 (Technology Requirements). This consistent prominence suggests that technological feasibility and infrastructure readiness constitute a decisive factor in RES selection, regardless of the underlying decision-making model employed. The stability of this finding across methods further indicates that stakeholders tend to prioritize advanced technological attributes while evaluating contemporary energy solutions.

Following C8, the second- and third-ranked criteria are C4 (Storability) and C10 (Accident Risk and Effects), respectively in TS. The relatively high importance assigned to C4 underscores the strategic emphasis placed on energy-storage capabilities, a domain that directly affects grid reliability and long-term sustainability. Similarly, the prominent ranking of C10 highlights the growing societal concern regarding operational safety and the broader environmental and human impacts of renewable energy deployment. These two criteria together reflect a balance between functional reliability and risk minimization, both of which increasingly shape modern energy policies.

Although intermediate ranking positions vary across the nine methods -reflecting the inherent methodological sensitivities and weighting dynamics- the majority of the results consistently identify C11 (Harms to Nature and Human) as the least significant criterion. This recurring pattern may indicate that, within the context of RES technologies, decision-makers perceive environmental and human harm impacts as comparatively lower or already sufficiently mitigated relative to other criteria. Alternatively, it may imply that such impacts are viewed as more uniform across alternatives, thereby reducing their discrimination power within the decision framework. Nevertheless, this finding highlights an important area for further investigation, particularly in policy contexts where environmental sensitivity is expected to play a more dominant role.

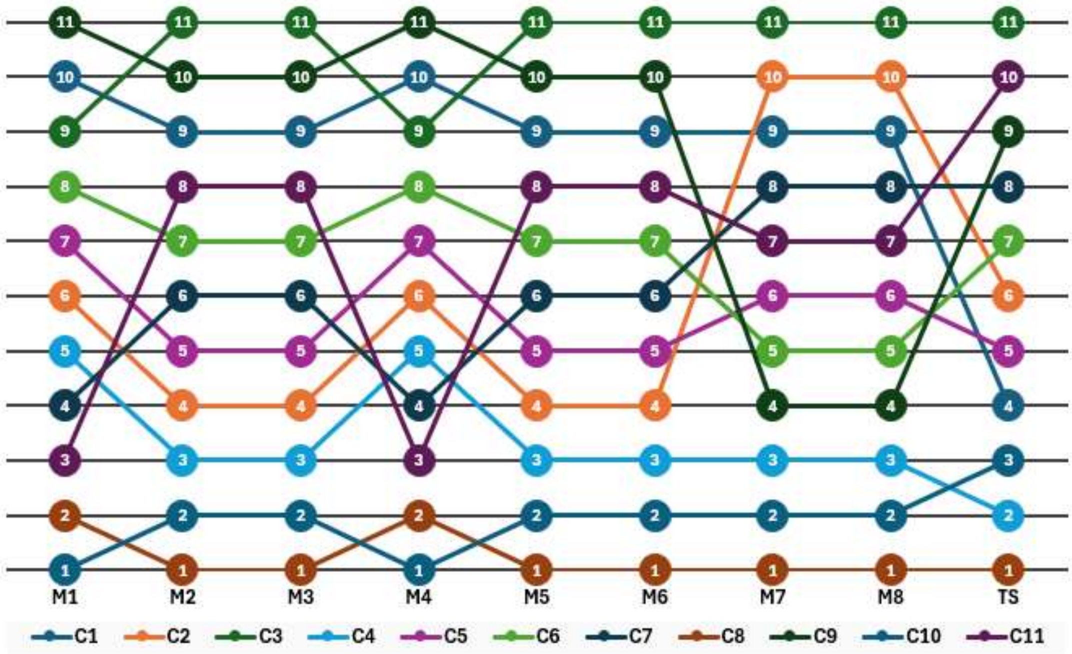

Figure 1. Comparison of Criteria Set Ranking Results of RES Evaluations with 9 Methods.

Figure 2, which presents the rankings of RES alternatives across nine different methods, reveals that Solar Energy consistently emerges as the top-performing alternative in nearly all approaches. This convergence across multiple decision-making frameworks underscores the robustness of Solar Energy’s performance profile, suggesting that its advantages -such as high availability, scalability, and rapidly decreasing technological costs- are widely captured regardless of methodological differences. The recurring identification of Solar Energy as the most favorable alternative also highlights the strong alignment of this alternative with contemporary energy policies emphasizing sustainability and low-carbon solutions.

Furthermore, Wind Energy is identified as the second best RES alternative by the majority of the methods, indicating its stable performance and relatively balanced trade-offs across RES evaluation criteria set. The persistence of Wind Energy in top rankings suggests that, while not as dominant as Solar Energy, it maintains a competitive advantage due to its technological maturity, widespread applicability, and relatively favorable environmental footprint. This consistency also points to the fact that criteria such as storability, accident risks, and technological requirements -each weighted differently across methods- affect Wind Energy less variably compared to other RES alternatives.

In contrast, the least preferred RES option is generally observed to be Geothermal Energy in most of the compared approaches. This recurring result may stem from limitations such as high initial investment costs, geographic dependency, and potential concerns regarding environmental impacts like induced seismicity. Interestingly, however, the proposed Interval-Valued Neutrosophic DEMATEL–ANP–TOPSIS Framework identifies Biomass Energy as the least desirable alternative, diverging from the other methods. This deviation highlights the methodological sensitivity of certain alternatives and suggests that Biomass Energy, when evaluated through the more detailed uncertainty representation of IVN numbers, may exhibit weaker performance under criteria such as environmental harm (C11) or technology requirements (C8). Such a finding offers a valuable perspective: while traditional methods may overlook certain deficiencies due to limited uncertainty modeling, the proposed framework may expose latent weaknesses, thereby presenting a more conservative and arguably more realistic evaluation of Biomass Energy.

Overall, the comparative analysis provided by Figure 2 demonstrates not only the general stability of rankings across different MCDM techniques but also the capacity of the proposed approach to reveal alternative insights, particularly in the lower tiers of performance. This contributes to a more comprehensive understanding of RES prioritization and emphasizes the importance of incorporating advanced uncertainty-handling mechanisms in complex energy planning problems.

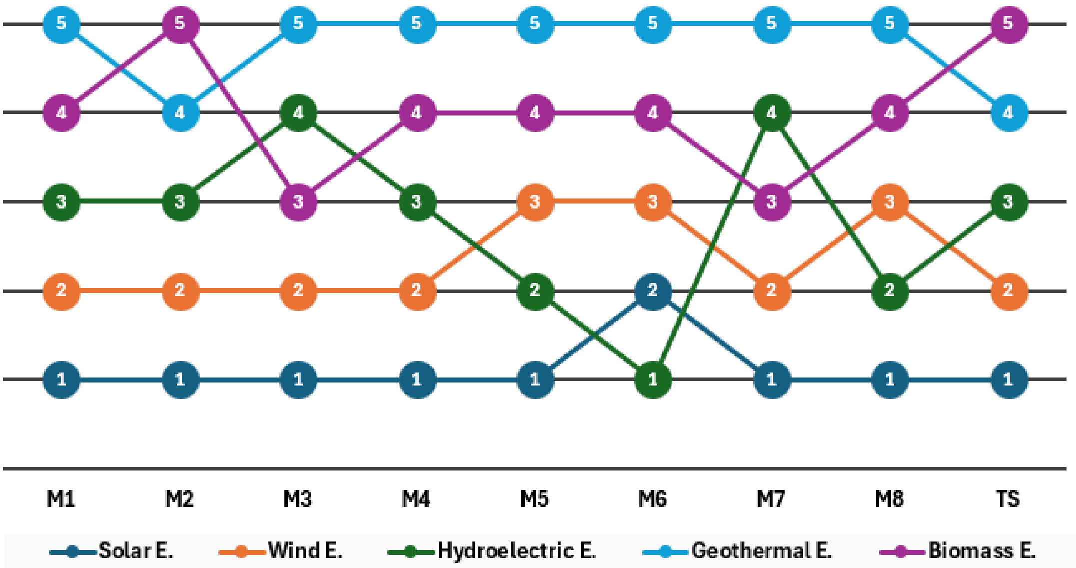

Figure 2. Comparison of Alternative Ranking Results of RES Evaluations with 9 Methods.

6. Discussions and Conclusions

This study provides a comprehensive and methodologically rigorous assessment of fuzzy-based multi-criteria decision-making (MCDM) approaches for renewable energy source (RES) selection. By benchmarking several established fuzzy MCDM methods on a common dataset and subsequently introducing a novel hybrid Interval-Valued Neutrosophic Fuzzy DEMATEL–ANP–TOPSIS framework, the research makes significant theoretical and practical contributions to the decision-making literature under uncertainty. The findings strengthen our understanding of how different fuzzy models interpret ambiguity, manage expert hesitation, and model interrelationships among criteria, all of which are critical in complex planning environments such as renewable energy transitions.

From a theoretical standpoint, the study advances MCDM research in several key areas. First, it demonstrates that fuzzy-based approaches do not behave uniformly; their ranking outcomes, sensitivity profiles, and weighting dynamics diverge due to their inherent mathematical mechanisms. For instance, distance-based models such as fuzzy TOPSIS exhibit different decision tendencies compared with compromise-based methods like fuzzy VIKOR, while hierarchical methods (fuzzy AHP) differ fundamentally from network-structured approaches (fuzzy ANP). Second, the study highlights the strengths of interval-valued neutrosophic fuzzy sets, which provide a richer representation of expert cognition by incorporating truth-membership, indeterminacy-membership and falsity-membership degrees. This creates a more granular modelling structure that surpasses the expressive capabilities of classical fuzzy logic. Third, by integrating interval-valued neutrosophic fuzzy DEMATEL, ANP, and TOPSIS into a unified framework, the study contributes a theoretically sound hybrid architecture that captures causal relationships, interdependencies, and ranking robustness simultaneously; an aspect rarely addressed in earlier research.

The practical implications of the study are equally noteworthy. Renewable energy planning involves complex and often politically sensitive decisions in which experts from different backgrounds must evaluate competing alternatives using heterogeneous information. The benchmarking results offer stakeholders a clear understanding of how each fuzzy MCDM method behaves under uncertainty, which can help energy authorities choose the most appropriate analytical tool depending on the decision context. For example, planning scenarios requiring strong causal clarity may prefer DEMATEL-based approaches, whereas scenarios requiring a robust overall ranking through alternative distances may benefit from fuzzy TOPSIS. The proposed interval-valued neutrosophic hybrid model strengthens decision integrity by combining causal mapping with interdependent weighting and transparent ranking, making it especially useful for policy development, long-term investment planning, and multi-stakeholder negotiations. Its structured and intuitive framework can support national energy agencies, regional development authorities, and private sector investors seeking to prioritize renewable energy projects under uncertain evaluation environments.

While the study contributes meaningful methodological innovations, it also acknowledges several limitations. The dataset, although carefully selected, represents a specific case context and a fixed set of criteria. In real-world settings, the importance of criteria may vary significantly across countries, climatic conditions, and socio-economic structures. Additionally, although interval-valued neutrosophic fuzzy logic enhances uncertainty modelling, the computational effort required for hybridized interval-valued neutrosophic systems increases with the number of criteria and alternatives. This complexity may pose challenges for practitioners lacking computational expertise or specialized software. Furthermore, the benchmarking does not include other emerging fuzzy paradigms such as picture fuzzy, hesitant, spherical or q-rung orthopair fuzzy sets, which could potentially provide alternative interpretations of expert hesitation. These limitations highlight opportunities for methodological refinement in follow-up studies.

A comparison with related literature shows that while numerous studies have applied singular fuzzy MCDM methods or simple hybrid approaches to RES decision-making, few have pursued a systematic benchmarking of multiple fuzzy methods under identical conditions. Even fewer studies combine causal modelling, interdependent weighting, and interval-valued neutrosophic fuzzy logic in a single framework. The present study differentiates itself by filling these gaps, offering a deeper cross-methodological insight that allows researchers and practitioners to understand not only which technique ranks alternatives differently, but also why those differences occur. In doing so, it situates itself as a methodological bridge between classical fuzzy MCDM research and next-generation uncertainty modelling techniques.

The key findings of the study can be summarized as follows. First, significant variability exists among the ranking outcomes of major fuzzy MCDM methods, reflecting their structural differences. Second, hybrid models demonstrate superior capability in capturing the multidimensional and interdependent nature of RES criteria. Third, the proposed Interval-Valued Neutrosophic Fuzzy DEMATEL-ANP-TOPSIS Framework enhances decision robustness, provides deeper causal and relational insights, and delivers more stable rankings than standalone techniques. These findings validate the methodological value of integrating causal mapping, network-based weighting, and distance-based ranking under interval-valued neutrosophic fuzzy environments.

Based on these findings, several policy and decision-making recommendations emerge. Energy planners should adopt decision frameworks that explicitly account for uncertainty, particularly during early-stage feasibility assessments where data incompleteness and expert disagreement are common. Governments and regulatory bodies are encouraged to support analytical training and software deployment for hybrid MCDM techniques, allowing for more evidence-based energy investment decisions. The hybrid model proposed in this study can be integrated into energy planning institutions as a decision-support tool to systematically evaluate RES portfolios. Additionally, decision-makers should consider complementing quantitative outputs from hybrid MCDM models with qualitative stakeholder insights to ensure policy legitimacy and social acceptance.

Future research directions are rich and varied. One promising is the incorporation of more advanced fuzzy environments, such as spherical fuzzy, neutrosophic, Pythagorean fuzzy, or q-rung orthopair fuzzy sets, which could provide even more flexible uncertainty modelling structures. Another involves integrating machine learning techniques with MCDM frameworks—for instance, using ML models to predict criteria weights, identify hidden causal patterns, or automate sensitivity analyses. Expanding the study across different geographical regions, applying dynamic decision-making models that adjust over time, or incorporating climate risk variables could further enhance the generalizability and policy relevance of the proposed framework. Finally, decision support systems and software platforms that operationalize the hybrid interval-valued neutrosophic fuzzy model could significantly strengthen its practical adoption in energy planning environments.

In conclusion, this study offers a comprehensive benchmarking of fuzzy-based MCDM approaches and proposes a robust hybrid interval-valued neutrosophic framework that advances both the theory and practice of RES decision-making. By integrating causal, relational, and ranking mechanisms within an uncertainty-sensitive structure incorporating truth-membership, indeterminacy-membership and falsity-membership degrees, the research provides valuable tools and insights for guiding sustainable energy transitions on local, national, and global scales.

Author's Note: This study was derived from the thesis of Çelikbilek (2016) (Thesis id: 398616) by using the dataset presented in the original thesis.

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